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The Role of Artificial Intelligence and Machine Learning in Financial Processes: Innovations and Impacts on Accounts Payable, Accounts Receivable, and General Ledger

Anil Kumar Komarraju[1], Veera Venkata Satya Chalamayya Batchu[2], Vishwanadham Mandala[3]

[1]*System Architect, anilkumarkomarraju@yahoo.com*
[2]*Senior Enterprise Architect, b.chalamayyab@yahoo.com*
[3]*Data Engineering Lead, vishwanadh.mandala@gmail.com*

This paper, issued by the International Group on Artificial Intelligence (Groupe International pour l'Intelligence Artificielle - IA), is the result of the research work done by a specially set up sub-group of GIIA, named GIIA-Fin. This review provides various insights into AI and machine learning and their impacts on finance processes. Artificial Intelligence (AI) and Machine Learning (ML) have penetrated our daily lives mostly for entertainment but also for the most sensitive areas, albeit in silo applications in sectors already benefiting from mature 0.1 versions of AI/ML like speech, face, object, or genius ID recognition. In the context of business and accounting, AI/ML is significantly and rapidly impacting the financial function in many areas such as the French Ciel Unique or the UK Transforming Audit for Tax purposes. This list keeps getting longer as businesses combine digitization initiatives with the data-driven wave. Indeed, the latest advances in AI/ML algorithms, transfer learning, distributed technologies, big data, and the cloud allow immediate economies of scale, directly impacting AI/ML developments for business.
From this strategic move on, there is no more choice for top management and consultants as AI-related capacities are broadly implemented in developed countries. In return, there is no more choice for auditing either: changes in AI/ML algorithms will require them to adapt top-down their 'financial sapience', - including a new field that could perhaps be named 'Artificial Intelligence Auditing' to tackle all AI-related financial risks - and bottom-up to engage their clients and attract the best financial talents to employ state-of-the-art accounting software. There's a general agreement between knowledgeable actors that only human judgment fulfills necessary explanatory mitigation whilst searching for fraud and assessing risk functionalities when non-human agents such as AI/ML algorithms distribute financial transactions over accounts such as Don Quixote's three nuts. This brief aims to help accounting professionals and business users with evaluating and identifying the best use for AI/ML applications within these transformational times of science when it unavoidably questions the usual practices punishing skepticism like hammers flapping on one another. Decision-support systems and their assisting machine learning 'whys' could help align accounting service providers' interests to client interests by identifying many not obvious patterns

in their clients' noisy data.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Finance Processes, Financial Function, Digitization, AI/ML Algorithms, Transfer Learning, Big Data, Auditing, Accounting Software.

1. Introduction

This text outlines how artificial intelligence (AI) and machine learning (ML) impact financial processes. We provide practical insights on the implementation of AI and ML tools, focusing on specific financial processes such as accounts payable (AP), accounts receivable (AR), and GL close, as well as the future of digital finance, such as intercompany accounting. Given our practitioner advisory and data science background, and hands-on experiences in defining, improving finance processes, and innovating accounting, we develop practical AI and ML concepts that are relevant to small, medium, and global companies. The goal of our study is to show that innovations in data, AI, and ML concepts can have tangible benefits in reducing accounting errors, improving accounting document efficiency, lowering transaction costs, and shortening financial close with higher data integrity.The introduction identifies the role of AI and ML in the evolution of accounting, specifically in finance processes such as accounts payable, accounts receivable, and general ledger close along a typical finance process flow. In the section "What is AI," we outline the foundational skills and build from this starting point with the question "What about Understandability?" Simply put, machines show promise in enhanced error detection capabilities because they rarely make the same mistakes twice. RAREs and Risk 4 require human decisions. With this philosophical groundwork, as well as an understanding of the limitations of financial process operations, we present an accounts payable and accounts receivable process alongside Close as an illustration of accounting operations on data with tools of R, ML, and AI managing data.In addition to enhancing error detection capabilities, AI and ML tools are instrumental in streamlining financial processes such as accounts payable (AP), accounts receivable (AR), and general ledger (GL) close. These technologies enable automation of routine tasks, reducing manual intervention and thereby minimizing errors. By leveraging data analytics and predictive modeling, companies can achieve greater efficiency in managing financial documents and transactions. Furthermore, AI and ML contribute to the acceleration of financial close processes, ensuring higher data integrity and accuracy. As the financial landscape continues to evolve, the integration of these advanced technologies offers significant opportunities for small, medium, and global companies to optimize their accounting operations and achieve tangible improvements in overall financial performance and decision-making processes.

