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Submission Guidelines for Al-Zaytoonah University Journal of Business (ZJJB)

Scopus-Compliant Instructions

1 Journal Scope

ZJJB aims to publish original scientific research in business, management, economics, financial technology, and administrative analysis, focusing on innovation and academic development. The journal is peer-reviewed and seeks international reach, adhering to academic standards and global publication ethics.

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2 Originality of Research

- All submissions must be **original** and not published previously or under review elsewhere.
- Authors must disclose any prior publications or related work.
- **Plagiarism or data fabrication** is strictly prohibited.

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3 Peer-Review Policy

- All manuscripts undergo **double-blind peer review**.
- The journal reserves the right to reject any manuscript that does not meet scientific or ethical standards.
- Authors are encouraged to provide a list of potential reviewers with reasons for their selection.

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4 Manuscript Structure (IMRAD – Scopus-Compliant)

Submissions must follow the structure below:

1. **Title Page**
    - Title in English and Arabic (if applicable).
    - Author names, affiliations, and corresponding author email.
    - Statement of **Author Contributions**.
2. **Abstract**
    - Maximum **250 words**.
    - Should include the study's objective, methodology, main results, and conclusions.
    - Preferably in English, even if the full manuscript is in Arabic.
3. **Keywords**
    - **3–6 keywords** directly relevant to the topic for effective indexing.
4. **Introduction**
    - Background, problem statement, and significance of the study.

5. **Literature Review**
    - Analysis of previous studies and identification of research gaps.
6. **Methods**
    - Description of research design, sample, instruments, and analytical procedures.
7. **Results**
    - Present findings clearly, using tables and figures where appropriate.
8. **Discussion**
    - Interpretation of results in the context of previous research.
9. **Conclusion**
    - Summary of key findings and practical or research recommendations.
10. **Acknowledgments**
    - Any financial, academic, or institutional support should be acknowledged.
11. **References**
    - Accurate and up-to-date references, preferably from Scopus-indexed journals.

Note: Authors must follow the **official journal template** available on the ZJJB website.

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5 Manuscript Length

- **Full Paper:**
    - **Pages:** 12–25 pages (including title, abstract, tables, figures, references).
    - **Word Count:** 5,000–8,000 words.
- **Abstract:**
    - **Word Count:** 150–250 words.
    - Must include objective, methodology, key results, and conclusions.
- **Keywords:** 3–6 relevant keywords.

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6 Publication Ethics

- Authors must adhere to **publication ethics** according to COPE and Elsevier/Scopus standards.
- Disclose any **funding sources or conflicts of interest**.
- Fabrication of data, results, or authorship is strictly prohibited.
- Manuscripts must undergo thorough review to ensure originality and scientific quality.

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7 Submission Process

- Manuscripts must be submitted via the journal's **online submission system**.
- Include a **Cover Letter** with:

- Manuscript title.
- Author names and affiliations.
- Corresponding author contact details.
- Suggested reviewers (optional).

8 Tips for Scopus Compliance

1. Follow the IMRAD structure and provide a precise English abstract.
2. Cite recent references from Scopus-indexed journals.
3. Ensure all sources are accurately documented for indexing purposes.
4. Focus on internationally relevant topics (e.g., Business Innovation, AI in Business, Fintech, Sustainability).
5. Maintain full transparency in authorship, funding, and conflicts of interest.

Contents

Al-Zaytoonah Journal of Business, Vol. 01 No. 03, November 2025

Artificial Intelligence and Big Data in Accounting: The Case of Commercial Banks in Jordan

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Abstract The integration of Artificial Intelligence (AI) and Big Data analytics is transforming the accounting and financial practices of commercial banks, particularly in emerging markets like Jordan. As the banking sector shifts from a product-centered to a customer-focused approach, the ability to analyze large volumes of data becomes essential for gaining insights into customer behavior, preferences, and financial patterns. This research explores how AI and Big Data technologies are being adopted by Jordanian commercial banks to enhance accounting processes, improve decision-making, reduce customer churn, and personalize services. By leveraging predictive modeling, segmentation, and behavioral analytics, banks can refine credit risk assessments, optimize marketing strategies, and improve customer satisfaction. Despite the promising benefits, challenges related to data quality, technological infrastructure, and ethical concerns remain. This study provides a contextual analysis of how AI and Big Data are reshaping the accounting landscape in Jordan's banking sector and offers recommendations for their effective implementation.

Keywords: Artificial Intelligence, Big Data, Accounting, Commercial Banks, Jordan, Predictive Analytics, Customer Behavior, Financial Technology, Banking Innovation, Data-Driven Decision Making.

1 Introduction

Over the past few years, banking institutions have undergone considerable change. The rapid growth of technology has impacted how banks do business now compared to just a few years ago. Financial institutions are primarily producing revenue by selling their products, such as loans, mortgages, or saving accounts. However, banks are transitioning from a production-oriented "push" distribution focus to a customer-focused, market-driven business model. As financial markets become more deregulated, banks are offering new products to alleviate the problem arising from customer "churn" and competition in local markets.

To retain existing customers and increase the current share of customers' deposits, credits, and products, financial institutions need deeper insights into client behavior, which can be gained through segmentation techniques, predictive modeling, and identification of target groups (Dvorski Lacković et al., 2016).

There are many possible applications of bigger data solutions in the banking industry. A greater understanding of customers leads to gaining insight into clients' habits, purchasing patterns, and evaluations of a bank's services. Such relationships subsequently lead to the ability to predict potential churners and design promotional activities to retain them. Consequently, banks may avoid costly marketing efforts to untargeted clients. With insights into what service aspects customers prefer to evaluate banks against competition, banks can improve their services and lower costs (Liu & Han, 2022)

Predictive scores may also help to deny services to applicants with a certain propensity to default or minimize the credit amount to be offered. By understanding how different aspects of their services impact customer satisfaction, banks may anticipate customer behavior and offer tailored products at the right time regarding how potential benefits are stressed.

2 Overview of Artificial Intelligence in Accounting

AI is rapidly changing the accounting profession, shaping what accountants do, how their work is done, and even how firms are organized. However, accounting education is lagging, threatening the survival of the discipline in its current form. The framework is specifically designed for academics to reflect on AI's potential impact on accounting education, though others may find it useful too. Societal shifts are creating both challenges and opportunities for accounting educators across multiple dimensions. Desired outcomes from AI are (i) benevolence on AI; (ii) avoidance of existential doubt; (iii) expansion of jobs; (iv) increased long-term positive employment ratio; and (v) equitable access for all (Mhlanga, 2021)

AI is fundamentally changing how work is done, worth, and even organized in firms. The accounting profession is not immune to these changes—indeed, it stands to be one of the most affected professions. AI may replace entry-level jobs, transform existing jobs, and create new jobs at various accounting and audit firms. AI products that change what accountants do, how they work, and how firms operate are considered "disruptive" and may threaten the survival of the accounting discipline unless countered. However, AI also offers unprecedented opportunities to improve accounting work, as it relieves accountants of tedious tasks and allows for the qualitative expansion of the profession's core activities (Lui & Lamb, 1970)

AI is based on data (specifically big data), which is defined as unstructured data easily acquired via the internet. Data widely accepted as the 21st-century oil theoretically augurs well for the growth of the global economy. Data, however, generate intelligent activities that could threaten human existence. Armageddon fears range from social media affecting civilization to other uses of AI, like deep fakes, jail-breaking AR goggles, and weapons of mass destruction. Accordingly, there are calls for self-assessment of AI's broad societal impact and the formulation of suitable and effective legal and ethical policy responses so that fears of a looming catastrophe do not materialize.

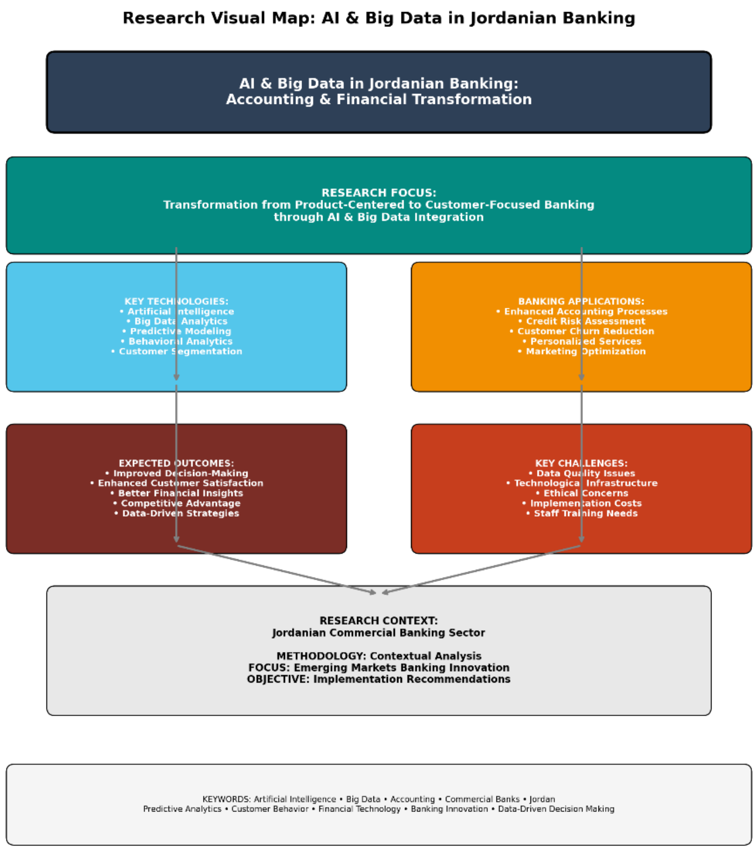
3 Big Data: Definition and Importance

Many definitions of big data exist, but it is generally defined as a large amount of data that cannot be processed with traditional database tools due to its large size and complexity. The commonly used definition indicates three dimensions (3V), namely: a high data volume (volume), high speed of data generation (velocity), and data in different formats, which are difficult to process and analyze using standard tools (variety). Big data are distinguished by their complex structure and unregulated sources, which stem from several processes in banking, i.e. e-banking, mobile banking, SMS banking, and ATM transactions.

Natural gas consumption and its determinant factors in Jordan Using traditional tools, data preparation, cleaning, and integration can last for several months due to unstandardized data. Innovative techniques are needed to clean the data in short time intervals to make them compliant for further analysis.

The importance of big data in financial institutions, such as banks, is reflected through its influence on decision making in business processes, marketing opportunities and strategies, fraud detection, risk measurement, predicting customer behaviors, and psychosocial factors influencing customer decisions. The value of data and analytical tools for making business decisions requires better understanding of collected data, available analytical tools, possibilities of improving existing processes and creating business models.

Big data is deemed as the fastest and biggest growing segment in global business. By gaining sustainable competitive advantage, the value of big data for increase of number of regular or potential customers and for observing customer's behaviors will be presented, and money-saving opportunities through better inventory management will be mentioned. The innovative financial technologies that are offered due to collected data will be presented (Dvorski Lacković et al., 2016)



4 The Role of AI in Financial Decision Making

Numerous aspects of financial decision-making and corporate governance in financial institutions have recently been transformed by digital technology. Users' medical data, shopping histories, and driving records are increasingly being analyzed and used to tailor marketing services. Similarly, as online banking, electronic bills, and mobile banking have proliferated, so too have consumers' payment behaviors and transaction data. An example is when a consumer uses a debit card to buy groceries at a supermarket, their payment data is recorded with details such as the grocery supermarket's property, location of the transaction, and the time of the transaction (Lui & Lamb, 1970)

This non-intrusive collection of data provides rich opportunities. Likewise, excess information can be fed into other intelligent digital tools to produce more accurate predictions of another comprehensive range of topics, including low-rated credit and subsequent defaults, loan applications' deliverables and requirements, and customer complaints and minimal rates (Liu & Han, 2022).

With data collection and processing technology development, such tasks that are time-consuming, financial resource-draining, and costly can be processed with a great volume of data in a wide set of dimensions. By adopting automation decision-making systems, decision-making tasks within financial institutions can also be promoted, as many factors can be considered to produce more accurate and fair decisions. AI technologies address decision-making tasks, including decisions regarding lending limits and interest rates, credit cards approval, money-laundering searching, bonuses, and fraud identification.

Nevertheless, it should also be recognized that such a rapid convergence of diverse technical instruments can lead to adverse adaptability and ethical governance risks. If excessive and redundant information about financial topics is acquired, with many dimensions, the decision-making institutions may be overwhelmed and incapable of achieving acceptable responses within a delay. Another potential dilemma is that the automation of decision-making governance and deployment technology within banks may lead to a reduction in the number of employees in financial institutions and thus a decrease in the population's purchasing power in the relevant demand-side industries. In addition, such rapid convergence may lay the foundation for existing discriminatory issues. For example, the label of 'wilderness area' in a credit report is a criterion of low credit risk. If such criteria can be derived or reached through conversation records, such discrimination can be uncontrolled, generating social tension.

5 Big Data Analytics in Banking

The emergence of big data and advanced analytics has opened up new horizons in every sector of the economy, including financial services. Banks face new competition, new regulations, and have new opportunities for innovation thanks to data. As with industries such as telecommunications and retail, analytics is gradually becoming a management culture, emphasised across business units and hierarchy levels. Banks are beginning to take action across dimensions such as data accessibility, analytics usage, and automation. In a few years, banks will reach a new data environment and significantly enhance customer experience, operational efficiency, and compliance, as well as new product development. This trend is especially relevant to smaller banks, which are typically lacking in talent and technology. However, the role of data frameworks or marketing models and the impact of their goal orientation in business development were highlighted, as well as potential targets for the future (Dvorski Lacković et al., 2016)

Furthermore, regulatory capital constraint gives an opportunity to make better investment decisions. Banks need to identify issues in a timely manner to avoid loss of reputation and profitability, as well as better understand business performance. They can put forward a holistic view of customer experience across all of its business units. Analytics on big data can ascertain how the provision of service affects revenue in real time, refine and optimise the risk appetite in business and operations, and forecast business bottom-line figures and the chance of occurrences (Hassani et al., 2018)

Banks operate in a unique environment, which is regulated with focus on credit and operational risk. The rapid change in business complexity and the abundance of information further expose banks to risks. The need for timely identification and in-depth understanding of these risks is therefore crucial. As most of qualitative information comes from report documents, big data is especially relevant to sentiment analysis. Meanwhile, structured data is becoming increasingly essential, as it reveals hidden relationships among items or events and leads to reasonable risk mitigation actions.

