World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

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Artificial Intelligence (AI) in working capital management: Practices and future potential

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World Journal of Advanced Research and Reviews, 2024, 23(01), 1436–1451

Publication history: Received on 08 June 2024; revised on 15 July 2024; accepted on 17 July 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.23.1.2141

Abstract

This study delves into how artificial intelligence (AI) transforms working capital management by addressing the limitations of traditional methods. The focus is to critically review research publications, case studies and industry reports using qualitative research methodology to examine how AI improves operational efficiency and decision-making in this area. The study demonstrates the practical application of advanced machine learning algorithms and big data analytics in optimizing inventory management, enhancing demand forecasting and improving cash flow predictions. A thorough review of recent research and case studies reveals additional benefits, including automated reconciliations, debtor risk analysis, accelerated cash inflows, invoice processing and proactive working capital management. Despite challenges in integrating AI with legacy systems, the potential for substantial improvements in financial health and operational efficiency is significant. The study also suggests future research directions, such as developing comprehensive AI-driven applications for broader working capital considerations, creating empirical validation frameworks for model performance and addressing ethical considerations to fully harness AI's potential in optimizing working capital management.

Keywords: Financial Management; Artificial Intelligence; Machine Learning; Working Capital; Accounting Innovation; Automation; Technology Integration

1. Introduction

1.1. Understanding the Traditional Working Capital Management

Working capital, which includes cash, inventory, accounts receivable and accounts payable, represents the funds necessary for day-to-day operations. Its effective management is crucial for businesses' financial health and operational efficiency across various industries. The typical traditional working capital management strategy emphasizes the maintenance of adequate liquidity to meet short-term obligations while optimizing cash flows. There is an emphasis on conservative practices, such as maintaining high cash and inventory levels, to mitigate risks associated with market uncertainties and economic fluctuations, ensuring operational stability and minimizing the need for external financing.

Businesses in traditional strategies focus on various aspects of working capital. When managing inventory, they strive to find the right balance between holding costs and stockout risks ensuring optimal inventory levels, meet customer demand without excessive costs and efficiently coordinate orders by adhering to minimum quantities and leveraging economies of scale (Porras & Dekker, 2005). Accounts receivable management involves establishing credit policies to ensure timely invoice collection and minimizing bad debt risk. Similarly, accounts payable management optimizes

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payment terms to maintain supplier relationships while maximizing cash availability, efficiently managing outflows and negotiating favorable terms with suppliers (Jordan et al. 2024).

Financial ratios that assess a company's liquidity and financial health are central to traditional working capital management. The current and quick ratios are two primary metrics businesses and financial analysts employ. The current ratio, calculated as current assets divided by current liabilities, measures a company's ability to meet short-term obligations with its current assets (Higgins, 2023). A ratio of one and above indicates a healthy liquidity position. The quick ratio, also known as the acid-test ratio, refines this assessment by excluding inventory from current assets, focusing on assets that can be quickly converted into cash (Pandey, 2017). This metric offers a more conservative measure of liquidity, emphasizing the immediate availability of cash equivalents to cover short-term liabilities.

Cash conversion cycle (CCC) analysis is another essential tool in traditional working capital management that indicates the time it takes for a company to convert its inventory and other resources into cash inflows from actual sales. It consists of three key components: days inventory outstanding, days sales outstanding and days payable outstanding. By optimizing these components, businesses can minimize the CCC, thereby reducing the amount of capital tied up in operational processes and enhancing overall liquidity.

Although these traditional strategies offer a framework for maintaining financial stability and liquidity, they highlight the trade-offs between liquidity and profitability, as overly conservative approaches can limit growth opportunities and reduce returns on invested capital. As markets evolve and technological advancements reshape business practices, companies must adapt to contemporary demands and challenges.

1.2. AI in Broader Financial Management

AI's application in financial management fundamentally transforms corporate operations and decision-making. Integrating advanced machine learning algorithms, big data analytics and automated systems has significantly improved the accuracy of financial information, business forecasting and investment strategies. AI facilitates real-time analysis of extensive datasets, uncovering patterns and trends often missed by human analysts, thereby enhancing decision-making efficiency. Li et al. (2023) and Oyeniyi et al. (2024) examine the significant impact of AI on financial management and reporting, highlighting its influence on functions such as forecasting, financial analysis and data-driven decision-making processes.

Predictive analytics applied to financial forecasting and planning leverages statistical algorithms and machine learning to predict future outcomes based on historical information and trends. With predictive analytics, companies can forecast future cash flows using both historical company data and broader industry data. Unlike traditional financial forecasts that require manual adjustments when circumstances change, AI-driven forecasts can automatically recalibrate based on new data, ensuring that forecasts and plans remain accurate and relevant (Manyika et al. 2011). Furthermore, generative AI can create contextual commentary without manual intervention to explain forecasts and highlight key factors driving predictions.

Effective cash flow management is a top priority for CFOs and AI is invaluable in this area. Traditionally, compiling the vast amounts of data necessary for accurate forecasts takes time and often leads to errors. Predictive analytics and machine learning hone this process by continuously compiling data from all relevant sources, enabling faster and more accurate cash flow forecasts. AI-driven cash flow management allows for proactive decision-making to maintain healthy liquidity levels, such as utilizing excess cash for early payment discounts or reinvestments and reassessing loan positions during tight liquidity situations (Raheman & Nasr, 2007). Additionally, AI optimizes working capital by applying appropriate early payment incentives based on market conditions and payment history.

Traditional models of expense management are inefficient and error-prone, with finance teams struggling to manually review each expense for compliance. Common errors include duplicate payments, missed payments, incorrectly applied payments and other issues. AI significantly reduces complexity and errors while accelerating the overall expense-related process. Through optical character recognition (OCR), AI scans receipts and invoices to automatically populate fields such as merchant name, date and total amount. Additionally, AI automates approval workflows, flagging only those expenses needing review based on predefined rules, promoting a "manage-by-exception" culture. AI-enabled assistants can also categorize expenses, populate and file required documentation and guide compliance policies (Manyika et al. 2011).

AI also enhances various financial reporting and analysis by extracting relevant financial information, cleaning data, processing data and notifying the finance team of areas needing attention. These enhancements lead to the creation of comprehensive financial statements and regulatory reports, ultimately reducing the time and effort required by finance teams.

Overall, the innovative application of AI in financial management lies in its ability to automate processes and enhance the predictive accuracy of forecasts, as well as the speed and precision of transaction execution and reporting.

1.3. Challenges with Traditional Working Capital Management

Traditional working capital management faces several significant challenges that can significantly impede a company's ability to manage its short-term assets and liabilities effectively. This method often relies on outdated systems and manual processes, leading to inefficiencies and inaccuracies that affect various aspects of financial management, including working capital optimization. Understanding these challenges is crucial for small businesses aiming to optimize their working capital and improve overall financial health.

Manual processes and outdated systems cause delays and inaccuracies in cash flow forecasting and management, making efficient cash flow management one of the primary challenges in traditional working capital management. Dechow and Dichev (2002) and Baños-Caballero et al. (2014) highlight that poor cash flow management hinders a firm's ability to invest in profitable opportunities, affecting overall profitability. As businesses grow and transactions become more complex, the limitations of manual cash flow management become increasingly apparent.