Fig 1: Challenges with the Traditional Cash Forecasting Methods

1.1. Background and Significance Artificial intelligence (AI) and machine learning (ML) are increasingly discussed topics in the business world. Many publications, including both scientific papers and industry reports, focus on the identification of innovative business processes empowered by these technologies in different departments or business units. At the same time, fewer articles focus on the impacts of these innovations (or more generally, the impacts of the use of AI and ML) particularly on finance departments and on the performance of financial processes. This paper aims to bridge this gap in the literature by identifying, discussing, and illustrating innovations empowered by AI and ML in financial processes, with particular attention to advancements in the field of accounts payable, accounts receivable, and general ledger functions. The use and implications of AI and ML in the financial processes are presented taking into account the digital transformation of the most relevant information systems as well as the opportunities empowered by the use of emerging technologies.The increasing availability of large amounts of data, which represent mostly transaction data typical of accounting records, contributes to the diffusion of these technologies in each context in which their use, potential impacts, costs, and benefits derived from their use need to be explored and addressed. Among technological advances in the field of AI and ML, the impressive results and the ability to support decision-making present the potential to generate competitive advantages for businesses. Their diffuse use, moreover, has provided economic advantages. The forecasting of market trends significantly improved the management of stock and reduced margins of error in the credit decision. The introduction of big data tools is the only solution for timely customer segmentation and predictive analysis. Good practices benefit from the ability of these technologies to interact efficiently with the customer, to draw up a strategy, to modify the processes, to redesign the organization and the human resources management, and also to face the risk of transition effectively. On the other hand, there are considerable risks as well. Their functioning is autonomous and underlying machine codes, difficult to understand, and only accessible by computer algorithms not by man. Perhaps they are not able to develop genuine intelligence, but they are avant-garde software for solving particular issues. Their ability to interpret and generate information is based on deep learning that does not have an intuitive meaning and its behavior may not be understood in detail by the programmers who implemented it [4].

1.2. Research Objectives

As a contribution to existing research aimed at treating the subject in greater depth, this chapter presents new and innovative possibilities of technological applications integrated into money management aspects, aggregating the capacity of judgments, optimizing processes, safety, and forms of financial auditing. Since automation with the help of artificial intelligence and machine learning tools should not be restricted to just accounting, it promises more efficient results without the risk of error and allows financial managers to maximize the time devoted to strategic curve issues.

The question that guides this study is: what are the possibilities of technology applications in financial management at the payable and receivable, cash, and management levels, and which applications are most promising in the respective areas?

For this purpose, the achievement of the following research objectives is foreseen: - To search or classify the research in financial management integrated with artificial intelligence that could help managers outline time windows or synchronize processes that could increase competitiveness and create safer environments. - To design a concept of technology integration used in financial processes at payable, receivable, cash, and management levels. - To reveal the potential risks and problems that could impact the integration of presented innovations of artificial intelligence and machine learning solutions in financial management at the payable and receivable, cash, and management levels.