6 Commercial Banks in Jordan: A Background

Jordan is classified as a developing country. Over the past decade, the Jordanian economy has undergone major changes, including structural transformations and modernization of economic policies. The banking sector is considered the backbone of the Jordanian economy due to its important role in securities transactions, issuing capital, credit control, and managing and investing funds. The banking sector in Jordan consists of several components, including capital provided by the Central Bank of Jordan. This sector plays an essential role in the national economy by contributing to economic growth and project financing (Younes Yameen & Sami Ali, 2016)

. The nature of the working environment and rapid developments in Jordan have resulted in the advancement of banking ideas that have made rapid progress over the past several decades in factories, agencies, and banks. The country's banking system has evolved into a modern, bank-based system in the three principal sectors of banking and financial institutions. Commercial banks provide various services to clients, including meeting their needs and providing financial growth. This paper focuses on the subject of commercial banks in Jordan, as they comprise the vast majority of Jordan's banks compared to industrial and investment banks. In addition, licensed and registered countries offer public services to the investing public (Kanakriyah, 2017).

. Commercial banks provide several financial services, including accepting deposits, providing loans, issuing debit and credit cards, and handling checks and money orders. They operate for profit and invest in securities or land, with profits primarily coming from loan interest, commissions on checks and letters of credit, and dividends on investments. Commercial banks are licensed by the central bank to issue cash and public money to the investing public, and they can conduct banking operations in Jordan and abroad.

7 Adoption of AI Technologies in Jordanian Banks

A set of questionnaires were developed in Arabic and distributed to the target group in Jordan banks to collect the most relevant data for this study. Three different means of collecting data were employed: by personal visit to the banks, through email with a covering letter inviting the banks to participate in the study and reassuring them about the confidentiality of the information provided, or self-administered questionnaires that the banks answered and sent back to the researcher. A letter of introduction was addressed to the chief executive officers of all commercial banks in Jordan, inviting them to participate in the study and assuring them that the information gathered would be kept highly confidential. Definitions of terms used in the questionnaire were briefly summarized, and the questionnaire was then translated into Arabic to accommodate the banking experts and employees who may not be fluent in English.

The researcher and research assistants visited the banks and personally handed out the questionnaires along with the introduction letter. The units of analysis were the banks themselves, which were asked to select a group of accounting experts and leading employees with higher degrees who use the accounting information systems to answer the questionnaire with high degree of reliability. Fifty-two banks were asked to fill the questionnaire. Twenty questionnaires were feed back; one was not included in the analysis as it was filled carelessly; therefore, 19 questionnaires were coded by the researcher to treat the data using statistical package. Another questionnaire was sent to audit departments in Islamic Sharia Banks. The banks self-evaluation approach using comparative financial accounts is considered one of the most popular methods of bank performance evaluation. However, the choice of relative indices to measure the bank's performance has been the subject of discussion for a long time. Many indices were used, but no standard, universally accepted lists were found. Therefore, the survey approach is adopted, and the expert questionnaire consists of 55 indices that measure bank performance, viz, input, output, and profit indices. Community-driven public banks are banks operating in public banks set up by communities and owned effectively by the communities.

To ensure that the research meets the expectations and standards of the faculty, it was reviewed carefully. Finally, the design was interviewed in a pilot study of 250. Consequently, it is ensured that the research design meets the criteria of content, construct, reliability, and validity.

7.1. Current Trends

Global accounting professionals have been vigorously debating the implications of artificial intelligence (AI) on accounting and auditing since ChatGPT, one of the most powerful generative AI language models, was made publicly available. Other business professionals have praised ChatGPT's capabilities in an age of increasingly automated digital transformation, while some accountants have raised concerns about whether text-generative AI models would render accountants obsolete. There are additional concerns about the potential misuse of generative AI text models to create misleading or illegal content, which could undermine public confidence and significantly impact professional firms and the auditing profession at large.

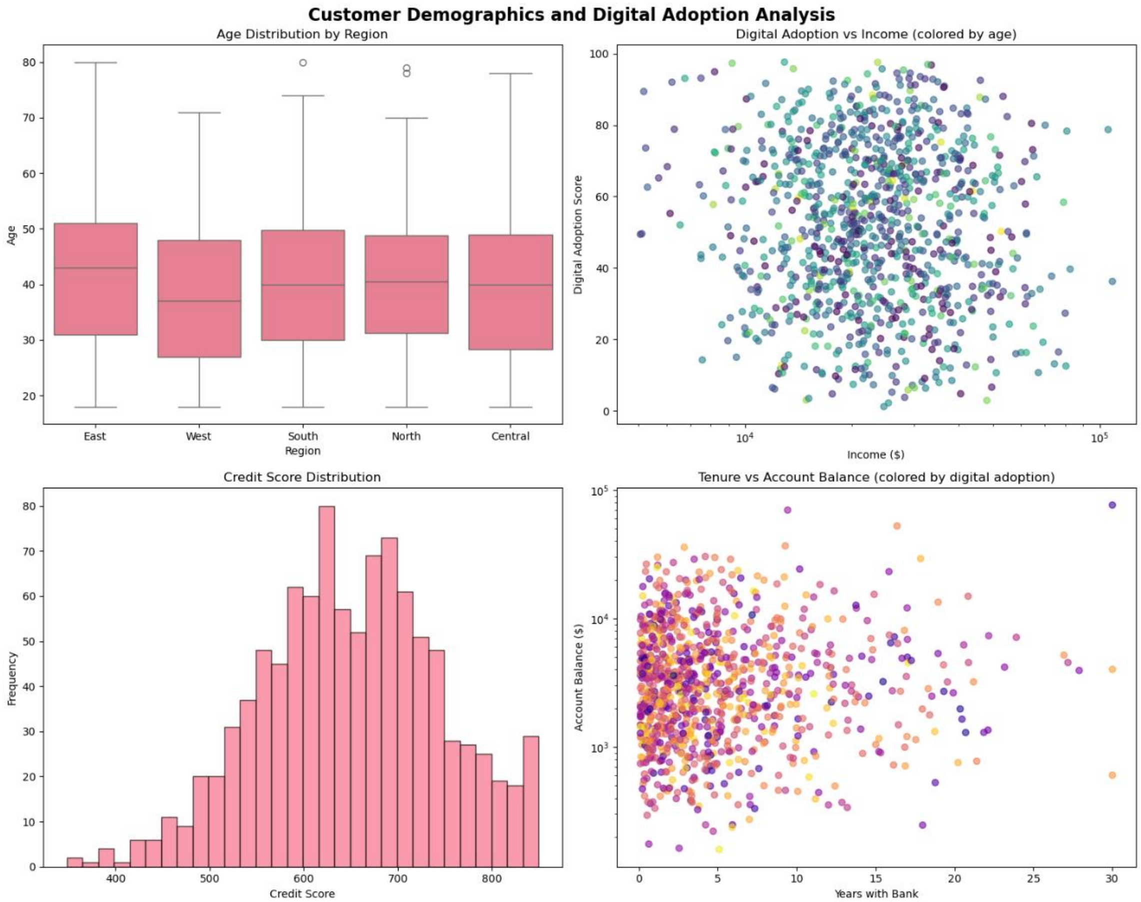
Notably, while many highly visible incidents of AI misuse have garnered huge media coverage and concern, there remains a dearth of knowledge about actual applications of AI in accounting, the extent to which AI is affecting accounting jobs, and how accounting programs, students, and professors are responding to the growing prominence of corporate interest in AI. This study aims to better understand pricing and wage setting in the AI-augmented accounting labor market. It highlights what is known and not known about AI's current and anticipated impact on accounting practice and education, as well as the ethical, regulatory, and economic considerations involved in understanding AI in accounting.

With respect to current trends and applications, while a sizeable body of scholarship on AI in accounting, audit, and advisory work existed prior to the release of ChatGPT, that work largely concerned AI as a futuristic agenda, rather than a significantly implicated technology in current accounting systems . At this intersection of the accounting profession and AI technology, it remains highly informed and significant to map professional technologists' experience of revised practices in an AI-augmented workplace. Also of particular importance is to track how accounting education adheres to, and wrestles with, the burgeoning expectations surrounding the teaching of AI . Understanding how these technologies and their attendant concerns come to shape the business of professional firms, and equally how accounting education (re)aligns to facilitate that burgeoning practice, is inherently significant—electrifying, perhaps, but fraught with urgency.

7.2. Challenges Faced

The continuous technological development and the increasing reliance on these technologies have resulted in great transformations in the economic and social structures of society, especially after the emergence of the phenomenon of electronic trading, the internet, and the World Wide Web . Over the past decade, the banking sector in Jordan witnessed major technological developments that led to the emergence of many banking systems based on the latest global technologies in banking and financial services. As a result, Jordanian banks developed new banking services with new forms and levels of risks, and an expansion of the information base that significantly affected the banking home bank accounting systems in Jordan. These systems provide the management with all accounting, financial, and statistical reports related to the bank's activities and the products of the banking services sector, which includes the thirty-five banks operating in Jordan. However, Jordanian banks constitute a gold mine for any hacker, which increases the dangers and threatens the security and integrity of the data in computerized banking systems. This has resulted in the emergence of new risks in the banking sector that are not completely similar to the apparent risks arising from traditional banking services.

The banking sector in Jordan is characterized by intense competition, and it was one of the earliest sectors in Jordan to use the computer and computer networks to improve financial and administrative performance. As with all computing and computer networks, this technology increased risks to a level that was not commonly known in traditional calculations. The total and integrated costs of this risk are difficult to estimate. In addition to average direct losses, the bank may face larger losses associated with adverse publicity and the considerable cost of defending against regulatory actions. The ultimate loss may exceed the defense costs, fines, and damages. Security problems are more numerous, more diverse, and pervasive than those confronting traditional information systems. In fact, the development of computers and systems made even an ordinary event like a power failure potentially disastrous, resulting in the loss of months of data. Client confidence may decline, which can result in the loss of customers and share prices. Rapid technological changes have stressed the rules governing the country's banks. Compliance and enforcement are often lagging behind changes in systems and processes. With the recent advancements in AI and Banking Information Technology, the study aims to assess the challenges and risks faced by some commercial banks in Jordan.



8 Impact of Big Data on Accounting Practices

The results of the main hypothesis show that big data has a significant positive effect on accounting practices, with an impact coefficient of 0.560. This means that for every 1% increase in big data, accounting practices will increase by 0.560, assuming the rest of the independent variables are constant (Kanakriyah, 2017)

. The t-value is 7.034, which indicates that the null hypothesis can be rejected, and thus, it can be said that big data has a significance effect on accounting practices. In order to apply the Big data technology in accounting practices, it is necessary to implement new provisions and changes in accounting, auditing standards, and procedures as well as establish the legal rules required to not only spread and maintain this technology, but also to ensure all data in its varied forms are safe. Furthermore, accountants and auditors need to be educated on utilizing the Big data technology. FinTechs should also compete by employing big data technology to provide low interest rates, online issuance of credit cards, tailor made loans, value added individual and corporate credit loans and their continuous follow up in competition with banks. The objective of the second sub-hypothesis was to test whether big data affects accounting practices. The results show that the value of the Pearson correlation coefficient is .726, indicating a strong positive correlation between the two dimensional variables with a significance level of .000, meaning there exists a statistically significant relationship. Data mining, real-time processing, deep learning, and machine learning were explicitly addressed in this hypothesis. As for the degree of importance of the dimensions, descriptive statistics revealed that all of the statements were above the midpoint of Likert scale (3), indicating that there exists a general tendency

onal approaches toward modifying processes and developing efficiency. The significance of employing big data analytics to extract valuable information for the organization's growth has previously been highlighted. The proportion of organizations deploying big data techniques on business-related endeavors has been represented as an organization's degree of data management. The measurement of business-based data focuses on the characteristics and purposes of the organization's existing data management technologies . The organizations that have embraced big data analytics are examined exclusively in terms of their targets and gaps along with a comparison against the situation in other sectors. Additionally, a comparison of banks and non-banks is also pursued to understand the difficulty of generalizing lessons among person-to-person services. For mergers and acquisitions, for the prediction of stock movements, forecasts of interest rate movements, assistance in risk management, fraud detection, and bankruptcy prediction, big data is a critical component in meeting banks' and non-banks' business purposes. Involvement in cross-marketing, prospecting, support for product development, and customer analysis is less common. For risk and operational management, big data is employed less extensively than expected by both banks and non-banks. Fraud detection and prevention, macroeconomic risk assessment, and daily cash prediction are important fields in risk management for mid- to large-sized banks deploying sophisticated risk management architectures. In the banking sector, outsourcing and use of contractors for work other than IT processes account for a significant amount of data breaches, pointing to capability limitations. Hence, the perspective of organizations regarding their data management situations and the implications of these perspectives on their intended use of big data spans is outlined.(Liu & Han, 2022)

8.2. Reporting and Compliance

Reporting and compliance are seen as an important tool in monitoring the implementation of banks' accounting policies and procedures. All regulatory authorities require compliance to the banking regulations. Banks have to prepare their reports after applying the accounting policies mentioned in the manual of accounting policy and procedures prepared by banks against the norms of the Accounting laws and standards. They have to report to the banks authorities and regulatory authorities monthly, quarterly and annually as per the requirement of the authorities. Reporting is the presentation of the summary of the application of accounting policies in the monetary terms to the interested users to enable them to understand how the accounting information has been applied and what it portrays about the performance and position of Banks. Reporting, in turn, is grouped into compliance and consumption. Compliance means "to conform, acquiesce or yield". Compliance is done first before reporting. It is the application of the accounting policies in recording the day-to-day transactions. Reporting on compliance means the report stating how far the accounting policies were complied with.