Poor inventory management can result in either excess inventory, which ties up capital, or insufficient inventory, leading to stockouts and lost sales. Excess inventory increases costs and the risk of obsolescence, while insufficient inventory causes missed sales opportunities and decreased customer satisfaction. Achieving optimal inventory levels is crucial for enhancing liquidity and minimizing costs. This requires accurate demand forecasting, efficient tracking and timely replenishment—features often lacking in traditional methods (Wild, 2017).

Manual accounts receivable tracking can result in delayed collections, higher credit default risk and cash flow issues that further strain the financial stability of companies. Howorth and Westhead (2003) conclude that traditional receivables management practices often lead to inefficiencies and a higher risk of non-payment, impacting the company's cash flow and financial stability. For instance, the retailer Circuit City experienced significant financial distress partly due to poor inventory management, leading to excess inventory that tied up valuable capital and contributed to its eventual bankruptcy (Berman, 2009). Similarly, the fashion retailer Forever 21 struggled with managing inventory levels, which resulted in overstocked items that could not be sold at full price, exacerbating their financial issues and leading to bankruptcy (Repko, 2019).

Inefficient management of payables also presents a significant challenge. Traditional methods may not enable the full utilization of credit terms, resulting in early payments that strain liquidity. Therefore, optimal accounts payable management is crucial, involving the strategic timing of supplier payments to maintain adequate liquidity while avoiding late payment penalties. By not leveraging available credit terms, companies miss out on potential cash flow benefits that could be used to support other operational needs.

The absence of real-time visibility into working capital metrics in traditional systems presents a significant challenge, impeding the ability of businesses to make swift, informed decisions and respond promptly to evolving financial conditions. Furthermore, manual processes' routine and costly nature reduces overall operational efficiency, profitability and the capacity to manage working capital effectively (Padachi, 2006). The issue of real-time data-driven decision-making is particularly problematic for many small businesses. They often need help integrating advanced data management and analytics into their daily operations due to limited resources and outdated systems.

The identified challenges underscore the need for a robust, accurate and efficient approach to working capital management. This will enable businesses to manage their finances better, optimize operations for profitability and achieve financial sustainability. With technological advancements occurring at tremendous speeds, companies must adapt or risk falling behind their competition. Incorporating new technologies into existing legacy systems can enhance working capital management and reporting, ultimately strengthening and improving business outcomes.

1.4. Potential of AI in Enhancing Working Capital Management

Effective working capital management requires meticulous liquidity forecasting and careful planning to ensure high-quality and collectable receivables, track short-term obligations and ensure the availability of liquid assets. AI will be instrumental in addressing the challenge of producing reliable cash flow forecasts by holistically forecasting companies' working capital needs or by forecasting individual working capital components.

Albayrak Ünal et al. (2023) highlight the growing interest in applying machine learning to inventory management. These algorithms accurately forecast demand patterns and optimize stock levels, reducing excess inventory and stockout. This optimization cuts inventory holding costs and frees up capital previously tied up in excess inventory, thereby enhancing overall working capital efficiency. Perez et al. (2021) concludes that while stochastic models yield superior results regarding supply chain network profitability, reinforcement learning models manage the supply chain network in a way that is potentially more resilient to disruptions, demonstrating the promise of AI applications in inventory and supply chain management.

Accounts receivable and other current assets are critical to companies due to their significance in cash flow management strategies. Consequently, their prediction and optimization are of foremost importance to businesses. Appel et al. (2020) achieved enhanced accuracy levels in modeling the probability score of an invoice being overdue in accounts receivables practices. The study incorporated machine learning to predict invoice status, used historical and temporal features to improve model accuracy and devised an effective method to rank customers' level of default risk.

Krieger et al. (2023) discuss the application optical character recognition (OCR) and natural language processing (NLP) to automate invoice processing by extracting and categorizing data. The study examines the use of machine learning in overcoming the challenges of fully electronic invoice exchange formats. The findings suggest the benefits of machine learning for processing invoices from infrequent suppliers, as the models can identify visual and semantic cues from invoices and apply them to unfamiliar layouts.

Machine learning algorithms automate the business processes for accounts payable and other current liabilities by applying the organization’s policies for invoice validation, vendor identification, line-item matching for purchase order-based invoices, general ledger code for non-purchase order-related invoices, approval workflows and payment scheduling. These algorithms ensure invoice accuracy, detect discrepancies and flag exceptions for human review, improving processing efficiency and reducing errors and fraud risks (Tater et al. 2022). This approach contrasts with traditional accounts payable management, which relies on manual data entry and is labor-intensive and error prone. Additionally, AI optimizes AP operations by strategically scheduling payments to take advantage of early payment discounts and favorable terms with suppliers, thereby conserving working capital and enhancing supplier relationships.

The potential impact of AI on working capital management and the main components of working capital can be summarized in three key areas. First, providing accurate and timely predictions and forecasts of working capital needs, whether at a universal level or for individual components. Second, automation of repetitive, labor-intensive tasks, accelerating processes related to inventory, receivables and payables and performing accurate calculations with large datasets that would be inefficient manually. Third, AI augments human productivity by enhancing efficiency through gathering and synthesizing multiple pieces of information into a coherent narrative (Agrawal et al. 2023).

1.5. Research Gaps and Future Directions in implementing AI for Working Capital Management

Significant research gaps still need to be addressed despite the growing interest in applying AI to working capital management. One primary gap is the need for more research on integrating AI with existing financial systems to optimize accounts receivable, inventory and accounts payable business processes. There is a need for empirical research that examines the effectiveness of AI-driven models in real-world business environments, considering the unique constraints and dynamics of different industries. Studies by Mahalakshmi et al. (2022) and Brock and Von Wangenheim (2019) emphasize these gaps and underscore the importance of expanding the application of these technologies while considering changes in the broader organization, IT systems, leadership and strategy. Additionally, frameworks for nuanced, industry-specific customizations are required to enhance strategic decision-making, improve liquidity management and provide visibility into working capital performance while identifying areas for improvement.

Another significant research gap is the need for comprehensive performance evaluation frameworks for AI applications in working capital management. While cost savings and efficiency improvements have been explored, more holistic performance evaluation models need to be developed that include qualitative aspects such as stakeholder satisfaction, strategic alignment and risk management (Kokina & Davenport, 2017). Perifanis & Kitsios, (2023) highlight the need to thoroughly analyze business needs and strategic objectives to determine where AI can be most effectively utilized for value creation. Future research should focus on developing robust assessment tools that provide a balanced view of AI's impact, ensuring that financial benefits do not overshadow potential drawbacks or ethical considerations.

The intersection of AI and working capital management raises significant ethical and governance issues that must be adequately addressed in the literature. Deploying AI technologies can lead to unintended consequences such as job displacement, data privacy concerns and biases in decision-making processes (Boden et al. 2017). Research should focus on exploring frameworks for ethical AI deployment, ensuring transparency, accountability and fairness. This framework should encompass guidelines and best practices for businesses to follow when integrating AI into their financial operations, thereby mitigating risks and enhancing stakeholder trust.

As AI and its associated technologies continually evolve, there will be numerous opportunities for further research. The identified gaps highlight the need for focused investigation into the application of AI in financial management, facilitating the development of more specialized and practical solutions. Achieving a focused application of AI in working capital management requires robust collaboration among industry practitioners, researchers and policymakers. Critical areas for collaboration include improving data availability, developing tailored AI applications and formulating policies that ensure AI's application adheres to regulatory and existing policy guidelines.

1.6. Objectives and Scope of the Current Review

This study aims to critically examine the application of AI in accurately determining companies' working capital needs, focusing on optimization, forecasting, regulatory and ethical considerations and future research directions.