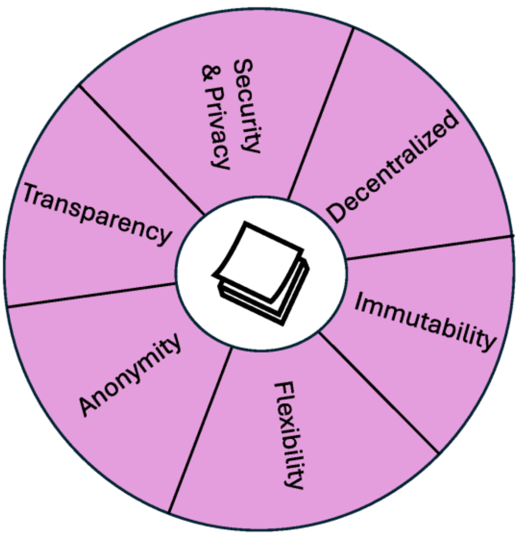

Fig 2: Basic Characteristic Possessed by a Blockchain Network

2. Foundations of AI and ML in Finance

The modern era of financial accounting systems (FAS) that compile and report the financial results of business activity tied to activities in business units and describe the financial state of the organization begins with T-accounts and the ledger book according to Luca Pacioli. Centuries of optimization followed before David Stone restructured the financial accounting function with modern computational technology to bring significant automation to recording in the ledger, reporting, and reconciliation with the introduction of the financial accounting system software market. This foundation has evolved as Enterprise Resource Planning (ERP) systems became the integration hub for business functions, and business units, and is a source for analysts to understand financial status by aggregating data into a reliable and audited production process. To accomplish these strengths, FAS relies on well-structured data to populate the books of record, and this data structure limits the flexibility to deliver incremental automation value by pre-processing recording, reporting, chart definition, and competitive processing via fear of unleashing data inaccuracies, lack of comparability, and violation of internal controls.The lineage of artificial intelligence (AI) and machine learning begins with Turing and Shannon harnessing the power of computation to address military strategy in the 20th century, as several mechanical simulation and learning paths were espoused before the successful creation of a chess-playing machine for the New York World's Fair in 1948. The present wave of increased data volume capable of fitting complex computation models and immensely scalable massively parallel computational capabilities has produced several data-derived models that are integrated into business processes, including finance.

2.1. Definition and Concepts In recent years, there has been an ongoing shift of corporate mindsets and priorities toward a more productive, intelligent, and automated finance organization. As companies become increasingly excited over the possibilities of enhanced analytics, productivity, and decision insight, intelligent finance automation, enabled by AI and machine learning, is touted as a "must-have" for any leading or aggressive enterprise. As a result, we are now at the tipping point where businesses and their finance organizations are finally able to harness the power of new AI and machine technology.At the most fundamental level, intelligent finance is the product of a multitude of technological advancements, including mature RPA, AI, machine learning, natural language processing (NLP), and blockchain - often in combination with a broad mix of other modernized technologies, such as distributed ledgers, predictive and prescriptive analytics, and big data. Together, these technologies enable enterprises and their finance organizations to now take a broad and long-awaited step toward much more complete business and process automation, while simultaneously providing more valuable intelligence, knowledge, and insights.The real benefits of AI and machine learning in finance are now being made possible as the underlying cost, scalability, and complex automation challenges in these technologies are being addressed. Companies are recognizing that considerable business value can be derived from a multitude of intelligence providers, such as cognitive technologies. Pragmatic companies are now leveraging AI and machine learning for lower-level and broadly repetitive tasks, like rules-based analytics and machine-based learning, rather than waiting for high-end analytics insights or advanced predictive and prescriptive forward-looking guidance.With less effort and cost devoted to retooling the underlying technology, days are gone when enterprises are only thinking of AI and machine learning as complex technology implementation challenges to their intelligent finance agendas.

2.2. Applications in Financial Processes

The lack of appropriate semantic knowledge is becoming an increasingly important problem in finance. Semantic analytics and the development and application of semantic knowledge bases are the key technologies making it possible for computers to contribute their natural strengths (accuracy, speed, and spread) to the human goal of economic decision-making. Semantic knowledge bases are large databases structured to enable the meaning of information and its mathematical properties to be easily retrieved both by direct interrogation and by recursive algorithms. The development of these assets and of the software that exploits them is the task of the new field of financial semantics.Currently, the capabilities of semantics and computational linguistics in semantics and their application to finance are limited, but the pace of progress is accelerating. These are primarily engaged in content classification. More sophisticated uses evolved from investment theory, where stock market indices are provided with the structure and connectivity properties of mathematics, physics, and biology, leading to various subtle financial time series patterns. Finance has a tradition of using unstructured text analysis to frame problems and suggest solutions. Indeed, at some prominent meetings of the several research institutes devoted to finance, analysts constantly discuss the semantics of the financial occasion and propose more activities of content classification aimed at a better understanding of the financial language. Financing research assists in refining unsupervised relations, generating them to join detected associations that could be of interest from an economic point of view, and allowing users to analyze lists to discover useful operational rules. These more advanced applications were the result of the general availability of the necessary ontologies, which led programmers to modify the data processing. During the last decade, thanks to cooperation between the BI Research Group, dedicated to ontology-oriented programming, and many industrial research laboratories, pioneers that have developed advanced research tools made their knowledge a crucial asset, and automatic institutions have been able to create more sophisticated ontologies [8].