Report on compliance prepared against the assessment of compliance is presented in the compliance section of the report on acceptance of external auditing. The report on compliance is presented to the board of directors, audit committee and regulatory authorities of the central bank. Reporting on compliance is seen as an important tool in tackling the financial crisis and monitoring the implementation of banks' accounting policies and procedures (Ismail Hossain, 2013). In Bangladesh, every bank is required to follow the Bangladesh bank guidelines in preparing reports on accounting compliance. Bangladesh bank is the central bank of Bangladesh. Four foreign banks did not comply with the Central Bank Bangladesh Bank Regulation, 1984 in respect of which their directors as well as chief executive officers were personally held liable by the sanction of fines and penalties. In Bangladesh, few studies have been found on compliance functions of banks (Shamim Hossain & Alim Baser, 2011).

H1a: There is a significant difference in the quality of reporting and compliance between traditional banks and internet banks.

H1b: There is a significant difference in the quality of reporting and compliance between local banks and foreign banks.

H1c: There is a significant difference in the quality of reporting and compliance between state owned banks and private banks.

9 Case Studies of AI Implementation

Commercial banks in Jordan have started recognizing the need for Artificial Intelligence (AI) and Big Data technologies in order to maximize their resources and provide personalized services to customers. In the Jordanian banking industry, many banks have been incorporating AI into their trends in recent years. Achieving control over human-relevant data has become a prerequisite for competitive advantage in banks. In order to capitalize on the strategic opportunity afforded by developments in AI, banks first need to invest in the construction of an integrated AI ecosystem for data acquisition and processing, therefore paving the way for the application of AI-based solutions in a wide range of service schemes, customer-facing or otherwise. Civic services and industrial projects with a large customer base, internet-wide transactions, or significant social impact are ideal subjects and venues for the testing and training of AI solutions and frameworks. Likewise, the cooperation with local regulatory authorities in developing financial compliance paradises is a promising area for the use of cutting-edge AI. The collective impact of the suggestions would promote the construction of a healthy and benign AI ecosystem supporting both banks' interest and customers' needs and withstanding the potential abuses of AI technologies.

More recently, AI-based systems have been adopted in banks. It is predicted that credit rating statistics of up to 10,000 companies will be available for banks to assess the risk of handshakes with different companies. Banks can further enhance their productions by using AI to analyze real-time stock market data and market news. AI may be used to evaluate this data, identify problematic data, perform risk prediction, timely tracking, and further determine if it fits the standards of bank transactions. Furthermore, AI can warn of difficulties in bank transactions, prohibit inappropriate transactions in real time, and significantly increase banks' risk management levels. AI may handle the loan process when banks lend. Network algorithms handle the analysis of personnel social graphs as the data sources of banks, identify suspicious social graphs, assist in credit risk assessment, and identify fraudulent customers.

Banks may also benefit from AI in general big data processing. The vast amount of data in social networks requires more and more processing and storage capacity than storage systems can handle. High-performance storage must be installed and maintained by engineers and managers devoted to data storage. Banks can collaborate with social service networks and allow them to host the data. Libraries of AI algorithms and intelligent processing capabilities to analyze bank-held social data can be added to the network. More likely, AI can analyze the public sentiment towards a company or an enterprise publicly. Banks can assess the credit risk of companies by searching the social network-relevant term searches, hence assisting loaners in deciding whether to lend to a company.

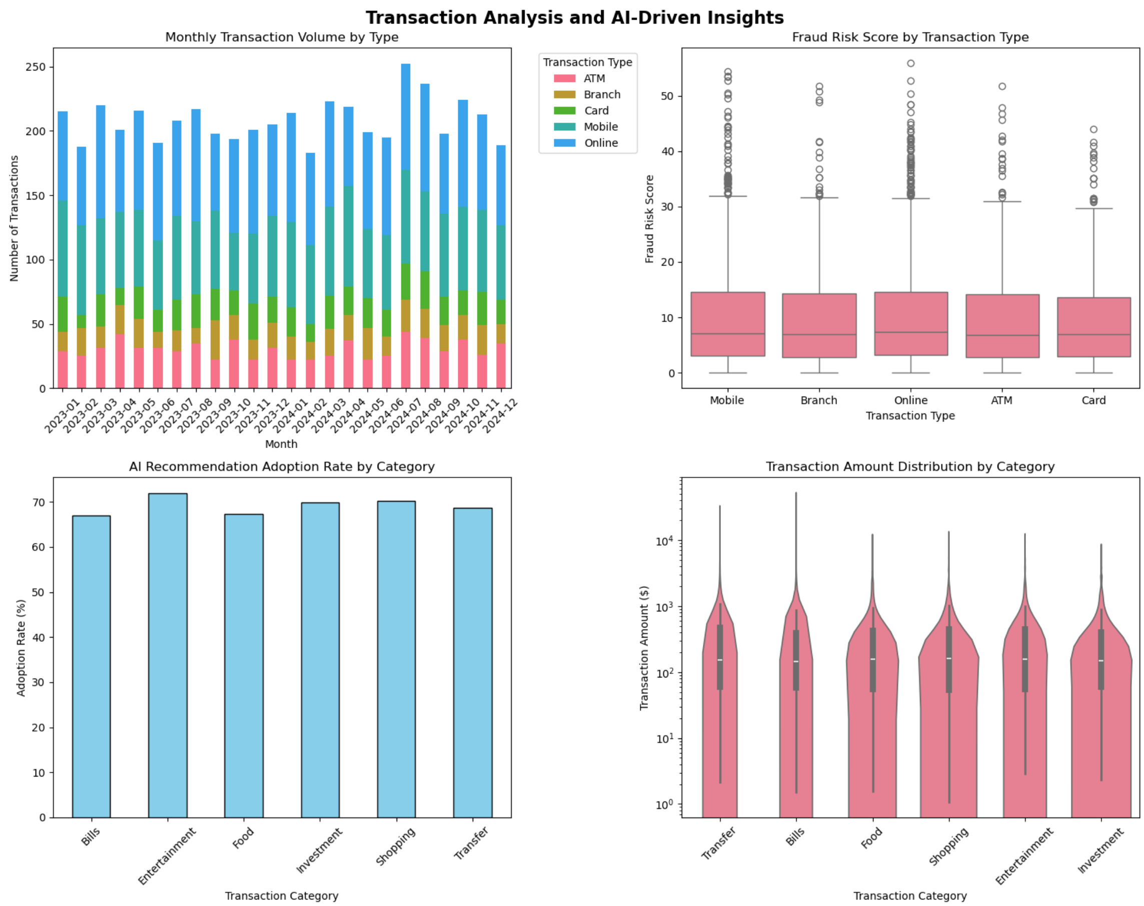
9.1. Successful Implementations

The modern world is characterized by rapid changes in all aspects. Thus, every civilization in particular and the world in general have become dependent on modern technology. Jordan offers adequate infrastructure to cope with the rapid development of modern technology. Success in providing such technology depends on the availability of suitable conditions. Banking values have increased with the evolution of banking services and substantial developments in banking operations. Banking services have expanded to cover a major part of the national economy, attracting substantial central master systems, required by customers' needs in light of fierce competition. This encourages managerial methods in banks and organizations to change accounting information systems from manual to computerized or semi-computerized, as computerization improves efficiency and quality (Kanakriyah, 2017). The objective of this paper is to examine whether such information systems affect the functions or banking methods (i.e. services, products, clients, design, promotion, and selling). The study proceeds as follows: A definition of banking operations, a brief examination of the principal characteristics of accounting information systems, and a literature review. A presentation of the survey methods utilized, a reporting of the research findings, a discussion of those findings, and a conclusion. The Jordanian banking sector began to function in 1964, and its growth, expansion, and evolution have kept pace with the more developed Arab and foreign banking systems. The number of banks at the end of 2005 reached 24, believing that Jordan offers adequate infrastructure to cope with the rapid development of modern technology. The banking sector is developing quickly with significant accumulations of funds on which many funds depend locally. There is widespread investment activity by individuals, companies, and financial institutions seeking a good return on their investment.

9.2. Lessons Learned

As a result of the case studies and interviews with a selection of Jordanian commercial banks regarding the application of AI and big data. The research offers Jordanian banks significant ways to keep pace with global banking development and provide a wide range of sophisticated smart banking services to improve the customer experience. The results show that, despite the difficulties facing Jordanian banks, more than half of them believe that AI/big data will help these banks outperform their competitors. Jordanian banks consider applying AI and big data to their operations in four major areas: risk management, internal auditing, marketing, and customer service. The AI/big data systems being implemented can continually detect anomalies, categorize suspicious transactions, assess default credit risk, conduct sentiment analyses on customer posts and reviews, assist sales agents with chatbots, and offer personalized alerts. More than half of Jordan's commercial banks have an AI/big data system either implemented or on the way. AI has a greater impact than big data on these banks' operations even though banks are also aware of the importance of big data.

Adapting and implementing AI/big data systems is challenging. The primary barrier to and fear of AI/big data, according to Jordanian banks, is their reliance on the human workforce, which cannot be effectively placed by AI. Jordanian banks believe that AI/big data need not to be immediately concerned about the possible negative impact on performance. Jordanian banks classify the advantages of AI and big data into short-term (immediate) effects, mid-term (two years), and long-term (three years) effects on operations (more than three years). More than half of Jordan's commercial banks anticipate that AI/big data systems will enhance their development and risk management in the short- to mid-term. The interview results confirm that today's global banking sector is shifting toward a knowledge-based intelligent banking sector, supported by AI, big data, and similar financial technologies.



10 Regulatory Framework in Jordan

The regulatory framework in Jordan consists of various laws, regulations, and directives developed to provide the legal grounds and standards for different aspects of commercial banks' operations. The following paragraphs provide some of the key laws governing commercial bank operations in Jordan. The regulation of commercial banks in Jordan commenced with the establishment of the Central Bank of Jordan (CBJ) in 1964, by virtue of the Banking Law No.28 of 1964. The CBJ is responsible for formulating, implementing, and following up with the monetary policy, maintaining the stability of the currency in Jordan, preserving and enhancing the stability of the financial system, and regulating the banking sector (Kanakriyah, 2017). Commercial banks in Jordan have occupied a significant position in the Jordanian economy, in terms of volume of assets, and providing employment opportunities. The interest in and attention to studying the impact of big data and artificial intelligence on the accounting and auditing processes in Jordanian commercial banks comes because of having the regulatory framework concerned with the accounting systems and their regulation in the various banks operating in Jordan.

The accounting regulation in Jordan consists of various laws, bylaws, directives, regulations, and decisions. The accounting legislation provides the legal grounds and standards for the regulatory effectiveness of the steps taken toward enhancing financial responsibility and improving public and private sector accountability. Financial accounting regulations involve the production of financial statements and books in general, as well as the best means to develop the quality of accounting systems and the manner of developing them, accompanying big data and artificial intelligence aspects compared to other developed countries. The Jordanian accounting legislative framework consists of the narrative and the technical material governing all aspects of the financial accounting system. It also includes the procedures adopted by organizations and institutions to record data, process them, and prepare comprehensible financial reports. Accordingly, commercial banks are required to adhere to the framework of laws, including the Banking Law No. (28) for the year 2000 and its amendments; the Financial Institutions Law No. (33) for the year 2010; and the Accounting and Financial Governance Law No. (1) for the year 2017.

The regulatory framework also includes by-laws and socalled instructions, such as the accounting instructions for commercial banks for the year 2002; the accounting instructions for mortgage finance companies; as well as the accounting instructions for non-banking financial institutions. In addition to the IASs issued by the IASB and so on. Financial statements sent out by companies don't usually provide digitized data and thus can't be efficiently analyzed. Generally accepted accounting principles have to be adhered to throughout the data gathering process. Enterprise knowledge of the legal structure has to be available in a meta-data repository to be able to query information about and access the data.

10.1. Banking Regulations

By observing the importance of the banking system for the global economy, financial regulations are considered essential to protect the money of individuals and companies from banks and other financial institutions as the custodian of funds. For this purpose, many regulations and monitors are imposed by countries or by international institutions. As far as the banking sector in Jordan is concerned, many banking regulations and instructions are imposed by the Central Bank of Jordan based on international instructions and other achievements. One of the more important regulations imposed on banks is to maintain a capital frame, meaning that a certain percentage of total assets should be preserved based on the average risk of the banking transactions. Also, many regulations were imposed to ensure the quality of both internal and external banking transactions; this includes instructions for record keeping, documenting, auditing, etc. In Jordan, these records clear transactions are stored in the ledger and the support for this transaction should be documented.

However, many of these regulations, controls, and instructions should accompany after ensuring that these transactions have already been secured; that means that the financial service providers should indicate beforehand the regulatory requirements in transactions before ensuring its compliance. On the other hand, and similar to the case for commercial banks in many countries, and by the increasing capability of financial data analysis and statistics, many financial transactions are becoming highly automated and very large in volume. Usually, large banks provide online trade, purchase applications that are powered by big data systems that handle these banking transactions. Also, a significant number of big data applications are seen in commercial banks like deleting some financial transactions records and changing the track pattern of money, etc. The governance and supervision of the financial transactions is crucial for controlling money laundering and in order to protect the economy from the negative impact of terrorism funding and criminals activities, and to ensure the complies of the banking transactions of the Jordan financial regulations.