1.6.1. Objectives

- Investigate existing AI-driven models and techniques used in working capital forecasting, assess their effectiveness and identify best practices. This study is crucial as it aims to understand how AI significantly improves working capital and liquidity management by focusing on accurate forecasting, real-time data analysis and risk assessment.
- Explore the potential applications of AI and its limitations, providing insights into how companies can enhance their financial management strategies through improved forecasting accuracy and efficiency.
- Identify the technological, operational and regulatory challenges that may impede the integration of AI with existing systems.

By addressing these objectives, this research will provide actionable insights for businesses, policymakers, investors and researchers interested in leveraging AI to transform working capital management practices.

2. Research Methodology

The research methodology employed in this study is tailored to analyze existing literature and studies comprehensively. This approach evaluates the current state of AI applications within working capital management, assesses their impacts and identifies the opportunities and challenges inherent in integrating AI into financial practices.

The approach involves conducting a thorough literature review by collecting, examining and summarizing relevant academic papers, industry reports, case studies and regulatory documents. The process commences with establishing specific criteria for inclusion and exclusion to ensure the review remains focused and pertinent. These criteria will be based on publication date, source credibility and relevance to AI applications in working capital management. This method allows for a comprehension of the landscape while drawing insights from diverse perspectives. The review will include thematic analysis to identify, analyze and report patterns within the data, thereby enhancing the analysis. Themes will be categorized based on the applications of AI in working capital management, the benefits and challenges of these applications, the outlook suggested by current trends. This qualitative analysis will help identify existing literature gaps and suggest future research directions.

The methodology for this review paper is informed by the works of Kaczynski et al. (2014) and Tranfield et al. (2003). These scholars advocate for integrating qualitative methods in management and organizational studies, including finance research, arguing that such approaches facilitate a more comprehensive exploration of the underlying reasoning behind financial decisions and behaviors.

3. Review Results

3.1. Accurate Prediction of Working Capital and Liquidity

Accurately predicting businesses' working capital and liquidity needs is paramount for financial health and operational efficiency. Traditionally, companies have relied on historical financial data and heuristic methods to forecast their working capital requirements. However, these conventional approaches often fail to capture modern business environments' dynamic and complex nature. The advent of AI presents an opportunity to enhance the accuracy of these predictions. AI-driven models can analyze vast amounts of data in real time, identify patterns and provide more precise forecasts, thus enabling better decision-making and resource allocation.

Mahmood et al. (2023) explore the relationship between working capital financing and firm performance using a machine learning approach. The study highlights that efficient management of working capital financing impacts a firm's profitability and overall performance, identifying critical predictors such as liquidity ratios and inventory turnover. The findings suggest that integrating advanced analytical techniques provide more accurate insights and foster better financial decision-making within firms.

Özlem and Tan (2022) predicted corporate cash holdings using supervised machine-learning algorithms such as decision trees, random forests, gradient boosting machines and support vector machines. This technique relied on historical financial data to enhance the accuracy of cash holding predictions. The findings demonstrate how machine learning models outperform traditional statistical methods, offering more reliable forecasts to improve business liquidity planning and financial stability.

Barongo and Mbelwa (2024) developed a supervised classification machine learning model for detecting liquidity risks. The model, designed to complement liquidity risk management tools in the banking industry, shows exceptional performance. The study applied machine learning data-mining techniques to study patterns of association between liquidity risk and its determinant factors and developed mapping functions from a combination of variables to liquidity risk classes. The model optimizes liquidity risk measurement, showing higher risk sensitivity and minimal errors.

While it is crucial to understand the broader application of AI and machine learning in firms' working capital management, it is also essential to dissect the specific application of these technologies to the most significant components of working capital.

3.1.1. Optimizing Inventory Management

Several challenges are associated with inventory management, including demand variability and forecasting accuracy, lead time uncertainty, high inventory holding costs, stockouts and overstock situations, inventory visibility and tracking and product life cycle management. The significance of these issues cannot be overstated, as optimizing inventory levels and minimizing costs while ensuring the availability of the right amount of inventory is crucial for companies. Applying AI and machine learning techniques to inventory management provides companies with innovative solutions to these persistent and recurring problems.

Dhaliwal et al. (2023) explore the application of AI in inventory management systems to enhance efficiency and accuracy. The study finds that using AI-based inventory management methods such as machine learning algorithms for predictive analytics, neural networks for demand forecasting and reinforcement learning for optimizing stock levels results in more accurate demand forecasting and optimized stock replenishment.

Albayrak Ünal et al. (2023) highlight the use of machine learning for demand forecasting, stock optimization and anomaly detection, demonstrating its versatility and robustness in handling diverse inventory management tasks. Artificial Neural Networks show substantial efficacy in predicting demand patterns and optimizing reorder points, suggesting their potential to enhance predictive accuracy and operational efficiency. Additionally, genetic algorithms are frequently applied to solve complex optimization problems, including inventory cost minimization and resource allocation. Integrating AI in inventory management addresses critical challenges such as demand variability, stockouts and overstock situations, leading to improved decision-making processes, cost reductions and increased efficiency.

Sathish et al. (2024) evaluate modern forecasting techniques in inventory management, comparing the exponential smoothing method with a gradient-boosting algorithm. The results showed that exponential smoothing had higher accuracy than gradient boosting, underscoring its effectiveness in predicting material needs and reducing inventory. This study highlights that advanced machine learning techniques can significantly improve inventory forecasting precision, optimize management and reduce costs, leading to better resource allocation.

Kara and Dogan (2018) demonstrate that reinforcement learning techniques, particularly Q-learning and SARSA, effectively address the complexities of managing perishable goods, which are prone to spoilage and have limited shelf lives. The study concludes that these AI methods significantly enhance inventory performance by optimizing order quantities and timing, reducing holding cost and stockout cost. The research highlights the ability of reinforcement learning to adapt to dynamic demand patterns, leading to more efficient and cost-effective inventory management strategies in the context of perishables. This approach outperforms traditional inventory control methods, offering a robust solution to the challenges inherent in perishable goods management.

Incorporating AI and machine learning into traditional inventory management methods improves the accuracy of demand forecasts, helping companies reduce costs and enhance efficiency. However, companies must assess the financial and operational feasibility to successfully integrate AI and identify the areas that will yield the most significant benefits.

3.1.2. Innovating Accounts Receivable Management

Traditional accounts receivable management is crucial for enhancing a company's financial health and operational efficiency. Despite these benefits, challenges such as handling vast amounts of data, tracking each debtor to ensure timely payments and finding the optimal point between profitability and offering early payment discounts to customers persist. AI technologies can be used to improve cash flow forecasting, reduce days sales outstanding and identify potential payment delays. By automating routine tasks and providing real-time insights, AI helps mitigate these issues, leading to better decision-making, increased efficiency and improved business profitability.

Zeng (2022) explores the application of BP neural network technology to optimize financial and management accounting processes, focusing on receivables management. The study concludes that applying BP neural network (BPNN) as the foundation for optimizing accounts receivable yields a much higher prediction accuracy than the other types. BPNN has the potential to help businesses take preemptive actions to avoid financial failures and to improve their operating conditions.

The use of AI and machine learning can greatly benefit companies' credit and collections process by automating payment reconciliation. Gunasekaran (2024) notes that reinforcement learning significantly improves the accuracy and efficiency of reconciling financial transactions. Automating this process not only speeds up the identification and correction of discrepancies but also reduces manual errors, thereby instilling a sense of reassurance and confidence in the process. The reinforcement learning model learns and adapts to changing patterns in transaction data, ultimately enhancing financial integrity and reducing operational costs.