3. Innovations in AI and ML for AP, AR, and GL

In this chapter, we will expand on the specific innovations that have already occurred and are in the early stages of transforming AP, AR, and GL. AI and ML are already playing significant roles in the enhancement of these financial processes. However, we are in the early stages of the large-scale deployment of these capabilities. The transformation that will occur over the next few years will be characterized by real-time processing and greater accuracy where the AI and ML cognitive engines will be trained to detect exceptions, propose adjustments, understand the context, and power more strategic processes. These innovations in Cognitive Applications are still in the developmental stages although the results examined in this chapter indicate a better understanding of the challenges associated with these financial processes. The results also define the path forward for the development and maturity of these cognitive applications.

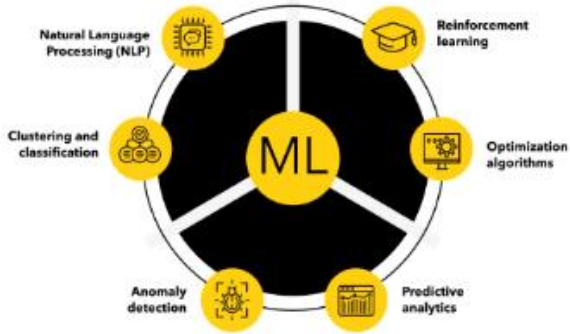

Fig 3: ML Algorithms and Techniques That can be used in Fintech

As depicted in Table 1 for AP and Table 2 for AR, AI, and ML are represented by a framework that consists of the following stages: planning, extracting, understanding, learning, forming, and interacting. The framework represents a set of steel threads that articulate the key innovations of AI and ML for the indicated financial process. This proposed framework reveals the perfect world where AI and ML successfully guide the financial process end-to-end, in line with current achievements from early best practices. Based on this understanding, it is then plausible to stand back and consider the personas involved in the process, as shown in Table 3 for the GL. These personas are at the helm of this perfect world. AI and ML in the context of the financial process have a certain degree of autonomy and supervision of exceptions and innovative liabilities. The personas must devote time to explain controversial mortgages, propose adjustments, rectify discrepancies, support decisions made by less experienced people, and more.

3.1. Automation and Efficiency Improvements The new AI and ML systems have the potential to deliver efficient, flexible real-time, and online financial process innovations in supply chain management transactions. Many tiring manual and human judgment tasks can be replaced with efficient decision-making AI and ML monitors by automating the data capture-monitoring efforts. The contemporary process benefits of workflow automation and integration resulting in efficiency are presented in section 3.1.1. We summarize the workflow optimization literature and develop hypotheses about conditions supporting and resisting automation efforts. Our subsequent study is a convenient sample-driven measurement of these effects. In this context, qualitative hypothesis development focuses on the role of various internal control and efficiency tradeoffs at the heart of process workflows to be automated.