10.2. Data Protection Laws

The regulation concerning personal data and privacy protection in Jordan mainly comes from a Data Protection Law promulgated on 05DI/2015. The Data Protection Law came into effect on 01/01/2018, which aims to safeguard personal data privacy rights by setting forth general rules to determine its conditions, guarantees, and usages and granting judicial protection against any breach thereof. Notably, Article (1) of the Law states that the Law shall apply to any data processing procedures applied to any personal data or public body files, whether it was performed in Jordan or outside it as long as such data is related to persons residing or having dealings in Jordan, or regardless of the location of the processing if it was carried out for the purpose of making personal data available to any public body or establishment in Jordan. Besides that, the Data Protection Law imposed many obligations on data controllers that any person shall be considered a data controller if he has knowledge of any kind about any matter relating to the collection or process or using of personal data relating to any person. As for the obligations of data controllers, they must obtain the data subject's prior written approval before processing any personal data. The law enumerated exemptions of data processing without prior written approval from the data subject. It also forbade data disclosure for third parties unless the prior approval of the data subject was obtained. It also allowed the data subject to request data review and the application of any related rights which should be processed without delay. Later, banking sector had to regulate such legislation and principles, especially with the deployment of big data analytics and AI.

The Central Bank of Jordan (CBJ) issued instructions to comply with data protection laws and to maximize benefits from the use of big data analytics as early as 03/04/2018. The instructions contained data types, collecting sources, collection methodology, the data management process, data storage, accessibility and withdrawal, data protection measures, awareness, user rights, as well as big data analytics user roles and responsibilities, big data techniques, applications, challenges, ethics, and the effect of using such technologies (Lui & Lamb, 1970).

11 Ethical Considerations in AI and Big Data

Artificial intelligence (AI) and big data have become an integral part of our lives and are essential business tools in many industries, including accounting. However, their growing importance has created concerns the world over regarding their ethical use (Belle, 2019). These concerns are compounded by the fact that the use of AI and big data can have serious implications for privacy and autonomy. Similar concerns have arisen among potential AI adopters and users (Lui & Lamb, 1970). Tackling ethical concerns head-on can help to proactively shape how AI and big data are used ethically, and how concerns can be addressed if they arise.

The ethical algorithms have been used previously to address ethics surrounding the core business of accounting firms. Publicly accounting firms are required to maintain confidentiality and the privilege and keep the secrets of clients. The predictable and repetitive accounting services are simple and routine tasks that have easily outsourced by to computers across different zones. Accounting firms use a variety of tools, techniques, and procedures to extract huge data from structured, semi-structured, and unstructured social media platforms. The advancement of hardware and software technology, as well as the variety of big data analytics tools, have made it easy. With the help of big data, techniques can assist in providing valuable insights into how to do business with customers. Along with the advantages of utilizing AI and big data, there are ethical issues and concerns arise across the profession.

Such ethical issues and concerns have classified into seven categories as over-reliance, data confidentiality and algorithms confidentiality, clients' trustworthiness, lack of professionalism and integrity, severe data breaches, hacking and cybercrimes, and breaches of human rights or rights of minorities. Ethical concerns regarding the environment and take into account how it affects the wellbeing of future generations are discussed. AI and big data techniques utilized in the accounting profession and before their adoption take into account the ethical issues and concerns highlighted in the survey. Call for more scholarly research regarding the ethical side of AI and big data is made.

11.1. Privacy Issues

With the growth of mobile, storage, web-based, and cloud technologies, the need for information is more significant than ever. These developments have caused an information explosion that has far outpaced the capacity of governments to monitor and supervise cyberspace activities, leading to massive privacy issues. The problem of privacy has become more complex than ever with the challenge of protecting legal boundaries while utilizing freely available online information.

Privacy is unparalleled in its potential impact on organizational revenue, branding, and corporate structure and policies. Organizations that gain trust, loyalty, and a strong brand equity value can expect profits, growth, and an organization that can sustain itself long term. For effective service, organizations must not only actively address privacy breaches or issues but also consider that breaches, especially those in data repositories such as government and banking sectors, can be ruinous.

Regulatory breaches concerning customer data can incur heavy fines and even lead to business closure. Compliance and data protection, as core tenets of banking ethics, can be the main focus of organizations striving to build a safety net against breaching issues. However, organizations can be proactive in avoiding breaches through keen targeting and defense. Defense against data breaches is a multi-pronged approach. Employees must be repeatedly trained and educated on illegal security risks. Organizations must channel data into fewer powerful servers, preferably within their premises, cutting off access to data by third parties and cloud services.

11.2. Bias in AI Algorithms

Machine learning algorithms have become ubiquitous in high-stakes decision-making applications. Indeed, the ability of machine learning algorithms to learn patterns from data enables them to incorporate biases embedded within those data. Accordingly, a biased model can make decisions that disproportionately harm certain groups, limiting their access to financial services. In response to this problem, the field of Fair ML has emerged, focusing on studying, measuring, and mitigating unfairness in algorithmic prediction.

However, the underlying causes for algorithmic unfairness remain elusive. Indeed, researchers are still divided about whether the blame lies with the ML algorithms used for the predictions or with the data these algorithms are trained on. To contribute to answering the questions posed in the title, first, an overview of the problem and its relevance to the community has been discussed. Second, a targeted taxonomy was proposed to characterize data bias, allowing one to model different types of bias and test how they interact with three specific ML algorithms, and study hypotheses regarding the fairness-accuracy trade-offs this type of fairness-blind ML algorithms exhibit under different data bias settings.

Heretofore, the fairness-blind ML algorithms implemented in the experiments are a direct consequence of the targeted taxonomy. However, specific fairness-aware post-processing interventions that do not require access to the training data can optimize the output of a biased algorithm by producing a new decision threshold. As a conceptual proof-of-concept, a specific algorithm was utilized to ascertain the best threshold given a bidirectional naive Bayes model. However, in future work, one of the open questions is how to determine the best threshold mathematically, considering that the combination of certain methods tends to achieve this performance for models trained differently than the bidirectional naive Bayes models used herein.

In practice, the feasibility of the proposed counterfactual fairness measurements is elaborated through a real-world use case with three different ML algorithms trained to predict decisions taken in a banking fraud risk use case. Results demonstrate how predictions are affected by training set bias, illustrating that each bias setting entails specific trade-offs, affecting fairness in expected value and variance. Lastly, a case study in which privacy-preserving ‘crowds’ of untrusted worst-performing models are combined to provide ‘trusted’ predictions.

12 Future Trends in AI and Big Data for Accounting

A trend in artificial intelligence and big data analytics recently came to the forefront outside of the accounting domain: The auto-generate poem created by AI. However, as a double-edged sword, new AI applications create both advantages and worries in terms of accountability. This study provides a glimpse of this promising, ambiguous, and thorny issue through the research agenda in the accounting context.

It was noted that entrenched professional skepticism and the collaborative nature of professional skepticism assessment should be the primary foci in the future research of AI applications in auditing. Lack of understanding of AI methods may create suspicion of inability to interpret complex systems, and therefore reduce professional skepticism. Junior auditors may also lack data and experience for appropriate and critical questions. In terms of audit committee turnover, as the gain theoretical knowledge about AI applications, professional skepticism would tend to be reduced through calibration.

On the contrary, audit firm rotation and large audit firms may act as means to improve professional skepticism due to higher entry barriers and secretive predilection, and a longer association with client may weaken professional skepticism. It is expected to establish an objective measure for professional skepticism and perform experiments through interviews later. In collaborative contexts, the examination of collaboration within auditing teams would shed light on the future research of AI-assisted professional skepticism assessment, bringing new insights into elite dual-process modeling. Despite these specific ideas, it was acknowledged that the scope of future research should be broadened ultimately to explore this promising yet ambiguous facet of AI applications in auditing.

It was challenged to redefine accountants in the era of the gig economy, and listed drivers for changes across time to change basic notions of accountants fundamentally. Quality assurance, social media, and integrated reports might be the key developments in future accounting practices. It believed that micro-level studies would provide deeper insights on the evolution of assumptions about accountants. On the other hand, expert judgment-like tasks are elusive to computers, hence considered that future moves of AI on "system" and "process" level would be developing question-and-answer systems instead of replacing accountants altogether.

It was made a commendation on the emergence of big data technologies, which might turn big data into smart data for automatic and optimal decision-making and enhance capacity to analyze capability abundance and speed. In the short run, it was believed that large background knowledge databases should be constructed, and regulatory compliance and accounting loopholes should be identified as loophole-hunting data technologies. It was then highlighted that prior studies having discussed opportunities and tips for audit data analytics might be of broader implications than intended. For both advisable and avoidable paths, it was indicated that insights from more fields should be applied in accounting research.

12.1. Emerging Technologies

Emerging technologies have affected competition in all sectors, and the finance industry is no exception. It has undergone significant transformation with the advent of technologies such as the Internet and mobile devices (Lui & Lamb, 1970). FinTechs, or technology-powered financial services, are characterized as flexible, innovative, and often equipped with high-end technologies such as Big Data, the Internet of Things (IoT), and Artificial Intelligence (AI). These have resulted in the establishment of new business models and revenue streams, revolutionizing the provision of financial services, and stimulating incumbent banks to change their strategy and management (Mhlanga, 2021).

Technological advancement has promised potential benefits and value-added service convergence for consumers. In addition to traditional roles, the finance industry through FinTechs have offered ancillary services such as automated financial advisory and portfolio management, payments and settlement, insurance, transaction tracking, trade financing, and regulatory compliance. With regards to supply-side benefits, competitive effects through market entrance of new players, technology utilization, and competitive service provision have a chance of income stream enhancement and cost reduction. Yet, emergent risks and challenges such as elevated systemic risk, cyberattacks, exposure to data silos, knowledge gap, vulnerability to fraud, and dual regulation by FinTech and Banking regulators have emerged. This study pertains to the competition and marketing strategy effects of FinTechs. With the rapid acceleration of emerging technologies, it is noteworthy to understand their roles in shaping the competitive landscape of an incumbent market participant. Therefore, two questions are proposed: how do the emergence of financial technology firms shape the competition to retail banking sector incumbents, and how do the incumbents respond to such changes?

Based on the discussions, research is needed to identify the potential effects of emerging technologies in the financial services sector, the retail banking subsector in particular. Investigating the potential opportunities, threats, and challenges posed is crucial. In addition, the competitive effects and strategic responses of a handful of retail banks in an Asian emerging economy will be studied. The end is to provide the basis for a competitive strategy re-evaluation. An addition is to explore competitive situations and strategies in multi-tiered, different finance sectors in emerging economies.

12.2. Predicted Changes in the Banking Sector

The new information generation methods, the shortening of the information age, and the acceleration of information dissemination all accelerate the transformation and reform of the banking industry into the digital economy era. With the broad application of modern technologies such as big data, cloud computing, and artificial intelligence, the overall informatization level and architecture of the banking industry will usher in more comprehensively new changes. Most traditional industries and businesses, including banking, are facing bifurcations and even scruples brought about by technologies (Liu & Han, 2022).

The application of AI technology will bring profound changes, which will quickly penetrate all business sectors of the banking industry. It will be applied in several important links of banking services, such as credit, payment, marketing, anti-money laundering, and customer interaction, and become a vital productivity tool for banks to accelerate profitable growth. Banks will become more technology-driven, pattern-oriented, and data-intensive, and a large amount of data from external sources will enter the knowledge base of banks. Banks will rapidly expand their investment in natural language processing, machine learning, and knowledge graphs, and the development of the banking industry will be farther away from traditional banking services to professional retailing-driven businesses and from profitability-driven to commercialization-driven businesses (SALEEM & Mary Mathew, 2022).

Fueled by information connectivity, virtual communication, and data analytics, customers and relationship managers will connect more efficiently and effectively than ever. Banking business services will become influenced by social media, intelligent assistants, and other proliferated clients. Banking services will no longer be confined to physical branches, shared ATMs, and online portals, but will increasingly become decentralized and diversified. The human customer 2.0 with advanced AI will have more amazing and fascinating intelligence, learning ability, and critical thinking than today's human customer 1.0. Most customer behaviors will not be committed by humans but will be conducted by info agents, chatbots, and purchase agents.

13 Comparative Analysis with Global Practices

It is worth noting that the challenges of adopting AI technology in accounting do not differ much from those in other areas of the world. The accounting profession worldwide is dealing with similar challenges in adapting AI and other technologies. The profession of accountants faces some of the most rampant technologies of the 21st century. The ability to collect, create, process, protect, analyze, and exploit data is what would determine the survivability and success rate of organizations in this computer age. Most modern technologies used to manage organizations today are a result of the accumulation of data and the fast processing of this data by algorithms. A notion of artificial intelligence (AI), machine learning (ML), and big data analytics (BDA) refers to a set of technologies and solutions that can be used by accountants to enhance their capabilities to execute unique, scalable, and repetitive functions of accounting. Although still nascent and growing, AI, ML, and BDA would be the future of accounting. Major challenges are linked with the management of technological differences and the liability corporations would face as a result of the intelligent systems they employ. AI systems used by an accounting function may make a wrong prediction on tax planning and exposure, for example, leading to a gross reporting error with financial, legal, and reputational implications for the organization. As a response, regulators may require technological audits, ethical influencers to assess lived experiences, and job descriptions of AI systems as needed to trace responsibility (Kanakriyah, 2017).

13.1. International Case Studies

International companies are forced to create and adapt new systems to meet the challenges posed by new technologies. This is why, during the preparation of accounting information, a great need for completion and presentation arose. The number of credit banks exposes a greater demand for controls and information disclosure. The emergence of artificial intelligence provides reliable and cost-effective solutions and opens better ways to deal with the problem of uncertainty. Traditional methods of data processing are becoming increasingly inadequate due to the increase in volumes, as well as the increase in variability in terms of their content and speed of delivery. The explanation and interpretation of this information requires new methods of treatment and presentation (Kanakriyah, 2017).

Banks and financial institutions in developing countries are adopting various AI methods to enhance their processing capabilities of rapid and large volume data. Customer services and decision-making problems in these institutions require real-time processing of huge amounts of historical data as well as current data. To deal with this highly rich volume of data and the speed of its delivery, it is important to adopt AI paradigms such as neural networks and fuzzy systems. The combination of traditional methods with AI paradigms can reinforce the efficiency and effectiveness of the utilized method in improving and enhancing the quality of decision making.