Peng and Tian (2024) explore an intelligent optimization model to enhance enterprise accounts receivable management. The study utilizes the BP neural network and K-means clustering algorithm to evaluate accounts receivable risk and the owner's credit. The study shows that integrating AI, particularly machine learning algorithms and predictive analytics, significantly improves the accuracy and efficiency of managing receivables by reducing overdue accounts, improving cash flow and minimizing financial risks. AI integration thus enables companies to analyze customer data and payment history to assess creditworthiness, allowing for more informed credit decisions and reducing the risk of non-payment and bad debt.

The combined results of these studies emphasize the targeted use of AI and machine learning to improve accounts receivable prediction accuracy and enhance risk management and credit assessment. These advantages are essential in mitigating risks and improving financial data quality, ultimately contributing to the more accurate prediction of companies' overall working capital requirements.

3.1.3. Enhancing Accounts Payable Management

Accounts payable management is resource-intensive for businesses of all sizes, requiring thorough validation of all transactions and ensuring that payments are made accurately and timely to the correct vendors. Optimizing the payables process with AI and machine learning methods enhances efficiency by automating routine tasks, reducing errors and ensuring compliance with payment terms. AI can analyze numerous payment data, predict cash flow needs and optimize payment schedules to take full advantage of supplier credit terms.

Kanaparthi (2023) demonstrates the significant impact of AI and machine learning on accounts payable management. The study addresses challenges such as manual validation checks, catalogue mismatches, duplicate invoices and changing tax codes. It proposes an automated invoice processing system that utilizes AI-based modules to reduce manual intervention and associated errors significantly. Additionally, the research proposes an automated risk detection system to identify and prevent duplicate payments and fraudulent transactions. Based on the study, integrating technologies such as natural language processing for invoice data extraction, machine learning algorithms for anomaly detection and robotic process automation for automating repetitive tasks enhances efficiency, accuracy and speed of payables-related transaction processing and execution.

The nature of accounts payable necessitates dealing with numerous physical and digital invoices, making data extraction, validation and automation challenging for businesses. Malladhi (2023) highlights that AI-embedded OCR systems enhance these processes, reducing errors and speeding up invoice processing. By automating routine tasks, AI enables real-time data processing and better adaptability to dynamic business needs. Despite challenges such as handling multilingual OCR, adapting to new fonts and styles and maintaining robustness against noise and distortion, it is crucial for businesses to recognize the transformative potential of AI in payables automation. Doing so can significantly improve decision-making capabilities and operational efficiency.

Modern accounts payable management practices also integrate AI and predictive analytics to optimize early payment discount programs. Machine learning algorithms analyze supplier data and predict the likelihood of discount acceptance, allowing companies to extend early payment offers to a broader range of suppliers, improving cash flow management and strengthening business relationships. These advancements in AI technology enhance operational efficiency and financial performance, representing a significant evolution in accounts payable processes.

Integrating AI and machine learning in accounts payable management transforms traditional processes, enhances operational performance and optimizes working capital management. As businesses adopt these technologies, the evolution in accounts payable processes promises significant improvements in financial management and decision-making capabilities.

3.1.4. Predicting the Overall Cash Needs of Firms

Predicting a company's cash needs is crucial for effective financial management, ensuring sufficient liquidity, operational efficiency and risk reduction. AI and machine learning advancements have transformed this task by utilizing advanced tools such as decision tree algorithms and logistic regression models to analyze large volumes of financial data to forecast cash requirements. These predictive models assist companies in maintaining optimal cash reserves, managing cash flow efficiently and making well-informed financial decisions.

Wu et al. (2021) evaluate the predictive accuracy of decision tree algorithms, including Simple CART, REP Tree, Random Forest and others, in forecasting firms' cash holdings, comparing their performance to the traditional logistic regression model. The study shows that random forest decision tree algorithms outperform logistic regression, providing higher accuracy due to their ability to handle non-linear relationships and variable interactions more effectively. Important financial indicators such as firm size, profitability, leverage and liquidity ratios were identified as significant predictors of cash holdings. The enhanced predictive power of decision tree models can aid firms in better anticipating cash flow requirements, optimizing cash reserves and mitigating financial risks, offering a robust tool for improved financial management.

Dadteev et al. (2020) investigate the prediction of cash turnover utilizing regression models, ARIMA models and MLP neural network models, highlighting the relative strengths of each method under different conditions. The study shows that the ARIMA model exhibited the highest accuracy in smaller regions with fewer data points. Conversely, in major economic centers with a larger volume of training data, the MLP neural network model outperformed others in forecasting accuracy, particularly compared to predictions in smaller and less economically active regions. This suggests that the MLP neural network model is more suitable for forecasting cash turnover than the ARIMA model for larger firms with diverse subsidiaries, business centers, or branches.

The results of these studies, coupled with the increasing levels of technology adoption and integration in the industry, underscore the growing role of AI and machine learning prediction tools. These tools outperform traditional methods in optimizing cash reserves, improving financial decisions and managing liquidity risks effectively, making them increasingly relevant in the current business landscape.

3.1.5. Success Stories on AI Implementation in Working Capital Management

AI integration in working capital management has led to significant innovations in firms' financial management and data-driven decision-making processes. These implementations not only showcase the efficiency and accuracy AI brings to managing financial operations, but also highlight the potential for cost savings and improved cash flow.

Marr (2019) highlights the innovative use of AI in transforming various aspects of business operations to enhance customer experiences, streamline operations and optimize financial management. Alibaba is a prime example of a company that utilizes AI to optimize inventory management and personalize product displays based on customer searches. By applying reinforced learning on its Taobao portal, Alibaba simulates customer behaviors using extensive historical data. This approach drives sales by automating content creation for millions of items available across its platforms.

Marr (2019) also pointed out Stitch Fix, a fashion retail company that applied AI to tackle the customer returns issue, a common issue faced by online retailers. Given the high costs associated with returns, such as processing, shipping and restocking, the company needed to stock the proper inventory and ensure customers bought items that met their design, fit and quality expectations. Stitch Fix implemented machine learning solutions to effectively manage its inventory by analyzing customer requirements and preferences, allowing the company to automatically send items customers are more likely to love. This approach helped reduce redundant warehouse space, shipping costs, return expenses and end-of-season overstock.

HNTB, a US civil engineering firm, faced challenges in producing accurate cash flow forecasts due to managing 1800+ projects with complex data. The lack of project-level visibility and a weak reporting mechanism led to poor liquidity planning and cash shortages. Implementing an AI-powered solution streamlined processes, reduced manual effort and improved forecast accuracy, resulting in increased accounts receivable and accounts payable forecast accuracy from 40% to 95%, improved workflow efficiency with end-to-end automation and enhanced cash management visibility (HighRadius, 2024).

Seismic, a leading sales enablement platform, faced challenges with its manual invoicing process, which was time-consuming and inefficient, limiting its accounts receivable (AR) capacity. The company also issues gaining real-time data integration with NetSuite for increased visibility and push. Seismic significantly enhanced its invoicing efficiency and bandwidth by implementing an AI-powered AR solution. This automation improved cash flow management and allowed the company to handle increased invoicing volumes without developing an internal system. These implementations demonstrate significant innovations in firms' financial management and data-driven decision-making processes, showcasing how AI enhances efficiency and accuracy in financial operations (Tesorio, 2024).