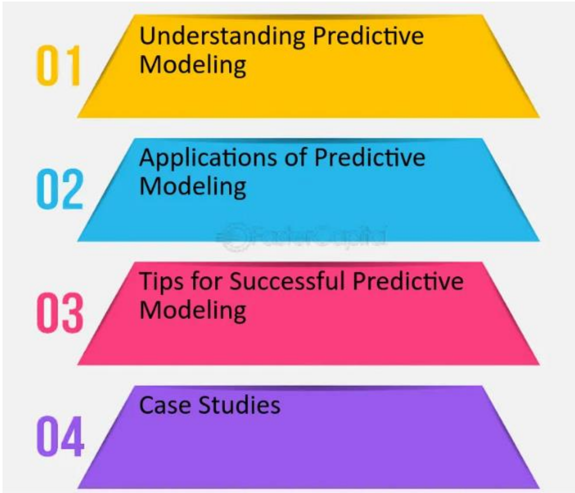

Fig 4: Forecasting Customer Behavior using Statistical Techniques

We look for more complex and efficient automation choices. We summarize and report contemporary production technology decisions about whether to automate accounting responsibilities. Data-rich environment choices about automated workflow features, including expenditure decisions about the level of detail and types of data used to automate workflows, reconciliation responsibilities, variances, efficiency responsibilities, real-time monitoring nature, and decision timelines. We template and summarize how contemporary control, efficiency, and monitoring technologies are combined with the location of source documents and other transaction data to automate the workflow of future monitoring examples of several financial reporting workflows: a chosen accounts payable process. Our paper seeks to rigorously consider the AI and ML change toward continuous accounting, real-time monitoring, and online transactions.

3.2. Fraud Detection and Risk Management

Fraud detection refers to the technology and techniques that businesses use to uncover risky financial transactions. Traditionally, fraud detection is financial-system-centric, where fraud is detected through understanding the patterns of account activities, especially transactions. Financial systems collect and store tremendous amounts of data on the daily behaviors of individuals. This is, in effect, user-account information: the data tracks how individuals act with their accounts. Financial fraud detection works by looking at the visible patterns of daily behavior of each user and then using 'flags' or suspicious patterns to signal unusual behavior. Non-financial data is equally important in a comprehensive view of fraud detection.

Besides, risk management in a business or business enterprise is a process that deals with the identification, assessment, and prioritization of risks, followed by the coordinated and economical application of resources to minimize, monitor, and control the probability or impact of unfortunate events or to maximize the realization of opportunities. Both financial and non-financial data should be used in risk management. All different types of risk call for different sources of data. For financial risk, there are equity risk, market risk, credit risk, liquidity risk, and operational risk; non-financial risk, reputational risk, strategic risk, operational risk, regulatory risk, and environmental risk are common attributes, to name a few. Each type of risk can be effectively managed by leveraging business-oriented financial and non-financial data through machine learning models [12].

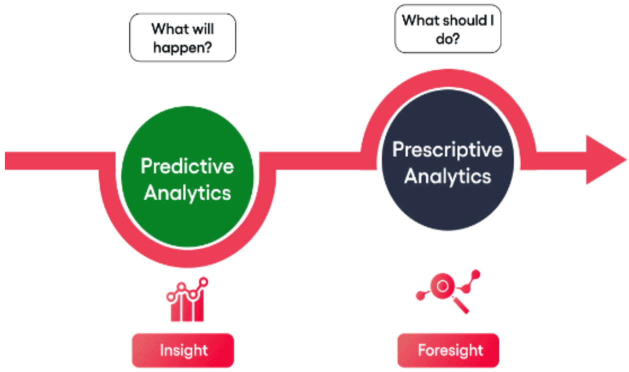

Fig 5: Different Approaches used in Credit Risk Management

4. Impacts of AI and ML on Financial Processes

This section provides insights on specific impacts related to AI and ML innovations in financial processes. Although AI and ML tools and techniques support all financial processes, we exhibit their specific use in the accounts payable, accounts receivable, and financial account (or even general ledger) processes. AI and ML tools and techniques impact the financial processes in different ways. We divide the impacts into four main categories: reducing human efforts, increasing efficiency, reducing errors, and improving insights.Reducing Human Efforts: AI and ML support employees' work by handling time-consuming tasks (especially manual and error-sensitive ones), so that the workforce can focus on strategic and value-adding tasks.Now we explore the accounts payable process. AI and ML tools and technologies can support activities for each phase of the accounts payable process. These include invoice data capture and extraction, digital data matching and validation, invoice processing, payment procedures, accounts reconciliation and resolution, tax recognition, and categorization of non-PO invoices. In summary, AI and ML tools automatically capture and extract relevant data from invoices and enable rapid invoice reviews. In case of exceptions, errors, and mismatches, the process needs the intervention of accounts payable specialists who can research, communicate, and solve issues. Automatic processing can avoid human errors.AI and ML technologies enable the identification and communication of improvement areas in the accounts payable process. They can generate relevant insights by analyzing the already existing data, even the unexploited ones. These insights can speed up and enhance the decision-making in AP-related activities. They lead to increased cost savings for companies and accurate information for better financial control and business support [16].