The immense transformations in the banking world resulting from modern banking techniques and technological advancement have necessitated the emphasis on the utmost effective utilization of resources. As a result, the current study investigates the impact of accounting information systems (AIS) on the success of Jordanian banks. To achieve this purpose, the researcher developed a questionnaire which was distributed to the head offices of the eleven banks. Out of the total distributed questionnaires, 46 were valid for analysis. The data was analyzed using SPSS. In addition to descriptive statistics, a simple regression analysis was utilized. The study revealed that with all of its dimensions, AIS significantly affected banks' success. Following the findings, a number of recommendations were suggested to assist bank managers in the needed decisions to ensure and reflect the desired banks' success.

13.2. Best Practices

The following best practices were deduced based on the results of this study and the responses received from the directors/managers of the commercial banks in Jordan regarding its items in the study tool, which had significant arithmetic averages. Furthermore, deep information mining tools such as data warehousing and data mart, data mining tools such as OLAP, and statistical data processing methods and tools are all used in the accounting system, which is compatible with big data and AI systems. The use of big data in accounting ensures good accounting practice in a bank by providing intelligent services, rapid analysis, informed decision-making, controlling accounting inaccuracies, increasing data quality, and clarifying customer segmentation. Commercial banks are aware of big data opportunities and capabilities and believe they should make great efforts to invest in it. Other accounting financial applications such as e-banking and M-awareness are used based on the old accounting system that lacks deep financial information mining tools or big data concerning the decision-making process of banks.

Heads of departments in the banks should be aware of the great capabilities of big data on customer management availability and personalization. They also believe that data warehousing and data mining methods and procedures have to be applied to their banks, which will aid them in clarifying customer and stockholders segmentation. It also enhances the possibility of the banks' prediction, which is one of the major accounting practices in a bank, and increases the availability of personalized products and services toward customers, allowing them to expand their market base or contribute to the growth of the capital market in Jordan and the region.

Internal and external challenges hindered the use of big data and AI in accounting. These challenges vary between banks, but the most significant challenges are the legacy accounting system, investment cost, organic non-standardized data, and lack of skilled staff in data processing. Despite these challenges, most banks in Jordan have made great efforts to overcome them using parallel systems to the old one and up-skilling the accounting department's staff. Most current banks are aware of the current lack of accounting effectiveness and have made big efforts in their big data investments to reach their improvement, which will involve great efforts in the future. Commercial banks in Jordan are in the second wave of big data applications, exert substantial efforts to be competitive, and are big data-ready systems regarding big data applications in accounting financial concerns that are considered on-going and dynamic processes.

14 Conclusion

The study aims to identify the factors inhibiting the adoption of Artificial Intelligence and Big Data in accounting by commercial banks in Jordan. It aims to provide recommendations for overcoming these obstacles, making it one of the few studies exploring accounting professionals' technology risks in Jordan. Bank executives who have accounting backgrounds or expertise were interviewed in the semi-structured style using an interview guide and questionnaire over two months in 2022. Interviews were coded and analyzed using the thematic analysis approach to obtain the study's themes. Twelve factors inhibiting the adoption of technology in accounting offices were identified, falling under the categories of attitudes and expectations, technical issues, work processes, control and inspection, perception of necessity, behavioral factors, planning, and knowledge and skills. Accordingly, the study recommended developing individual, working group, and organizational awareness while controlling and inspecting the adoption process.

The number of published papers on the topic has increased in recent years and is expected to rise in the future. However, attention given to accounting professionals' perspectives on the factors affecting the adoption of pronouncements is still limited. This study is significant because it seeks to address some of those calls. More importantly, this study explores the various factors affecting the adoption of pronouncements in Jordan, where such research has not been previously conducted.

Technological advancements have positively affected organizations. Interviews were conducted with the managers of selected commercial banks in the Amman Stock Exchange to investigate the adoption of Cloud Computing in accounting information systems. The analysis followed the qualitative thematic analysis approach to obtain nine themes that are both enablers and barriers to the adoption of Cloud Computing along with the benefits linked with this technology.

15 References:

1. Abaddi, S. (2025). AI's call: Jordan's MSMEs answer with intent. Journal of Entrepreneurship in Emerging Economies. [HTML]
2. Al Marzooqi, M. (2024). The contribution of artificial intelligence (AI) to disaster response and management. figshare.com
3. Al-Billeh, T. (2022). Legal Controls of the Crime of Publishing a Program on the Internet in Jordanian Legislation.. Pakistan Journal of Criminology. pjcriminology.com
4. AL-BILLEH, T. N. (2024). Legal framework for protecting the right to private life in the digital space: the extent to which Jordanian constitution and legislation takes into account international …. Revista de Investigações Constitucionais. scielo.br
5. Ali, M. S., Swiety, I. A., & Mansour, M. H. (2022). Evaluating the role of artificial intelligence in the automation of the banking services industry: Evidence from Jordan. Humanities and Social Sciences Letters, 10(3), 383-393. academia.edu
6. Al-Khawaja, H. A., Yamin, I., & Alshehadeh, A. (2023). The COVID-19 pandemic's effects on Fintech in banking sector. Review of Economics and Finance, 21(1), 316-322. academia.edu
7. Al-Khawajah, N., Al-Billeh, T., & Manasra, M. (2023). Digital Forensic Challenges in Jordanian Cybercrime Law. Pakistan Journal of Criminology, 15(3). pjcriminology.com
8. Alkowmi, H., & Al-Safadi, M. E. (2024). Factors Affecting Big Data Analytics in Jordanian Commercial Banks. In Sustainable Horizons for Business, Education, and Technology: Interdisciplinary Insights (pp. 231-239). Singapore: Springer Nature Singapore. [HTML]
9. Almashawreh, R. (2023). Determinants of adoption and impact of digital technologies by SMEs in Jordan. canberra.edu.au
10. Alrfai, M. M., Maabreh, H. M. A., Sharairi, J. A., Saatchi, S. G., Haija, A. A. A., Rahahle, M. Y., ... & Al-Hawary, S. I. S. (2024). The role of big data analytics capabilities in risk management: an empirical investigation of insurance companies in Jordan using structural model. In Business Analytical Capabilities and Artificial Intelligence-enabled Analytics: Applications and Challenges in the Digital Era, Volume 2 (pp. 43-56). Cham: Springer Nature Switzerland. researchgate.net
11. Al-Shormana, H., Al-Zyadat, A., Khalayleh, M., Al-Quran, A. Z., Alhalalmeh, M. I., Mohammad, A., & Al-Hawary, S. (2022). Digital service quality and customer loyalty of commercial banks in Jordan: the mediating role of corporate image. Inf. Sci. Lett, 11(6), 1887-1896. aaru.edu.jo
12. Belle, V. (2019). The Quest for Interpretable and Responsible Artificial Intelligence. [PDF]
13. Dvorski Lacković, I., Kovšca, V., & Lacković Vincek, Z. (2016). The potential for big data application in the marketing of banking institutions. [PDF]
14. Gupta, R. K. (). Strategies for long term business survival and growth (What you do today to stay in business tomorrow). researchgate.net. researchgate.net
15. Hamid, M. A. & Rana, M. W. (2022). Impact of customer relationship management, technological turbulence, and customer-centric management on financial performance. humapub.com
16. Hassani, H., Huang, X., & Silva, E. (2018). Digitalisation and Big Data Mining in Banking. [PDF]

17. Ismail Hossain, M. (2013). Compliance of Corporate Governance of the State Owned Commercial Banks : An Empirical Study. [PDF]
18. Kanakriyah, R. (2017). The Impact of Accounting Information Systems on the Banks Success: Evidence from Jordan. [PDF]
19. Liu, X. & Han, L. (2022). Artificial Intelligence Enterprise Management Using Deep Learning. ncbi.nlm.nih.gov
20. Lui, A. & Lamb, G. (1970). Artificial intelligence and augmented intelligence collaboration: Regaining trust and confidence in the financial sector. [PDF]
21. Mhlanga, D. (2021). Financial inclusion in emerging economies: The application of Machine learning and artificial Intelligence in Credit Risk assessment. [PDF]
22. Mohammed, A. B., Al-Okaily, M., Qasim, D., & Al-Majali, M. K. (2024). Towards an understanding of business intelligence and analytics usage: evidence from the banking industry. International Journal of Information Management Data Insights, 4(1), 100215. sciencedirect.com
23. Müftüoğlu, M. (2024). Customer Loyalty and Relational Marketing Practices in The Banking Sector. International Journal of Social and Humanities Sciences Research (JSHSR), 11(114), 2743-2748. jshsr.org
24. Odunmbaku, A., Diyaolu, G., Salami, W., & Ganiu, S. (2024). Customer Relationship Management and Organisational Performance of Selected Insurance Firms in Ogun State, Nigeria. UNIZIK Journal of Marketing, 1(3), 124-133. unizik.edu.ng
25. Paragi, B. (2022). Caring control or controlling care? Double bind facilitated by biometrics between UNHCR and Syrian refugees in Jordan. Society and Economy. In Central and Eastern Europe | Journal of the Corvinus University of Budapest, 44(2), 206-231. akjournals.com
26. Rozario, M. K., Shanmugapriya, M. R., & Muthukrishnaveni, D. (2024). The Essentials of Marketing Management-Theory, Tools and Practices. [HTML]
27. SALEEM, S. H. A. N. I. M. O. N. & Mary Mathew, S. (2022). APPLICATION OF ARTIFICIAL INTELLIGENCE IN BANKING: A STUDY BASED ON SBI-SIA VIRTUAL ASSISTANT. osf.io
28. Shamim Hossain, M. & Alim Baser, A. (2011). Compliance of IAS-30: A Case Study on the Specialized Banks of Bangladesh. [PDF]
29. Sonmez Cakir, F., Ozdemir, S., & Adiguzel, Z. (2025). Harnessing knowledge management for enhanced performance: the mediating roles of market orientation and customer relationship capability in e-commerce. Business Process Management Journal. [HTML]
30. Stellenberg, C. (2024). Leadership styles and the retention of transaction managers in South African investment banks. [HTML]
31. Tabassum, S., Siddiqui, I. H., Mangrio, I. A., & Rauf, S. (2021). TOTAL QUALITY MANAGEMENT AND PERFORMANCE: A COMPARATIVE STUDY OF PUBLIC AND PRIVATE BANKS OF PAKISTAN. International Journal of Management (IJM), 12(1). academia.edu
32. Yali, L. & Xuanke, Z. (2024). Exploration on innovative mode of marketing work of independent sales products of oil field companies. Industrial Engineering and Innovation Management. 166.62.7.99
33. Younes Yameen, I. & Sami Ali, M. (2016). Evaluating the Financial Soundness of the Jordanian Commercial Banks by Applying BankoMeter's Model. [PDF]

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Challenges and Opportunities for Artificial Intelligence in Auditing

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Abstract Artificial Intelligence (AI) is rapidly transforming industries, and auditing is no exception. As AI technologies evolve, they offer unprecedented opportunities to enhance audit quality, efficiency, and effectiveness. AI can automate complex and repetitive audit tasks, analyze large volumes of financial data in real-time, and detect anomalies or fraud patterns that may elude traditional methods. However, this integration also presents significant challenges, including concerns about data privacy, algorithmic bias, lack of transparency, and ethical accountability. The complexity and opacity of AI systems may reduce auditors' ability to interpret outcomes or explain decision-making processes, potentially undermining trust. Moreover, regulatory uncertainties and the fast-paced development of AI tools necessitate a rethinking of audit standards and professional responsibilities. This paper explores the dual landscape of AI in auditing—its transformative potential and the pressing concerns that must be addressed to ensure its responsible and effective implementation.

Keywords: Artificial Intelligence, Auditing, Audit Automation, AI Challenges, AI Opportunities, Explainability, Algorithmic Bias, Audit Efficiency, Ethical AI, Trust in AI Systems

1 Introduction

Artificial Intelligence (AI) is undoubtedly one of the biggest driving forces behind the next technological revolution. AI is already interacting with its users in many applications, from daily tasks like using Google Maps and language translations to serious applications in healthcare, finance, and law as well as threatening applications like hacking, producing fake news, and generating hate speeches. All such tasks can be performed more or less automatically (Belle, 2019). Advancements in AI are widely anticipated to deeply and irreversibly affect business and economic models, economic productivity, wealth distribution, and even humanity itself. This leads to grand overhyped predictions and anxieties. At the same time, an explosion of research into what constitutes responsible or interpretable AI (from understandability to explain ability) is observed. An ethical debate, partly driven by the potential social consequences of AI technology, is ongoing. Governments, NGOs, and big tech companies are working to devise regulations to avoid catastrophes.

The field of AI goes hand in hand with the research on its understanding, interpretation, explainability, trustworthiness, acceptability, and accountability. An explanation refers to what information should be given to the human user for him or her to trust the AI system. An explanation could exhibit all kinds of reasons as to why something happened, why something was predicted, and why something was concluded. This could be a single number, a chart, a picture, a structured report, a natural language explanation, and so on, either directly or indirectly related to the data. The recent advancement of big data, internet of things, and cheap storage has allowed the accumulation of massive data, together with the rapid advancement of computing power and algorithms, has led to AI systems that could discover patterns and structures in these massive data in an automated manner. Highly sophisticated AI systems are now adopted across a wide spectrum of applications. One such application domain is auditing.