These case studies illustrate successful AI implementation in various aspects of working capital management. They underscore the transformational role of AI in a move towards data-driven decision-making, achieving higher reporting accuracy and eliminating error-prone manual processes. As AI continues to evolve, its integration into legacy or standalone systems will drive further innovations and improvements in managing working capital.

3.2. Complexities and Challenges of AI Adoption and Integration

Adopting and integrating AI into existing systems pose numerous complexities and challenges for organizations. Navigating legacy infrastructure, data compatibility issues, operational hurdles and regulatory concerns require strategic planning and expertise. This transition demands significant investment in technology and talent, necessitating a comprehensive understanding of the potential benefits and the obstacles to successful implementation.

3.2.1. Integrating AI with Legacy Infrastructure

Legacy systems are deeply embedded in business processes, making it essential to adapt them carefully to utilize AI's potential fully. This process requires thorough planning to address compatibility issues, integrate data and minimize disruptions while embracing technological advancements. Odonkor et al. (2024) note that integrating AI with accounting systems originally not designed for it can lead to compatibility and interoperability issues, resulting in significant costs and delays as businesses update or replace their systems to accommodate AI technologies.

Companies must invest in modernizing their IT systems to overcome integration challenges, often through phased approaches that allow for the gradual integration of AI technologies. Phased approaches involve leveraging middleware solutions to bridge the gap between old and new systems, thus enhancing data flow and operational efficiency. Additionally, ongoing training and development for staff are crucial to ensure they can effectively work with the new technology. Ultimately, a strategic, well-planned integration process that includes comprehensive assessments, defining clear objectives, adopting agile methodologies, documentation and phased implementation can help mitigate risks and unlock the transformative potential of AI within legacy infrastructures (Ponnusamy & Eswararaj, 2023).

3.2.2. Issues with Data Compatibility

AI algorithms need vast training data, often from diverse sources with varying formats, structures and standards. Data from different departments or external sources can be stored in different formats, leading to inconsistencies that hinder integration (Alma'aitah et al. 2024). Issues like missing data fields, duplicated records, or mismatched data types can disrupt the training process, causing models to perform poorly (Maharana et al. 2022). Harmonizing these disparate sources requires extensive preprocessing, normalization and transformation to ensure the AI system can correctly interpret and use the data.

Achieving compatibility requires rigorous data governance and management practices, including establishing standardized data formats, implementing robust data validation protocols and employing advanced data integration tools (Manoharan, 2024). Organizations must address these compatibility challenges to ensure organizations can deploy AI solutions that are efficient, accurate and even harmful, ultimately undermining the potential benefits of AI technology.

3.2.3. Security and Regulatory Concerns with AI Adoption

The adoption of AI in working capital management presents significant security challenges, particularly regarding data privacy and cybersecurity. AI systems, which process vast amounts of sensitive financial data, can become prime targets for cyberattacks. Ensuring the protection of this data requires robust encryption, multi-factor authentication and continuous monitoring for vulnerabilities. The U.S. Federal Trade Commission's amendments to the Gramm-Leach-Bliley Act's Safeguards Rule highlight these concerns by mandating stricter security measures for financial institutions, including fintech companies, to protect consumer information (FTC, 2024).

Regulatory frameworks for AI in financial services are evolving to address these security challenges and ensure the ethical use of AI. In the U.S., several regulatory bodies, including the Federal Reserve and the Consumer Financial Protection Bureau, have issued guidance on managing AI risks, focusing on transparency, data protection and preventing algorithmic discrimination (FRB, 2021; CFPB, 2024).

Meanwhile, the EU's forthcoming AI Act will usher in comprehensive regulations categorizing AI applications by risk levels, with stringent requirements for high-risk applications such as those used in managing and operating critical infrastructure and in financial decision-making. These regulations aim to enhance accountability, transparency and consumer protection across jurisdictions, necessitating global compliance efforts by multinational corporations (European Parliament, 2023). Ensuring compliance with different jurisdictions' regulatory requirements and maintaining stakeholders' trust is crucial in this context.

Integrating AI in organizations requires overcoming legacy system integration, data compatibility and regulatory and security concerns. Success hinges on strategic planning, investment in technology and talent and adherence to evolving regulatory frameworks. Addressing these challenges is essential for harnessing AI's potential to drive innovation and operational efficiency, ultimately transforming business processes and enhancing decision-making capabilities.

4. Discussion of Review Results

4.1. Assessing AI in Working Capital Management

Integrating AI in working capital management marks a pivotal shift in how businesses approach financial decision-making and operational efficiency. AI's ability to analyze vast amounts of data in real time and identify complex patterns has the potential to revolutionize traditional financial practices. This technological evolution goes beyond improving existing processes, fundamentally transforming working capital management to adapt to modern business environments' dynamic and complex nature.

Many businesses struggle to accurately forecast their working capital needs using traditional methods, which often struggle to keep up with the rapid changes in today's markets. This lack of agility can lead to financial difficulties in meeting short-term obligations. Özlem and Tan (2022) demonstrate that AI-driven models play a crucial role in significantly improving predictions of cash holdings by processing large datasets in real time. The predictive and continuous data processing capabilities of AI empower businesses to anticipate and respond to liquidity needs with unprecedented accuracy and speed, thereby enhancing operational efficiency and providing a competitive edge in managing financial resources effectively.

A critical AI application noted across the review is accurate forecasting of optimal inventory levels to achieve economic order quantity and lower holding costs, providing companies with precise predictions to manage stock levels efficiently (Dhaliwal et al. 2023; Albayrak Ünal et al. 2023; Sathish et al. 2024). Additionally, machine learning-driven OCR data extraction and validation, duplication checks and receivables and payables reconciliations were highlighted, enhancing the accuracy and reliability of financial transactions while reducing the time-consuming manual processing of transactions (Gunasekaran, 2024; Malladhi, 2023; Kanaparthi, 2023).

These studies highlight the potential of AI to enhance specific aspects of working capital, aiding companies in adapting to market shifts and maintaining a robust financial standing. However, they often need to pay more attention to the broader use of machine learning to evaluate a company's overall working capital needs. Without considering their broader impact, businesses must realize that a selective application of advanced AI technologies to different working capital elements can lead to inefficiency. For instance, trying to predict the optimal inventory levels and sales without considering cash availability, accounts receivable collections and the potential benefits of early payment discounts from suppliers could be counterproductive.

AI can be applied to the broader working capital by developing a system that integrates various AI domains—such as machine learning, natural language processing, computer vision, expert systems and reinforcement learning—to provide a holistic assessment of working capital requirements. By individually analyzing different working capital components and synthesizing these insights, such a system could significantly reduce implementation costs and enhance prediction accuracy. This comprehensive view would streamline financial management and empower businesses to make more informed, strategic decisions that support long-term stability and growth.

4.2. Navigating Challenges of AI Adoption and Integration

Adopting and integrating AI into existing systems is a transformative but complex process. Businesses and organizations face many challenges as they strive to harness AI's potential to enhance efficiency, productivity and innovation. Among the most significant hurdles are integrating AI with legacy technology infrastructure, addressing issues with data compatibility and managing security and regulatory concerns. Practical and balanced strategies to navigate these challenges are essential for successful AI implementation.