Fig 6: Intelligent Document processing

4.1. Improved Accuracy and Decision-Making One of the greatest characteristics of artificial intelligence and machine learning applications is the ability to analyze and consume a very large amount of data, which allows them to make good decisions. This has an impact on financial processes, such as accounts payable. For example, when choosing to approve payments, making a wrong decision can generate monetary impacts and goodwill loss. Up to a certain point, accounts payable processes can help analyze patterns and support the decision of payment. Giving autonomy to machines to make decisions after observing these patterns can be a good way to avoid some types of fraud.In accounts receivable, this application can be seen in decision support systems that help decide the best time to send an invoice or notify the company about possible insolvencies or inability to pay. Here, too, you can see applications in decision support systems that help accountants better manage general ledger processes. In decision support systems, accountants provide input and receive output from artificial intelligence and machine systems independent of accounting processing systems. This is very common in accounting because the accounting data processing system supports the recording and monitoring of transactions but doesn't usually offer help with financial analysis, reports, and synthesis of information.

4.2. Enhanced Customer Experience Depending on the capabilities of the machine learning software, it can make specific recommendations that would mathematically maximize the chances of the customer completing a purchase on the first try. So instead of training customers on how to use the features of the software, the software should train users on the features of the product or service. In other words, instead of making adjustments at the front end of the process, get rid of artificial bottlenecks that slow down the "No" response. If your line of business is consumer retail, one of those things is almost always customer service. So instead of scrambling to reduce refunds, return rates, chargebacks, gate declines, abandonment, customer complaints, and other measures of dissatisfaction, coach users to respond in ways that reduce the likelihood of a problem developing in the first place.This, by definition, will increase the accuracy of predictive models while at the same time reducing the common root-cause problems that contribute to inaccurate forecasts. Out at the leading edge of financial process transformation, the same IBM Watson machine learning services that you use to train customer service personnel can be used to train front-office businesses with predefined custom models that have specific applications, such as detecting indicators of fraud or material misstatements of financial statements before the fact. Machine learning can be used to detect errors quickly and either promptly address them or at least measure the likelihood of harm to financial reporting. Moreover, simultaneously monitoring all of the millions of transaction records that funnel through an AP or AR process. Even the strongest predictive models can be affected by feedback loops that call negative attention to particular customers or vendors, causing a business to inadvertently crowdsource their fraud limit to machine learning [20].

5. Challenges and Ethical Considerations

Data-driven AI technologies need to handle, manage, and provide crucial data to train a machine learning model from both the Internet and public data sources, as well as private data sources. A private company's financial and administrative data, such as supplier invoice details, is considered to be sensitive and valuable information. During these processes, this information is generally accessible via documents.Ethical concerns arise when machine learning algorithms train the model using internet or public domain documents, or when a company voluntarily shares its data with the machine learning technology company. An ethical burden is provoked when the personal data of individual employees and the data privacy of business documents are handled during the selection, procurement, development, and evaluation of AI technology.Organizational principles and legal and ethical consideration of how a machine learning technology company collects, limits, and protects sensitive data and personal information are key for the company management, legal compliance, IT, and procurement departments, as well as for the company's data protection, HR, and GDPR data privacy officers.In addition to the practical aspects of creating a process at the confluence of accounts payable, accounts receivable, and the general ledger, other challenges also exist. These challenges fall into several categories, such as ethical challenges, including issues related to privacy and consent; governance transparency and bias, including the need for transparency and a governance model, as well as bias avoidance and principled system design; managing data, including the need to organize and tag data, create datasets, and train models; and worker displacement, which is an important response to consider. Among these issues, the ethical concerns that AI raises are primary [24].