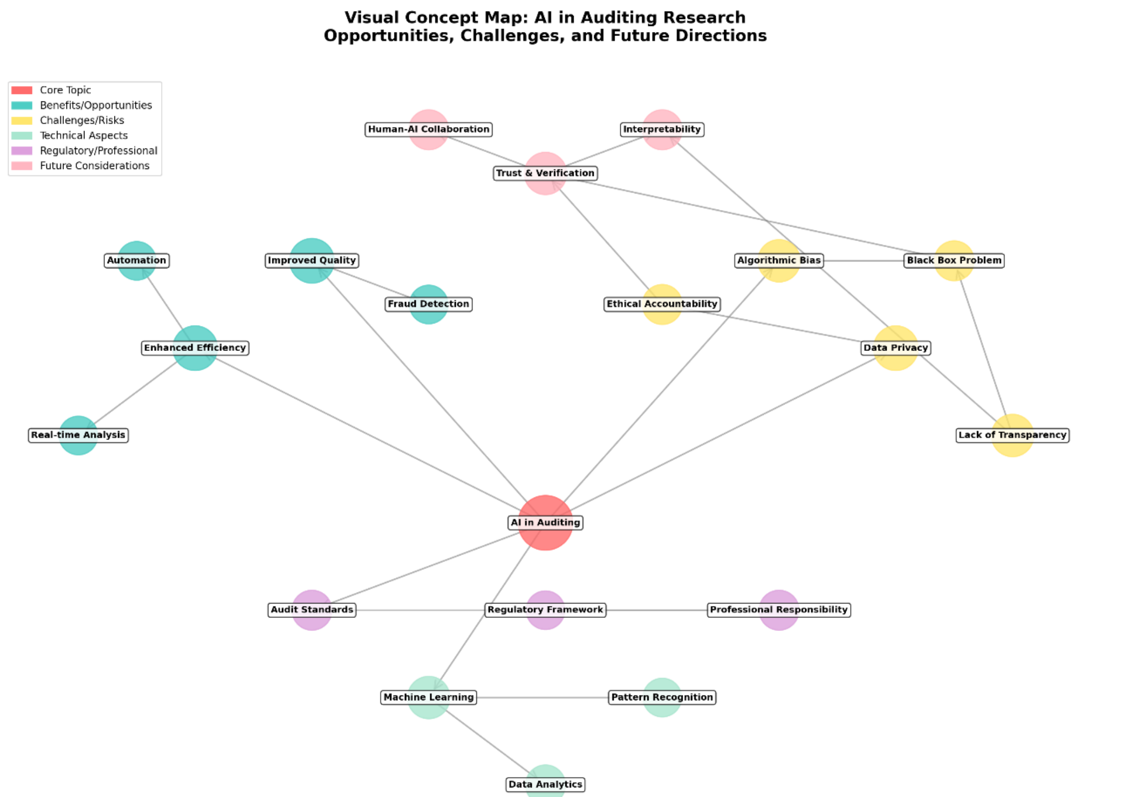
Business organizations are very much interested in the interaction with AI systems in the audit domain. AI systems could improve audit efficiency by multitasking many audit subtasks and processing huge volume of data simultaneously, and improve audit effectiveness by better and more comprehensive detection of errors and fraud. On the other hand, large-scale AI systems may introduce new challenges for audit as the sheer scale and complexity may render the systems unmanageable. Lack of understanding and interpretability, coupled with biased training data and rogue algorithms and systems, may lead to biased and unfair outcomes, raising concerns for fairness, accountability, and compliance with regulations (Lal Joshi & Marthandan, 2019).

2 Overview of Artificial Intelligence in Auditing

Technology is evolving rapidly and playing a crucial role in almost every area of business and life. One of the most popular technologies is Artificial Intelligence (AI), which refers to any device that is powered by a computer that is being controlled by software, simulating human thoughts or behaviors. Mobile phones, intelligent cameras, robots, and drones are just a few examples of AI-based devices. It's hardly conceivable that private and public life can exist without AI (Belle, 2019). AI has already transformed personal lives: just think about automatic spelling corrections, navigation apps, stock prediction programs, or predefined computer-generated recommendations. The application of AI to discover patterns or structures in large troves of data in an automated manner is a core component of the now-omnipresent and widely used data science tools.

An overwhelming share of familiar applications derives from data science techniques and mass data availability: these techniques, examining and predicting intimate feelings and behavior of millions of permanent and temporary users can be found in financial predictions, marriage-matching systems, search engines, social networks, tv-series suggestions, blog applications, police surveillance, and even voting forecasts (Lal Joshi & Marthandan, 2019). However, the unique potential of machines working potentially better than humans is coupled with risks and challenges. The unprecedented intelligence and speed of the machines surrounding humanity can make undesired decisions, being it visible as one-sided honey traps or just unnoticed threats stemming from privacy violations. Exploiting personal but sensitive data for discrimination is another issue.

The waxing influence of AI experts can be abused, who can produce the necessary datasets or exploit the software coded functioning in complicated wise. Finally, successful machines can make any decisions but most of the time, humans are unable or at least not straightforward to understand and verify machine decisions. Hence, to avoid dropping faith in technology, the responsibility and meaningful verifiability of machine decisions should become a civic right just as the right for privacy. Unfortunately, there is currently a lack of efficient, transparent, or at least interpretable white box candidate systems. To ensure transparent and responsible robustness of AI-based systems, understanding black boxes is essential.



3 Historical Context of Auditing Practices

Auditing is the practice of examining the corporate records of a company and serving as a reminder of the limits of management. Auditing focuses on economically important information and is practiced in the private sector for regulatory as well as quality assurance concerns (Manheim et al., 2024). Financial auditing is the best-established form of auditing. It began in Italy in the 15th century with emphasis on inventory security; once companies grew larger, the need for independent auditors grew, leading to the establishment of the profession in Great Britain in the 19th century. Efforts to standardize practices began in the early 20th century. Auditing practices, technology, and regulation were adapted to grapple with problems raised by the growing digitization of data, and issues of systemic risk and public trust remain unresolved. Software auditing has taken place under the rubric of virus scanning, vulnerability assessments, and source code reviews. New processes for documenting requirements and generating software artifacts that are not seen prior to deployment are problematic. The lack of structure makes it difficult to notice problems and remember what decisions were made. Similarly, automated processes can use data in unexpected ways that are difficult and time-consuming to track. With massive amounts of data scrapped, it is essential to better manage safeguards and expectations for accounting and data retention. Data is often considered disposable, and concerns about collection purposes and lengths of retention are often not explicitly considered. Those charged with governance often lack sophistication in how models, data, and dependencies interact in practice, leading to chaos and inconsistent consideration. Furthermore, reliance on one vendor creates rigidity in processes and awareness of systems. There is also a massive disparity between AI developers invested in using the technology and governments, regulators, and the public tasked with understanding it.

4 Current Trends in Artificial Intelligence

Developments in AI come from research programs that seek to reproduce particular cognitive processes deemed intelligent, with the most successful working with the neural networks that are loosely inspired by the brain. From a complex thrash of connections, hierarchies form, which can recognize higher order composites. These trains of processing can be parallel, and they undertake computing in a radically different way to human minds. The trained networks are capable of making predictions, ranking images that contain desired attributes, and undertaking complex tasks SKU search, detecting fraud, or even writing music. AI systems are far beyond the ability of the developers to explain the processes that led to a given result. They are more approaches than systems, but as such can be combined. For example, some type of NLP models take a second, more extensible, form that generates explanation candidates. These candidates can then be filtered further, using other ML techniques (Belle, 2019).

Machine Learning and AI currently work best in contexts that are well defined and limited. These ranges afford supervision, allowing for the development of good models using large troves of labelled data. Successful systems also require the task to be well established, clearly articulated, and agreed upon. None of these systems are intelligent in the ways in which human intelligence would normally be defined and understood. CNNs have no notion of concepts such as ‘car’ or ‘spaceship’ they simply process pixel data and produce a value that is later interpreted. Once the DSL and the model are in place, there is little that a human operator can do other than indicative testing and evaluation of new input data (Tredinnick, 2016).

5 Key Technologies in AI for Auditing

Machine learning interpretable models such as Generalized Additive Models, Generalized Additive Mixed Models, LIME, SHAP, Bayesian Rule Lists, and Anchors will rise in popularity as users demand an explanation of predictions to building trust in the AI model and its building blocks. This explanation sufficiency leads to further investigation into ulterior motives by users. Knowing that AI systems reveal patterns and structures from the data, an on-going battle attempts to interpret the resulting analysis. Current efforts focus on providing credence or explainability in retrospect to the AI inputs. This leads to the desire for interpretability by transparency, where one seeks the comprehension of the decision process of DL models via the AI outputs (Belle, 2019). Current discover and predict ML-covered patterns in the data are oblivious to the users unless the model or its predictions are adapted to provide explanations. Helping users comprehend why an explanation is deemed appropriate, tradeoffs between action and destruction of a lack of explanation poison further action framed by an explanation.

Important, the key regulators emphasize the deep-rooted desire for explainable designs. Consequently, the ongoing EU AI Act implies a need for compliance with discovery by design. Tradeoffs with trust, a large portion of implementations become unregulated black boxes. Independent research could encompass the broader situation faced when expected to rationally consider AI-based expert guidance. Incorporation of introduction uncertainty under equivocality in controlled socio-technology experimentation could study whether algorithmically induced radical pro-predictions sufficed as a sufficient change to defeat somewhat informed majority blocks. Additional research could gainsay this question by studying how to combat it (C. Oldhouser, 2016).

5.1. Machine Learning

Machine learning is regarded as one of the important aspects of AI. It is implemented as systems that automatically learn from experience X and improve on their own. In general, machine learning systems realize the problem involving X in one of the three following frameworks: Supervised, Unsupervised, and Reinforcement learning (Belle, 2019). It is a setup that has both a learning algorithm and a teacher. The teacher provides an example with a correct answer and the machine learns the relationship between the input and the output. The learning process continues with a new example that it has never seen before. Every time the machine makes a mistake, the teacher corrects it. Through experience X, the tasks with the training set T are done better by these methods (Shook et al., 2018).

The task to be learned T is normally specified in an indirect way. This is a kind of game played with an environment E, which provides a piece of information about the state S and an act A directly affecting S. The detailing action generates a reinforcement value R, which is a reward if positive and a punishment if negative. A reinforcement learning algorithm aims at acquiring a good policy (A|S) mapping the state S into the act A. Since it sets the reinforcement value R as a consequence of a chosen act A, the learning algorithm does not require a teacher. It can make use of its own experience to improve its performance. RL problems have usually been formalized as a temporal discounting stochastic dynamic programming problem. In general it contains a set of possible states and actions resulting in both a new state and a reinforcement value.

On the other hand, the approach does not uniquely solve all the issues. Because of this circumstance, the model selection is part of the learning. Two types of machines are pointed out. The market selection machines will control a large variety of either very general machines or very specialized machines. By executing a random selection scheme or trial-and-error exercise the user tends to find a machine best suited to the problem at hand, also for dynamic problems. The auction selection machines will provide a number of alternative solution schemes that are mathematically closely related to the mathematical model adopted.

.5.2. Robotic Process Automation

Robotic Process Automation (RPA) refers to a set of tools for automating the execution of routine activities that are carried out manually by users in systems, on which they act as "software robots" (Gajjar et al., 2022). RPA lies between screen-scraping, which is the pure low-level automation of Graphical User Interfaces (GUIs) at the pixel level, and tools that use computerization, which is the re-implementation of human-made business logic. So, there is not a single RPA tool; generally, there are two types of tools used for RPA, which are process automation tools and software robots. The basic understanding of RPA is either through software robots or through automation tools using robots. Organizations worldwide can implement RPA to partially or entirely automate the execution of routine follow-up processes controlled by business logic and structured inputs. These processes can range from high-volume data entry and transaction processing across multiple systems to complex back-office support for financial services with minimal human intervention.

This type of software robots can be called bots. A bot is defined as a piece of software that can act automatically on a computer network, executing repetitive tasks at a lower cost and possibly at a higher speed than human labor. RPA can be implemented in virtually any industry. RPA software robots can automate a simple task or full-fledged business processes across organizations running different systems, located in different countries, and using different languages. Popular usages of RPA include processing credit card applications, matching invoices to purchase orders, sending e-mails over certain trigger events, and putting downloaded statements or data into a database. However, the classification of RPA depends on the capabilities of the bots. RPA tools available nowadays range from fairly simple and low-cost on-line chat bots answering customer inquiries to multi-million-dollar deployments that automate large back-office processes for banks, insurance companies, or credit card firms.

6 Potential Benefits of AI in Auditing

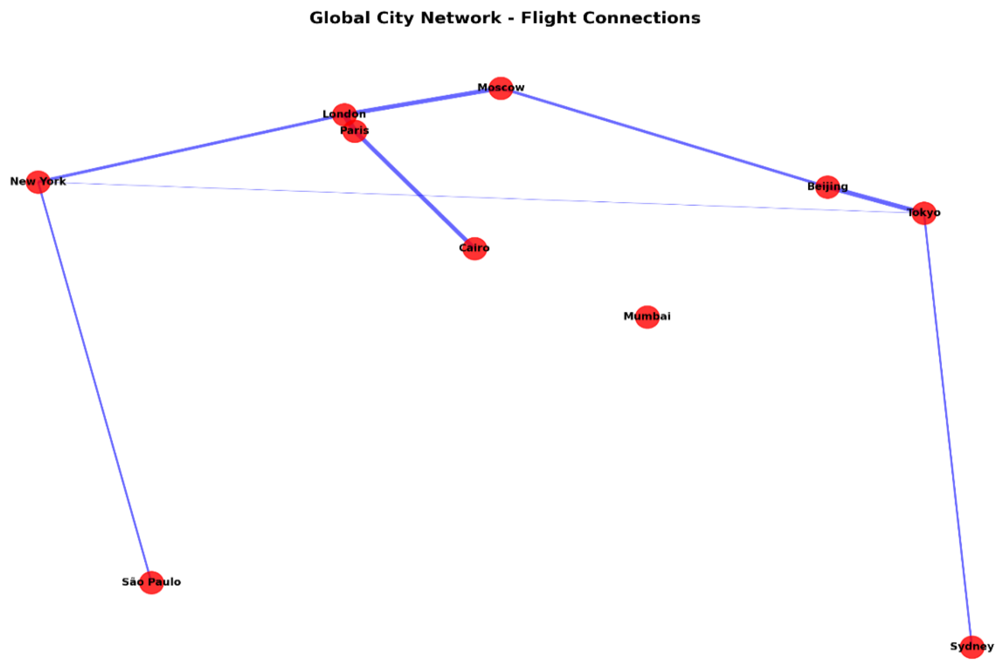
Artificial Intelligence (AI) is not only able to succinct and comprehensively summarize documents, but it is also assumed to have the potential, through the use of sentiment analysis, to analyze news and financial reports for parameters that are relevant for stock market changes. Through the aforementioned techniques, AI could come up with efficient introduction algorithms which aggregate the data describing an IPO and assess its pricing and after-market stability. AI techniques can be used to implement execution algorithms that will price and time the orders considering the trade-off between liquidity and market impact. In secondary markets, AI could facilitate proprietary order flow generation by learning clients' data. It could be used to price derivatives and assess the risk for trading desks as well as to exploit price discrepancies in and across exchanges by trading agents which learn from transactions using reinforcement learning. In the second-best market, AI could automate surveillance and control based on statistically analyzing/learning trade behavior and market micro-structure tailoring.