Legacy systems, often built on outdated infrastructure, pose significant barriers to AI integration due to compatibility issues, scalability concerns and limited data processing demands. To navigate this challenge, Singh & Adhikari (2023) and Ntafalias et al. (2022) suggest the use of middleware solutions that can bridge the gap between legacy systems and new AI functionalities, cloud-based platforms to offer scalable data processing capabilities and the use of advanced data management frameworks for efficiently handling large datasets required for AI applications.

Data compatibility issues arise from the heterogeneous nature of data sources, formats and standards. Organizations must establish robust data governance frameworks to ensure data is clean, consistent and interoperable across platforms. Albahra et al. (2023) notes that navigating these issues when integrating AI with legacy systems involves standardizing data formats, cleaning and preprocessing data to remove errors and implementing middleware solutions to act as an intermediary layer between legacy systems and AI technologies. These strategies collectively facilitate smoother integration by addressing the technical challenges of data compatibility.

Implementing data lakes and data warehouses centralize data storage, enabling standardization and data preprocessing for AI applications. Harby and Zulkernine (2022) highlight the benefits of data lakes in storing raw, unstructured data and their flexibility in handling diverse data types, which addresses compatibility challenges. Additionally, the concept of a data lake house combines the scalability and flexibility of data lakes with data warehouses' data management and processing capabilities, providing a unified platform that can seamlessly integrate and process data from legacy systems, facilitating AI adoption and enhancing data compatibility.

Integrating AI into business processes introduces new security vulnerabilities and regulatory challenges. Therefore, organizations should adopt robust cybersecurity measures and data anonymization techniques to protect privacy and mitigate these risks. These measures include incorporating AI-driven security tools for real-time threat detection and response. Although comprehensive AI regulations are still in development, companies can comply with existing data governance and security standards such as GDPR to safeguard proprietary business information and personal data of clients and employees. Establishing clear policies and protocols for AI usage and conducting regular audits and assessments to maintain security and regulatory compliance is essential.

From an ethical standpoint, it is crucial to note that AI systems, if not carefully designed and supervised, have the potential to perpetuate or exacerbate preexisting biases. Specifically, within working capital management, biased AI algorithms can yield inequitable credit assessments or misapply resources, disproportionately impacting specific segments of businesses or individuals. Organizations must ensure their AI models are transparent and regularly audited for biases. Employing diverse datasets and implementing fairness-aware algorithms can help create more equitable AI systems. Mehrabi et al. (2022) emphasized the need for comprehensive fairness evaluations and continuous monitoring to maintain ethical AI practices.

Transparency in AI decision-making processes is vital for ethical AI adoption in working capital management. Stakeholders must understand and trust the decisions made by AI systems and this requires clear documentation of AI model development, training and validation, as well as the rationale behind their decisions. Additionally, companies should establish accountability mechanisms to address any adverse outcomes resulting from AI use. Fostering an environment of transparency and accountability is essential for the ethical integration of AI into business practices, ensuring that AI-driven decisions are explainable and justifiable (Floridi et al. 2018).

By addressing these critical challenges through strategic planning and adopting best practices, businesses can effectively navigate the complexities of AI adoption and integration, thereby unlocking the full potential of AI technologies.

4.3. Future of AI in Working Capital Management

As organizations increasingly adopt AI technologies, intelligent systems will become integral to operational, financial and regulatory compliance functions. This level of integration will equip companies to precisely determine their broader working capital needs, ensuring robust financial health and stability.

Intelligent systems integrated across organizational operations and financial functions will offer a unified platform for managing working capital, ensuring data consistency, enhancing prediction accuracy and improving overall efficiency. By embedding AI into existing enterprise resource planning (ERP) and financial management systems, businesses will streamline their workflows, reduce manual errors and achieve higher precision in financial reporting and analysis. This integration will enable automated reconciliation of accounts, real-time tracking of receivables and payables and optimized cash flow management, allowing firms to allocate resources better, predict liquidity needs and maintain optimal working capital levels.

AI technology will facilitate real-time monitoring of working capital metrics, providing businesses with up-to-date insights into their financial health. This capability will enable quicker decision-making and timely adjustments to working capital strategies, allowing organizations to respond swiftly to changing market conditions. In real-time, advanced AI-driven analytics will monitor key metrics such as cash conversion cycles, inventory turnover ratios and days sales outstanding (DSO), ensuring optimal liquidity management. Brynjolfsson and McElheran (2019) demonstrate that real-time data analytics powered by AI significantly improve the responsiveness of financial management processes, enabling firms to maintain optimal liquidity levels and mitigate potential cash flow issues.

Furthermore, AI algorithms capable of analyzing historical data, market trends and forecasts of macroeconomic indicators will play a crucial role in predicting future cash flows, demand dynamics and supply chain disruptions. This predictive capability will empower businesses to make more accurate forecasts and proactive decisions, thereby improving liquidity management and reducing the risk of cash shortages. A study by Chen et al. (2012) demonstrates that AI-driven predictive analytics will enhance the accuracy of financial forecasts, leading to better resource allocation and risk management.

Overall, the future of AI in working capital management is set to bring significant advancements by integrating intelligent systems, enabling real-time monitoring and leveraging predictive analytics. These innovations will improve the accuracy and efficiency of financial operations and enhance organizations' strategic decision-making capabilities. As AI evolves, its impact on working capital management will become increasingly profound, driving better financial outcomes and fostering sustainable business growth.

5. Conclusion

This study critically explored the application of artificial intelligence to transform traditional working capital management, a crucial yet often overlooked aspect of financial management. It highlighted the downsides of the traditional methods of managing working capital, such as manual intervention leading to the preponderance of human errors, inefficiencies in real-time data analysis and data-driven decision-making, lack of clear picture of businesses' overall working capital needs that expose the business to liquidity and credit risks. Through comprehensive literature and case study reviews, the study successfully demonstrated how AI's integration with legacy systems achieves optimization and accuracy in predicting the individual components of working capital, such as inventory, accounts receivable, accounts payable and other current balances on a company's balance sheet.

The study noted the challenges of adopting and integrating AI into a business's core financial management systems and recommends a balanced approach that considers the nature of legacy systems, data compatibility, regulatory requirements and ethical standards. Despite these hurdles, AI's benefits in transforming working capital management processes are undeniable.

It is crucial to note that while there is a lot of research and case studies showcasing the use of AI for specific working capital elements, there is a need for comprehensive AI applications that encompass all AI domains, such as machine learning, natural language processing, computer vision, expert systems and reinforcement learning. These applications are necessary to enable real-time financial data analysis to understand any business's overall working capital requirements at any given time. By adopting this approach, businesses can fully harness the potential of AI in financial management to mitigate liquidity risk, credit risk and the potential for increased losses due to higher costs.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Agrawal, A., Ellencweig, B., Sood, R., & Tam, M. (2023). 'Gen AI: A guide for CFOs'. *McKinsey & Company*. Available from https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/gen-ai-a-guide-for-cfos.

[2] Albahra, S., Gorbett, T., Robertson, S., D'Aleo, G., Vasudevan Suseel Kumar, S., Ockunzzi, S., Lallo, D., Hu, B., & Rashidi, H. H. (2023). 'Artificial intelligence and machine learning overview in pathology & laboratory medicine: A general review of data preprocessing and basic supervised concepts'. *Seminars in Diagnostic Pathology*, 40(2), 71-87. https://doi.org/10.1053/j.semdp.2023.02.002.

[3] Albayrak Ünal, Ö., Erkayman, B., & Usanmaz, B. (2023). 'Applications of Artificial Intelligence in Inventory Management: A Systematic Review of the Literature'. *Archives of Computational Methods in Engineering*, 30(1). https://doi.org/10.1007/s11831-022-09879-5.