5.1. Data Privacy and Security The driver for focusing attention on the privacy and security aspects of AI and machine learning models is the importance of keeping sensitive personal information private and secure. Some accounting and finance processes, however, are driven by the use of sensitive data. Accounts payable and accounts receivable processes, for example, comprise a large portion of a company's finances. Machine learning models that use the similarity of payments as a way of detecting anomalies become trained (and hence rely on) the distribution of these payments. If sudden changes in behavior occur, additional training to keep the model current may require the inclusion of these payment changes for the improvements to occur. Similarly, financial planning and analysis commonly make use of human resource data, driving salaries, benefits expenses, and tax payments. If activity in the form of hiring, laying off, promotions, and other workforce changes occurs, this process requires additional training for the model to anticipate its occurrence in the future.Moreover, the sensors being used to track things such as activities, location, emotion, vitals, purchases, and lifestyle have the potential to reveal a lot about a person, their work habits, and their health. For the data scientists creating these models, there can be a level of intimacy with the individuals being affected by the data and the predictions that researchers could not have previously anticipated. Hence, the development of protocols for managing the privacy and security of personal data is critical. One paramount necessity is explaining how personal and sensitive data are being used and why data privacy and security concerns have been addressed in the process. Backend mechanisms to safeguard information include the pseudo anonymization of the data, removal of unnecessary data from the system post-training, and demonstrating that even if the system were to be compromised, the amount and sensitivity of the data "exposed" is minimal if not useless. Research is also necessary to develop models that do not rely on sensitive data to the same extent to minimize the exposure of personal and sensitive data.

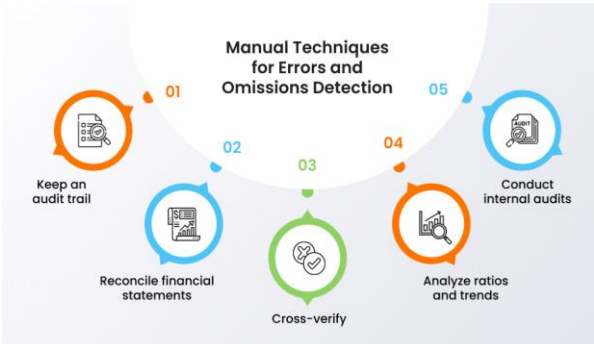

Fig 7: Manual Techniques for Errors and Omissions Detection

5.2. Bias and Fairness in AI Algorithms

Bias in AI algorithms deserves attention. Just as AI algorithms can efficiently manage the content and context of big data, the potential access to flawed or unfair data may also produce mass-production-sized flawed or inequitable results. Part of making AI algorithms transparent and accountable includes ensuring the data these algorithms are trained on is also fair, and there are reasons to doubt its fairness [28].

Crispino et al. (2019) investigated two audit management problems faced by firms conducting external audits. This is an example in the accounting and finance arena and not the ethics in accounting classes. In the present setting, client firms hire external audit teams to ensure the preparation of their financial reports is fair, accurate, and prescribed according to generally accepted accounting principles, which collectively serve as a public signal for both brooding and savvy investors. These quality signals, along with the proactive outreach of the financial markets and companies, drive working in the media, including financial analysts and news reporters, are gained with timeliness and ceiling accuracy. These quality signals help to facilitate resource allocation decisions by providers of capital.The commonly designed measure, which is normally the first choice decision made on the extant financial quality of news reports or analysts' earnings forecasts, is a high or low-performing condition. In this Split Management problem, a consulting firm that is using a legally required auditing report about a contingent (e.g., the Securities and Exchange Commission is a public entity, or the Bank of Germany for its security is a requirement). Split from the other dimensional client management consulting firm, requires a reasonable contingency of the audit engagement as a growth opportunity to restrict its activities. If market participants acquired information about the relative audit quality of the Split Management client from their decision to audit with a particular audit firm (e.g., short-selling costs are postponed, increased earnings management was required to erase the firewall of the Sarbanes Act for a financial reporting requirement), then short-run financial impairment appears to exist as an advantageous outcome to the Split Manager. Short-term financial impairment does not help, and may even hurt, the user of the financial report.The trigger for this Split Management problem is a capital base, which is largely established by balance sheet quality information, compromised by income quality information. After doing Split Management, the consulting firm may strive to make capital duration contracts (e.g., investment earn-out 'equity-market' valuation model triggers; loan tenure ranges) consistent with Split Management, and the problem confidentially survives. In this Split Management problem, financial accounting data contribute to the solution of a resource allocation problem. Data from BEA and COMPUSTAT document the impact of the Tax Cut and Job Act of 2017 on capital asset investment-related impairment of the information quality signals. Data from the Reuters News Archive are used to document that the asymmetry of market reaction to news publications supports that short-term financial impairment is an important regression result. The new empirical evidence of audit cost, particularly the increased need for Split Management decisions in response to recent ethics environments, supports an empirical argument for forthcoming legislation [32].