A bespoke personalization of the digitized regulatory framework means adapting the ones fitting the institution's needs in terms of risk profile, internal workings, client and product characteristics, and which will be delivered to each employee. Each financial institution could proactively identify gaps in compliance and supervision through benchmarking institutions with the market and client universe in terms of breaches. Supervision could be performed in a much more focused way through examining behavioral, network, transaction data of fewer grand clients/users, focusing on the ones showing signs towards undesirable behaviors such as complaints, possible fraud, AML risks, etc. AI could inform the regulators supervisions on the level of automation and compliance enhancing regulators as a whole prerequisite to compliance. Regulators could foresee firm departures/leavings offside policy through examining behavioral data, and anticipation of float-ons to another system through connections with equally positioned known financial institutions (Brozović, 2019).

6.1. Enhanced Data Analysis

Artificial Intelligence techniques can be leveraged to improve data analytics by auditors, increasing their quality and efficiency. One of the advantages of data analytics is the ability to analyze all audited transactions rather than a sample, thus allowing for greater quality. In addition, the results of the analysis can also be compared with previous periods of data, thus supporting analytical review procedures. There is a clear opportunity for auditors to improve data analytics based on Artificial Intelligence and added machine learning techniques. Where a human audit assistant is required to understand an audit case, the written text of the auditor's understanding and risk assessment will be analysed by an intelligent machine audit assistant through natural language processing to determine analytical queries of machine learning models that create historical audit trial patterns. Based on this query, a query language is produced that creates a larger data set on analytics. Based on both the query language and the "risk" parameters of the case, data analytics that quantifies "risk" is generated. Lastly, data analytics will aid the auditor in maintaining and documenting the audit record and their professional considerations.

One opportunity involves enhancing auditing in client systems with Artificial Intelligence analytics. Artificial Intelligence and machine learning-based analytics can be deployed in client ERP systems to enhance data coverages and normalizations. Where a human audit assistant attends the client's queries and requests missing documents and data, a machine learning and Artificial Intelligence agent will interrogate the client's machine through intelligent bots and robotic processing. Through text mining, the intelligent bot will interrogate the query "what is the desired document," thus gathering information on document formats, sending queries to the original ERP system. Furthermore, similar bots will classify document contents and catalogue documents into acquired management systems database. In turn, the analytic probes will crawl the client system. First, with case-related keywords and queries, normalizations are performed to improve short sampling data and create analytic-friendly data spaces. Then, continuous-monitoring rules of data extraction are generated as analytic probes for quick re-assessment (Lal Joshi & Marthandan, 2019).



7 Challenges in Implementing AI in Auditing

Auditing AI refers to the ongoing analysis of, methods for examining, and standards for resource allocation and decision-making in AI systems in order to achieve specific social goals regarding risks and ethical behavior. Auditing AI has attracted significant interest as a way to help understand and manage the ethical problems and social risks that are some of the most visible concerns regarding modern AI systems. This idea is often connected to a proposal for very specific forms of auditing, often described as algorithmic audit or fairness audit. These audits would review only the final models and data of a trialed ML system to evaluate a score along a single axis, for example, that it "is not biased" or "is interpretable," and often issuing only a narrow assurance of equivalence to other models rather than any strong conclusions about the underlying machinery or control over it.

An enormous numbers of bodies seeking to develop audit standards for AI systems have sprung up, with different approaches and much duplication of effort. There are many well-meaning groups trying to create a large number of standards for many specific aspects of AI and indeed, there are standards that address various aspects of algorithms that are already before it. But the clear concerns raised by current AI systems have only increased the scale of this problem, as they have already outstripped existing standards intended to manage their risks (Manheim et al., 2024).

There are many reasons to question the utility of auditing AI as it is commonly conceived, but three clearly stand out: it is very likely to be incomplete; that very incompleteness will, in turn, be leveraged to advance undemocratic, harmful goals; and no existing body has the necessary breadth, skillset, or mandate to consider the underlying issues. In the absence of thoughtful auditing standards for AI, there would be not only a poor quality audit but a competing industry of grifts and snake oil salesmen, each of them trying to audit with a different and contradictory set of strategies and being able to claim that they complied with the standards.

7.1. Data Quality Issues

Digitisation and the consequent emergence of Big Data has invited auditing firms to either rethink their way of performing audits or risk being rendered redundant by technological audits. Clients are more aware of audit quality and audit outcomes today, and, as a result, this mounting scrutiny has resulted in auditors feeling pressure to manage a portfolio of clients with reduced fees and greater risk (Lal Joshi & Marthandan, 2019).

The emergence of new data, more data sources, new types of data, and faster data results in higher demands on reporting, new risks, new risk assessments, and stakeholder expectations. These developments have drawn attention from regulators as well as organizations as the importance of data has dramatically increased concerning the reporting of a broader set of factors. The emergence of Big Data, Internet of Things (IoT), and rapidly developing data generation tools has made the conduct of audits or assurance increasingly pervasive. Increasing volumes of data generated by not only enterprise systems, but also operation technology, IoT devices, sensors and streaming data introduces complexity for auditors. This is further accentuated by the rapidly changing technology landscape. Auditors increasingly have to integrate client provided data extracted through multiple tools into formats and systems used for audit evidence evaluation, while ensuring that the data provided is sufficiently accurate, complete and relevant to the audit. The diversity, volume and velocity of Big Data create quicker schedules and deadlines for audits. In times of growing complexity, budgetary concerns can negatively impact audit quality, as can diverse and rapidly changing technology on audit performance. However, auditors need to realize that biggest gains are to be had by auditing in the era of Big Data. Mainly, paradigm shifts in audit approaches need to be reflected in the audit profession. More widespread use of data analytics offers opportunities for auditors to exploit the full potential of comprehensively covering the entire data set in rapid timescales. Predictive based monitoring using streaming methods offers the potential to forecast the data future and subsequently report irregularities to management early in the data life cycle. Therefore, Big Data can potentially enhance audit quality if adequately monitored. Such potential will require shifting paradigms on audit expectations and upfront planning choices.

7.2. Integration with Existing Systems

As previously mentioned, the deployment of AI or ML systems requires the creation of a pipeline to update the model with new data and re-train it as needed. Businesses frequently lack experience utilizing AI systems. Some specific contexts may call for a closed research system that is infeasible to adapt or implement universally (Barta, 2018). As a consequence, a general AI that can examine a wide range of datasets without further training is not easy to develop. Nevertheless, some techniques employed in existing models for comparable use cases could be broadly adapted. Moreover, the dataset is seldom presentable in a final form immediately. Most data privacy laws and compliance frameworks mandate data minimization. Organizations should train AI exclusively on anonymized data applicable to the domain of interest, such as logs and declarations. As a result, the implementation of AI systems tends to be a multi-stage and lengthy process.

Utilizing AI for auditing requires exceeding current practices with a more complex pipeline. Data manipulations require greater expertise. Workforce capabilities may need upskilling or hiring to implement and retain the new system. Furthermore, strict laws are also prevalent for AI. They require justification for using a model and transparency for it. As a result, most complex models are black-box ones, which cannot provide justifications for certain results. Nonetheless, consulting third-party organizations or using simpler adaptable alternatives could be transparent enough. Furthermore, audits for algorithms may be implementing in practice as well. All things considered, the use of AI is relatively challenging but could lead to competent insights and findings requiring further testing.

7.3. Regulatory Compliance

Artificial Intelligence (AI) models are increasingly utilized in diverse sectors, such as finance, healthcare, and manufacturing, to support broader and more significantly critical decisions. The resulting compliance concerns are heightened due to an implicit responsibility gap. As regulatory scrutiny escalates, cohesive compliance across diverse stages of the model lifecycle becomes indispensable. Furthermore, the complexity of AI systems is ever-increasing, leading to concerns about the scalability and effectiveness of current compliance practices. This paper outlines the challenges faced by financial institutions concerning the compliance of complex AI systems and discusses opportunities to structure integrated and sustainable AI model governance frameworks.

A self-regulating, system-level structure is proposed to address compliance concerns across the AI model lifecycle in a more coherent manner for increased automation. The increased sophistication of AI systems raises concerns about structural robustness in compliance processes, highlighting the importance of a more systematic approach. The assessment of legislation abidance would benefit from a wider view of AI systems, enabling examination of how downstream processes digitally ingest upstream modeling artifacts (Kurshan et al., 2020). The model governance practices for AI systems find their precedence in audit, validation, and model governance frameworks for traditional modeling enhancements. However, the unprecedentedness of AI technologies in industries such as finance, credit risk, and anti-money laundering raises uncertainties concerning the effectiveness of current practices. The integration of inspection outlooks of design and operations through AI system models would flatten the structures of the model compliance process as much as possible.

Compliance with Trustworthy Artificial Intelligence (TAI) governance best practices and regulatory frameworks is a fragmented process across various organizational units. This fragmentation generates compliance gaps that may expose organizations to compliance risks. Organizations struggle to comply with TAI best practices, such as data governance, conformance testing, and transparency requirements (Pery et al., 2021). Moreover, compliance with new TAI regulations adds layers of complexity and uncertainty to the governance environment. Some requirements can be ambiguous, incomplete, and inconsistent, providing leeway for interpretation that may lead to non-compliance. The set of compliance requirements is also expected to evolve over time. Process mining offers several opportunities to counter these challenges regarding TAI regulatory compliance. Automated mining of standard operating procedures significantly enhances overall process transparency and accountability across the organization.

8 Case Studies of AI in Auditing

Artificial Intelligence (AI) holds significant promise to radically improve the performance of current auditing practices. Discovering novel patterns and structures underlying large data is a core component of the emerging field of data science, and this aspect of data science–driven auditing is beginning to have a noteworthy impact on the practice of auditing (Belle, 2019). Data auditing on large data sets can yield counterintuitive insights that could not be obtained from the limited perspectives of human auditors. Nonetheless, this impact raises important challenges: In the data science group, these new opportunities are accompanied by innovative data science and probabilistic/statistical, computational, and visualization methods that come with technical, theoretical, and statistical difficulties. Such new mathematical methods are typically considered black boxes, and auditing the inner workings of these methods is challenging. Patterns discovered in data remain abstract without an ontological interpretation, exemplifying the necessity of an effective connection between data science and domain knowledge (Khaliq et al., 2022). The underlying decisions suggested by many of these trained models to clients, on which someone's wealth could depend, must be interpretable to ensure that the decisions may be trusted. Although auditing practices and the field of AI can be said to be using methods and technologies aligned with their classification, a gap exists in the literature on the intertwining of the two. An unanswered question of practical significance to the auditing community is how AI can improve auditing decisions and performance; in turn, the auditing literature should provide insights into the information requirements of client firms in order to expand AI applicability in other settings. Additional research questions that arise from the auditing literature include defining the general scope of expected decision performance; distinguishing areas of easier application of AI, where economic and public benefits may be cognized sooner, from outlier domains of inherently limited applicability; and covering methods adopted by humans, which their organizations view as core and central to success, with other methods that are potentially more transparent.

8.1. Success Stories

Numerous companies are incorporating the automation of analysis into their audit processes. (C. Oldhouser, 2016)

The analytical tools market includes many new entrants, especially in the field of data mining. The three main areas are process mining, security mining, and data mining. Process mining involves mapping data into process models and setting it as a baseline for continuous monitoring or auditing. This field currently experiences a higher influx of tools. Security analytics encompass log and event correlation approaches to prevent unauthorized access to systems. Industrial data mining encompasses statistical have-a-go tools for early detection of risks in the processing, such as clustering for operational effectiveness purposes.

The use of prediction markets to assess the effectiveness of analysts or others in forecasting audit risk is in its infancy but could gather momentum. In theory, data scientists could determine the outcome of a significant one-off transaction and construct a prediction market for it. If this market leveled on a particular analyst being incorrect, sufficient interest could develop (Belle, 2019). Another development is the increasing dependence on external cloud providers for large-scale data processing. This either relocates the auditing requirement to the cloud or imposes new data access restrictions on the auditors established by the cloud provider. Academic literature's self-sustainability, especially revolutions outside the US, is of concern. The decline of auditing research in Europe could be a harbinger of unsustainability elsewhere.

8.2. Failures and Lessons Learned

In late 2022, OpenAI's Chat GPT garnered extreme attention and user growth. As the API was opened up for third-party applications, and usage exploded, serious failures began occurring. One cherry-picked example, which illustrates a variety of pre-existing issues with LLMs, including the rate of such issues, is a series of legal documents forfeit that were adjusted to be inaccurate but still repeated back plausible-sounding specifics after one prompt. Other examples relevant to financial audits include an online aggregator of multiple large LLM services returning correct, but harmful answers, and an example explained directly to entirely exploit a fault that allowed special access to single API keys to be leaked. Financial engagements related to these were similarly work-generalizable and undid the level of effort put into them, possibly dating back to the private training phase of these products. In all these documented cases, if there had been a reasonable third-party audit performed before public availability, these outcomes could be avoided.