[4] Alma'aitah, W. Z., Quraan, A., AL-Aswadi, F. N., Alkhawaldeh, R. S., Alazab, M., & Awajan, A. (2024). 'Integration Approaches for Heterogeneous Big Data: A Survey. Cybernetics and Information Technologies'. *Bulgarian Academy of Sciences*, 24(1). https://doi.org/10.2478/cait-2024-0001.

[5] Appel, A. P., Malfatti, G. L., Cunha, R. L. F., Lima, B., & de Paula, R. (2020). 'Predicting Account Receivables with Machine Learning'. *KDD Workshop on Machine Learning in Finance (KDD MLF '20)*. ACM, New York, NY, USA, 9 pages.

[6] Baños-Caballero, S., García-Teruel, P. J., & Martínez-Solano, P. (2014). 'Working capital management, corporate performance, and financial constraints'. *Journal of Business Research*, 67(3), 332-338. https://doi.org/10.1016/j.jbusres.2013.01.016.

[7] Barongo, R. I., & Mbelwa, J. T. (2024). 'Using machine learning for detecting liquidity risk in banks'. *Machine Learning with Applications*, 15, 100511. https://doi.org/10.1016/j.mlwa.2023.100511.

[8] Berman, D. K. (2009). 'Circuit City: The Long Road to Bankruptcy'. *The Wall Street Journal*. Available from https://www.wsj.com/articles/SB123137374345286561.

[9] Boden, M., Bryson, J., Caldwell, D., Dautenhahn, K., Edwards, L., Kember, S., ... Winfield, A. (2017). 'Principles of robotics: regulating robots in the real world'. *Connection Science*, 29(2), 124–129. https://doi.org/10.1080/09540091.2016.1271400.

[10] Brock, J. K. U., & Von Wangenheim, F. (2019). 'Demystifying AI: What Digital Transformation Leaders Can Teach You About Realistic Artificial Intelligence'. *California Management Review*, 61(4), 110-134.

[11] Brynjolfsson, Erik and McElheran, Kristina (2019). 'Data in Action: Data-Driven Decision Making and Predictive Analytics in U.S. Manufacturing'. *Rotman School of Management Working Paper No. 3422397*. http://dx.doi.org/10.2139/ssrn.3422397 .

[12] CFPB. (2024). 'CFPB approves rule to ensure accuracy and accountability in the use of AI and algorithms in home appraisals'. *Consumer Financial Protection Bureau*. Available from https://www.consumerfinance.gov/about-

us/blog/cfpb-approves-rule-to-ensure-accuracy-and-accountability-in-the-use-of-ai-and-algorithms-in-home-appraisals/.

[13] Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). ‘Business Intelligence and Analytics: From Big Data to Big Impact’. *MIS Quarterly*, 36(4), 1165-1188.

[14] Dadteev, K., Shchukin, B., & Nemeshaev, S. (2020). ‘Using artificial intelligence technologies to predict cash flow’. *Procedia Computer Science*, 169, 264-268. https://doi.org/10.1016/j.procs.2020.02.163.

[15] Dechow, P. M., & Dichev, I. D. (2002). ‘The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors’. *The Accounting Review*, 77(s-1), 35-59. https://doi.org/10.2308/accr.2002.77.s-1.35

[16] Dhaliwal, N., Tomar, P. K., Joshi, A., Reddy, G. S., Hussein, A., & Alazzam, M. B. (2023). ‘A detailed Analysis of Use of AI in Inventory Management for technically better management’. *In 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 197-201). Greater Noida, India. IEEE. https://doi.org/10.1109/ICACITE57410.2023.10183082.

[17] European Parliament. (2023). ‘EU AI Act: First regulation on artificial intelligence’. *European Parliament*. Available from https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence.

[18] FTC. (2024). ‘Gramm-Leach-Bliley Act’. *Federal Trade Commission*. Available from https://www.ftc.gov/legal-library/browse/statutes/gramm-leach-bliley-act.

[19] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). ‘AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations’. *Minds and Machines*, 28(4), 689-707. https://doi.org/10.1007/s11023-018-9482-5.

[20] FRB. (2021). ‘Agencies seek wide range of views on financial institutions' use of artificial intelligence’. *Federal Reserve*. Available from https://www.federalreserve.gov/newsevents/pressreleases/bcreg20210329a.htm.

[21] Gunasekaran, S. (2024). ‘AI-Powered Transaction Reconciliation: A Reinforcement Learning Approach’. *International Research Journal of Engineering and Technology*, 11(06), e-ISSN: 2395-0056, p-ISSN: 2395-0072.

[22] Harby, A., & Zulkernine, F. H. (2022). ‘From Data Warehouse to Lakehouse: A Comparative Review’. *In IEEE International Conference on Big Data 2022* (pp. 1-10). Osaka, Japan. https://doi.org/10.1109/BigData55660.2022.10020719.

[23] Higgins, R., Koski, J., & Mitton, T. (2023). ’Analysis for Financial Management (13th ed.)’. *McGraw-Hill Education*. ISBN10: 1260772365 | ISBN13: 9781260772364.

[24] HighRadius. (2024). ‘5 AI Cash Flow Forecasting Use Cases in 2024’. *HighRadius*. Available from: https://www.highradius.com/resources/Blog/ai-revolutionizing-cash-forecasting-in-2024/.

[25] Howorth, C., & Westhead, P. (2003). ‘The Focus of Working Capital Management in UK Small Firms’. *Management Accounting Research*, 14(2), 94-111. doi:10.1016/S1044-5005(03)00022-2.

[26] Jordan, B., Westerfield, R., & Ross, S. (2024). ‘Fundamentals of Corporate Finance (2024 Release)’. *McGraw Hill.* ISBN10: 1265066833 | ISBN13: 9781265066833.

[27] Kaczynski, D., Salmona, M., & Smith, T. (2014). ‘Qualitative research in finance’. *Australian Journal of Management*, 39(1), 127-135. https://doi.org/10.1177/0312896212469611.

[28] Kanaparthi, V.K. (2023). ‘Examining the Plausible Applications of Artificial Intelligence & Machine Learning in Accounts Payable Improvement’. *FinTech*, 2, 461–474. https://doi.org/10.3390/fintech2030026.

[29] Kara, A., & Dogan, I. (2018). ‘Reinforcement learning approaches for specifying ordering policies of perishable inventory systems’. *Expert Systems with Applications*, 91, 150-158. https://doi.org/10.1016/j.eswa.2017.08.046

[30] Kokina, J., & Davenport, T. H. (2017). ‘The emergence of artificial intelligence: How automation is changing auditing’. *Journal of Emerging Technologies in Accounting*, 14(1), 1-17.

[31] Krieger F, Drews P, Funk B. (2023) ‘Automated invoice processing: Machine learning-based information extraction for long tail suppliers’, *Intelligent Systems with Applications*, 20, 200285, ISSN 2667-3053. https://doi.org/10.1016/j.iswa.2023.200285.

[32] Li, X., Sigov, A., Ratkin, L., Ivanov, L.A., and Li, L. (2023). 'Artificial intelligence applications in finance: a survey', *Journal of Management Analytics*, 10(4), pp.676-692. DOI: 10.1080/23270012.2023.2244503.