6. Conclusion

This paper has assessed the impact of AI on key financial processes such as AP, AR, and GL. The impacts range from relatively small through to the major transformation of the financial system, including the radical automation of the entire end-to-end process of SD. The unique features of financial processes and their distinctive priorities have been highlighted and revisited. The fundamental accounting perspective conceptual basis includes accounting objectives, accounts and journal entries, information, and accounting-specific technologies. AI and machine learning - oral history - journal history reviewed for the financial profession has been included. The fundamental accounting triangle relationship among cash, revenues, and receivables has been extended in the context of financial innovation with a significant AI element, i.e. AR financed by the assignment of the purchaser credit claim or factoring. Advances in artificial intelligence and RI in AP and GL were identified as preparatory examples. The timeframe and research implications (how and why studies) were outlined from a wider context of AI and the autonomous enterprise. Areas for future research were identified and material for extension work was identified.

To sum up, this paper has highlighted certain salient features of financial processes. It has indicated various substantial impacts in terms of both the role and the advent of financial innovation(s) in enabling these emerging new kinds of financial processes. The aim has been to illuminate what may be distinctive in the developments, requirements, and priorities of the innovation trajectory considering financial processes. The innovations are unveiled through illustrative examples from the commercial sector where AI-based research and development projects have led to advances in financial processes. A coherent framework that adds value by recognizing the key role played by accounting has been developed. Central to the innovation sequencings and dependencies analyzed has been a perspective on how digital technologies have already affected and will continue to facilitate the financial processes. The aim has been to move from a deterministic consideration of the impacts of artificial intelligence on the least affected financial roles with value to the consideration of all financial processes with values - as they are currently defined and as the artificial intelligence revolution unfolds for the accounting profession. The fundamental considerations involved help achieve a clearer view of the standing of financial processes in the general AI revolution that otherwise arguably overshadows them to some degree [36].

6.1 Future Trends

As the realization of automation technologies is currently being mainstreamed in finance, research has expressed multiple paths for the future outlook and possible outcomes. One area of uncertainty is the actual implementation of the technology, soberly noting that if the rollout of RPA follows previous software deployments, despite the hype it will fall short of expectations and potential. In contrast to AI and ML applications on a plane of typical productivity, outwardly poised to revamp systems into a level of intelligent systems surpassing traditional automation trajectories, much of this guidance is speculation but generally nods to the current and accelerating opportunities within the marketplace. It is feared that the only requirement of RPA, its ease of embedding within legacy software, doesn't lead to 'meaningful process improvement'.6.1.1. Intelligent Automation There is recognition that there have been potential difficulties incorporating RPA into existing systems. Limitations of (early-stage) intelligent automation technologies are conspicuous in the latency of data processing and in the rigid, rule-based processes into which RPA is being integrated. Furthermore, rudimentary programming could curtail the software's adaptability to more complex operations. There have been suggestions that intelligent automation, of which RPA is a component, presents a means to utilize human talent more strategically by offloading dull and repetitive activities onto networks. It has been estimated that intelligent automation could affect a 35% cost reduction, 60% accuracy improvement, 42% product delivery, three times faster throughput, and twice the capacity when rendered into a software robot. AI was conceptualized as the major contributor to such an operation. With a combination of technologies, the finance function could undertake period-end reporting solely by exception, assistive technology for business operations, not far from industry presenters who describe positions shared with software robots and indicate that the software either 'removes the monkey off their back' or 'the software does 60-70% of their work' [40].

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