[33] Mahalakshmi, V., Kulkarni, N., Kumar, K. V. P., Kumar, K. S., Sree, D. N., & Durga, S. (2022). 'The Role of implementing Artificial Intelligence and Machine Learning Technologies in the financial services Industry for creating Competitive Intelligence'. *Materials Today: Proceedings*, 56(Part 4), 2252-2255. https://doi.org/10.1016/j.matpr.2021.11.577.

[34] Maharana, K., Mondal, S., & Nemade, B. (2022). 'A review: Data pre-processing and data augmentation techniques'. *Global Transitions Proceedings*, 3(1), 91-99. https://doi.org/10.1016/j.gltp.2022.04.020.

[35] Mahmood, F., Ahmed, Z., Hussain, N., & Ben-Zaied, Y. (2023). 'Working capital financing and firm performance: A machine learning approach'. *Review of Quantitative Finance and Accounting*. https://doi.org/10.1007/s11156-023-01185-w.

[36] Malladhi, A. (2023). 'Transforming Accounts Payable Management: Harnessing the Power of AI-Embedded OCR and Digitalization in the Accounting Sector'. *International Journal of Science and Research*, 12(4), 1517-1523.

[37] Manoharan, G. (2024). 'Data governance frameworks for AI implementation in banking: Ensuring compliance and trust'*. International Journal of Advanced Research in Engineering and Technology*, 15(3), 101-109. https://doi.org/10.17605/OSF.IO/7HK3J.

[38] Manyika, J., Chui, M., Bughin, J., Dobbs, R., Bisson, P., & Marrs, A. (2011). 'Big data: The next frontier for innovation, competition, and productivity'. *McKinsey Global Institute*. Available from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/big-data-the-next-frontier-for-innovation.

[39] Marr, B. (2019). 'Artificial intelligence in practice: how 50 successful companies used AI and machine learning to solve problems'. *John Wiley & Sons*. ISBN: 9781119548218, 1119548217.

[40] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2022). 'A Survey on Bias and Fairness in Machine Learning'. *arXiv*. Available from https://doi.org/10.48550/arXiv.1908.09635.

[41] Ntafalias, A.; Tsakanikas, S.; Skarvelis-Kazakos, S.; Papadopoulos, P.; Skarmeta-Gómez, A.F.; González-Vidal, A.; Tomat, V.; Ramallo-González, A.P.; Marin-Perez, R.; Vlachou, M.C. (2022). 'Design and Implementation of an Interoperable Architecture for Integrating Building Legacy Systems into Scalable Energy Management Systems'. *Smart Cities*, 5, 1421-1440. https://doi.org/10.3390/smartcities5040073.

[42] Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., & Farayola, O. A. (2024). 'The impact of AI on accounting practices: A review: Exploring how artificial intelligence is transforming traditional accounting methods and financial reporting'. *World Journal of Advanced Research and Reviews*, 21(01), 172–188. https://doi.org/10.30574/wjarr.2024.21.1.2721.

[43] Oyeniyi, D.O., Ugochukwu, C.E., and Mhlongo, N.Z. (2024). 'The influence of AI on financial reporting quality: A critical review and analysis'. *World Journal of Advanced Research and Reviews*, 2024, 22(01), 679–694.

[44] Özlem, S., & Tan, Ö. F. (2022). 'Predicting cash holdings using supervised machine learning algorithms'. *Financial Innovation*, 8(1), 15. https://doi.org/10.1186/s40854-022-00351-8.

[45] Padachi, K. (2006). 'Trends in Working Capital Management and its Impact on Firms' Performance: An Analysis of Mauritian Small Manufacturing Firms'. *International Review of Business Research Papers*, 2(2), 45-58.

[46] Pandey, K. (2017). 'Financial Management'. *Lulu Press, Incorporated*. ISBN: 9781365671050.

[47] Peng, Y., & Tian, G. (2024). 'Intelligent Optimization Model of Enterprise Financial Account Receivable Management'. *Journal of Applied Mathematics*, ID 4961081, 9 pages. https://doi.org/10.1155/2024/4961081.

[48] Perez, H. D., Hubbs, C.D., Li, C., Grossmann, I.E. (2021). 'Algorithmic Approaches to Inventory Management Optimization'. *Processes,* 9(1):102. https://doi.org/10.3390/pr9010102.

[49] Perifanis, N.-A.; Kitsios, F. (2023). 'Investigating the Influence of Artificial Intelligence on Business Value in the Digital Era of Strategy: A Literature Review'. *Information*, 14(85). https://doi.org/10.3390/info14020085.

[50] Ponnusamy, S., & Eswararaj, D. (2023). 'Navigating the modernization of legacy applications and data: Effective strategies and best practices'. *Asian Journal of Research in Computer Science*, 16(4), 239-256. https://doi.org/10.9734/AJRCOS/2023/v16i4386.

[51] Porras Musalem, E., & Dekker, R. (2005). 'Controlling inventories in a supply chain: A case study'. *International Journal of Production Economics,* 93–94, 179-188. https://doi.org/10.1016/j.ijpe.2004.06.016.

[52] Raheman, A., & Nasr, M. (2007). 'Working Capital Management and Firm Performance: Evidence from Non-Financial Firms in Pakistan'. *International Review of Business Research Papers*, 3(1), 279-300.

[53] Repko, M. (2019). 'Forever 21 Files for Bankruptcy, Will Close Up to 178 U.S. Stores'. *CNBC*. Available from https://www.cnbc.com/2019/09/30/forever-21-files-for-bankruptcy.html.

[54] Sathish, T., SaiKumar, D., Patil, S., & Saravanan, R. (2024). 'Exponential smoothing method against the gradient boosting machine learning algorithm-based model for materials forecasting to minimize inventory'. *AIP Advances*, 14(6). https://doi.org/10.1063/5.0208491.

[55] Singh, N., & Adhikari, D. (2023). 'Challenges and Solutions in Integrating AI with Legacy Inventory Systems'. *International Journal for Research in Applied Science & Engineering Technology*, 11(XII), 609. https://doi.org/10.22214/ijraset.2023.57376.

[56] Tater, T., Gantayat, N., Dechu, S., Jagirdar, H., Rawat, H., Guptha, M., Gupta, S., Strak, L., Kiran, S., & Narayanan, S. (2022). 'AI Driven Accounts Payable Transformation'. In *AAAI*.

[57] Tesorio. (2024). 'Seismic Replaces Manual Invoicing with Tesorio, Boosting Its AR Capacity and Saving Bandwidth, Avoiding an Internal System Build'. Available from https://www.tesorio.com/resources/seismic-replaces-manual-invoicing-with-tesorio-boosting-its-ar-capacity-and-saving-bandwidth-avoiding-an-internal-system-build.

[58] Tranfield, D., Denyer, D., & Smart, P. (2003). 'Towards a methodology for developing evidence-informed management knowledge by means of systematic review'. *British journal of management*, 14(3), 207-222.

[59] Wild, T. (2017). 'Best Practice in Inventory Management (3rd ed.)'. *Routledge*. ISBN-10: 9781138308077| ISBN-13: 978-1138308077.

[60] Wu, H. C., Chen, J. H., & Wang, P. W. (2021). 'Cash Holdings Prediction Using Decision Tree Algorithms and Comparison with Logistic Regression Model'. *Cybernetics and Systems*, 52(8), 689–704. https://doi.org/10.1080/01969722.2021.1976988.

[61] Zeng, Y. (2022). 'Neural network technology-based optimization framework of financial and management accounting model'. *Computational Intelligence and Neuroscience*, 2022, 4991244. https://doi.org/10.1155/2022/4.