Common questions, requests, and pats on the back flew around on online discussion forums for marketing teams, PR, and legal departments. Watching the industry grapple with the results of the extreme decisions was painful, especially with regards to the security shoulder systems that had evidently been overlooked (Manheim et al., 2024). Regardless of how external scrutiny might prioritize and encourage a logical response, LLMs had long been trained in largely private ways, and obvious issues along with their dependencies had been ignored. Communications and alignment remained optional, and development plans were self-imposed. The general feeling was that there were now few clear paths to control the damages; notable examples were now beforehand and were seemingly indiscriminate in their demands. As the public expected greater scrutiny, the frantic efforts were sub-scoped to out of sight areas.

Amazing progress had been made via the use of remote service and zero-zero deployments, but it came at an extreme risk and reliance. An initially inspired surge of new capabilities had generated threats to existing businesses, but insisting on rapid changes to business model and strategy quickly leveled off. Audits of availability and of systems security could highlight gaps and as time would show them to be severe, but a successful upgrade-downgrade system to be different and equally successful was never devised. Exploitation attempts had undoubtedly begun on the devices that were now removed from general data feeds. The side-channels at vastly greater-than-human prompt frequency were clearly useless. But there was no effort towards understanding nor any due or limit calculations of medial costs. Near extremes made for great demos and prompt systems which continued to produce eye-opening results, but defence by dumb luck was no defence.

9 Future Trends in AI and Auditing

AI auditing technologies automate and streamline the audit process, enabling remote audit processes to improve efficiency without incurring additional costs as they grow. With the development of these technologies, there is a growing fear that machines will replace human auditors. This fear is warranted, especially for basic, repetitive, and low-level audit tasks that add no value to the audit. However, machines are not fully autonomous and require auditing by human auditors. Therefore, it is imperative to discuss how some opportunities are available for auditors to exploit the advanced AI audit technologies and cope with the coming disruption.

Auditors must study AI technologies, especially ML, to understand the underlying mechanisms. Basic requirements of AI, including data issues, need to be understood. AI and human collaboration can be built by interpreting the decision-making process of AI models. Contemporary research in interpretable ML is creating models that are not only accurate but can also be explained in terms of human-understandable attributes (Belle, 2019). Discussions should move to practical aspects of how to audit AI models. AI becomes a black box when the number of inputs and the size of the model increase. Future research should focus on investigating how AI model training can be re-formulated in an auditable way.

Auditors should explore advanced AI technologies like ML. These technologies have been effectively used in generic domains. Researchers have recently explored the application of ML in auditing, including anomaly detection, classification, natural language processing, clustering, and extraction and analysis (Lal Joshi & Marthandan, 2019). Currently, AI audit technologies deal with common and sector-specific deviations in data distributions. However, such opportunities are often neglected by auditors to exploit these advanced technologies – i.e. advanced AI technologies in generic domains should be explored in audit contexts and compared with emerging AI audit technologies.

9.1. Predictive Analytics

According to (Belle, 2019), while uncovering patterns and structures in large troves of data in an automated manner is a core component of data science and a great opportunity to organizations, this highly positive impact is accompanied by significant negative effects and challenges. An automatic system may turn out to be biased and unfair. Treating a person unfairly may be the result of a biased dataset. Automated predictive policing may disproportionately target a certain area and lead to a vicious cycle of crime. Nevertheless, this only addresses the problem of data bias and cannot guarantee that if the data is considered fair, the predictions and recommendations will still be. Following the same logic of pattern discovery, when humans build machine learning classifiers, they are provided with a specific dataset of normal and abnormal instances. Instead of directly providing the complete criteria for separation, humans simply provide training examples.

(Lal Joshi & Marthandan, 2019) discuss the issues arising from the availability of Big Data to firms as well as the various consequences of using Big Data in audits. Big Data may be highly informative and rapidly democratized and as a result a democratized society of economic agents that is far more efficient and deserving. Big Data may act as a threat to various aspects of democracy. This scenario ultimately focuses on the easier and less expensive surveillance of Big Data by companies and governments; a growing income and wealth inequality; fraud detection, avoidance and prevention; threats to consumer privacy and human rights; and advance fraud and manipulation.

It enables auditors to work smarter with the analysis of patterns in numerous sources of unstructured data. By providing a wealth of information to the auditors, Big Data helps auditors discover complex relationships within the model and relevant constraints. It enables auditors to test complete sets of accounts on a given range of transactions, instead of sample testing, and hence providing greater assurance of detection of material misstatements. Big Data can be used in planning field works, fraud detection through continuous transactions monitoring, and improving forensic accounting. Extensive usage of Big Data in accounting systems increases the need for a fully automated audit process. Major auditing firms are developing software for the complete automation of audits and the development of tools and frameworks that greatly facilitate auditing systems have been proposed. There has been no mention of how predictive approaches may improve forecasting.

9.2. Continuous Auditing

Today, firms are constantly gathering large volumes of events and transactions, but this data is underused and unevenly corrected. Compiling and analyzing this information at the end of the accounting period in a traditional audit is equivalent to performing an analysis ex-ante after an event. As a preventive approach to ensure information integrity, it is essential to enable discussions, verifications, and analysis ex-post just after the events have occurred. Continuous auditing is an audit approach that operates at the transactions or events level, incorporating new event-driven technologies to automatically collect and analyze the data relevant to the audit. Continuous auditing refocuses the audit on the audit assurance points, incorporating intelligent streaming engines to detect fraudulent events, anomalies, and other significant events. New event-driven architectures come into play to support the event-driven continuous audit and compliance functions. Continuous auditing could eliminate the spreadsheet time lag and poor controls over financial error checks. With continuous auditing, checks would be completed instantaneously as entries were seconded between systems (Pierre Junior D Aboa, 2014).

Over the past decade, the structure of corporate auditing has undergone tremendous changes. The development of increasingly cost-efficient computing technology, the introduction of the Internet, the rapid advancement of database technology, the inception of enterprise resource planning (ERP) systems, and the strong competition with consulting firms have forced auditors to rethink their roles and to develop new audit strategies. Auditors are eagerly exploring new strategies to enhance the efficiency and effectiveness of audit processes. Nevertheless, the crisis of confidence in accounting assurance quality raised profound questions on auditor independence and the provision of non-audit services. History suggests that the emergence of any new major technology takes time before organizations understand it and assimilate it into their practices. The slow internalization of continuous auditing and its correspondent acceptance might be considered as a systematic resistance to change.

10 Stakeholder Perspectives on AI in Auditing

The introduction and continued development of artificial intelligence (AI) creating great uncertainty throughout the world. In several professional fields, however, AI is seen as beneficial, or even transformative. Notably, AI has the potential to significantly alter and enhance auditing. Such a transformation would not be unprecedented; similarly transformative technologies have infiltrated auditing in the past to mixed reception and effect. Auditing, and audit firms, must understand what AI is, how it works, and how it will interface with auditing in order to best incorporate the technology and prepare for its proliferation. AI consists of a collection of technologies that together afford machines the capacity to take in data, analyze it, use it to create predictions, and use those predictions to generate output (Manheim et al., 2024). These technologies include machine learning methods, natural language processing methods, and machine vision methods. In order to understand the capabilities of these methods, audit firms must understand how these inputs are used to generate predictions, how those predictions are used to generate output, and the potential difficulties and complications that ensue from their design and use.

Auditing is broadly defined as an independent examination of financial statements to express an opinion on their fairness, out of respect for a marketplace's need to protect investments. Aspects of the profession that will not be altered by AI deployment include inquiry and analytic review. However, other aspects of the audit process, such as planning, control testing, substantive testing, and documentation will be altered. The gradual insertion of AI into auditing is therefore an appropriate time for audit firms to consider how to embrace this new technology. Enhanced documentation of the audit process can be an incremental response to AI risk. As AI becomes incorporated into audit, control risks will evolve, their presentation will change, and audit tests will need to adapt. These changes must be made clear in order to maintain audit quality. Audit firms must anticipate these changes in risk before AI is widely adopted. AI integration will have a mixed impact on audit quality. However, if AI is incorporated properly, the benefits should outweigh the drawbacks. A comprehensive inquiry into the capabilities and ramifications of AI on auditing is necessary to understand how its design and use will impact data processing and information generation.

10.1. Auditors

By definition, auditing is an evidence-driven scientific rational and judgment process designed to evaluate the integrity of an organization's products and services. Creditability is a critical component of an audit quality that is threatened amid globalization, increasing complexity of financial instruments, accelerating change of technologies, heightened regulatory scrutiny, and severe scandals that shook market confidence. Honesty can only be credible by rely-on audit trails, and therein come the demand on securing data integrity and traceability through log files verification (Lal Joshi & Marthandan, 2019). Yet, log security was hardly effective due to either a hacker can easily dump the log file logs, or a privileged user is able to delete security logs with no traces. The computer forensic based analyzers including commercial and academic ones are ground-up direct verifiers on the database logs. Nonetheless, they are either proprietary-based closed products with unsound motivation or costly investment for small organizations or college systems.

While many researchers study algorithms and designs for log files verification, computer forensics is still a new discipline and still missing standards thereof. The dissertation is the first to study top-down metrics to mathematically ensure accuracy in mission-critical data management. The findings suggest that the log integrity can be verified through a hybrid of both hardware and software means. The trust-query verification in SQL is proposed to check on-the-fly in contrast to log analysis with reviews.

What is worth noting, told (C. Oldhouser, 2016) that the audit profession is facing a myriad of challenges nowadays, but the auditing is not to be dead. The social reformation in transparency, objectivity and independence is a must to retain confidence in financial audits, to comply audit requirements in data privacy, and to foster a community to share and review audit knowledge and materials, and for data auditors a need to innovate a verifiable transparency scheme, for organization auditors something is wrong as to why two opinion?

Many believe that those challenging situations in auditing are risks that prohibit auditors from doing their work. Otherwise, they may view such highlighted issues as opportunities to help audit firms in facilitating clients, and regulators in monitoring activities, and silly companies in-ranking. Nevertheless, there need to be more rigorous and transparent in providing relevant backgrounds.

10.2. Clients

The auditing profession has been continually evolving with the development of the business environment and the advent of information technology. The latest topics such as the digital economy and Artificial Intelligence (AI) catch the attention of auditors, researchers, and regulators. AI is gradually becoming an essential part of modern businesses and lifestyles and considered the second wave of the IT revolution after the Internet. AI has attracted mass attention due to its impacts on various aspects of individual lives. For instance, social media platforms recommend products through its intelligent algorithms.

The growing importance of AI encourages audits and researches in the auditing profession. Aspects of AI such as Machine Learning (ML), a part of AI affecting multiple fields, can do huge data analysis and similar tasks. Auditors and audit support documents such as working papers traditionally use systems of risk assessment and tests that rely on human analysis. However, such traditional systems will cause low efficiency and low effectiveness as a person's limited experience to handle the growing complexity of audit environments. Meanwhile, illegal tusks may bring lost data mass, and it is challenging to search and check all.

Most external auditors, especially in a small scale, do routine tasks and fields that prevent them from doing impossible ones. Generally, auditors are short of ICT researchers or less advanced XP techniques for carrying out AI research projects (Lal Joshi & Marthandan, 2019). Currently, most machine models and heuristic algorithms remain less transparent and easily able to leave joint log evidence on the audited system, raising questions on assessing participants' professional care and competence.

Although the AI applications in auditing are at the nascent stage, it provides auditees with several indisputable opportunities. For example, process automation and applied ML techniques could help scape and analyse financial statements to generate evidence-based questions, which will require auditor responses and further investigation. Also, acoustics modelling tools such as trajectory analysis could be used to improve or design documentation templates.

Specifically, auditing, risk assessment, and collecting audit evidence tasks can benefit from applications of AI in financial statement analysis, anomaly detection, or attribute extraction. However, it will also require audit and regulator intervention to avoid applications from overlooking common threats of deeply analysing, producing, and deciding upon mathematical based automated systems. It will need auditor tech-savvy to upskill and watch out for system blind side effects.

10.3. Regulators

With an eye toward practicality, a number of more specific recommendations can be made about what the regulators should do. Where possible, these recommendations fall into a hierarchy, with those that are the most straightforward and least controversial presented first, and those that are more ambitious presented later. The list will be pared down to the most important and actionable items, but there are many other possibilities that could be explored to good effect.

Formulate a regulatory framework that values and builds upon existing auditing frameworks and techniques rather than dismissing them out of hand. Moving too quickly in imposing new frameworks or techniques risks outrage from critics who are wary of these technologies but who might otherwise have been allies.

Establish a whitelist for allowable systems along the lines of a framework for defining allowable cryptographic algorithms. This would include more specific recommendations about acceptable methods for auditing. For instance, it would outlaw the use of LLMs in high-stakes scenarios like determining bail.

Create incentives for institutions to establish their own auditing frameworks. These would warrant public attention, particularly if there is a mechanism for cross auditing. One could also avoid creating new regulatory rules by emphasizing existing rules that apply to new technologies as much as to old technologies.

Establish a regulatory agency to implement the list. In practice, much of this work will require vigorous involvement in scientific and technical discussions. While excessive and overly granular regulation by rule is what happens when agencies don't do this. A specialist agency is necessary. With sufficiently robust authority and mechanisms for public transparency and input, even if it fails, it could provide fertile ground for the development of norms propagated by other sources.

11 Conclusion

Artificial Intelligence (AI) takes the world by storm, affecting all facets of our lives. It seems the whole world has suddenly leapt into a futuristic world where all processes are more intuitive, productive, and organized. However, integrating AI technologies and systems is a complex process that requires the careful handling of various aspects of the processes. Many scholars have highlighted some key challenges of AI-based systems as well as their respective, longer-term implications. The importance of auditing and documenting AI decisions, models, training processes, and important interactions between classic AI and new models has been explained, as well as the ethical implications. Criticism is accompanied by early attempts of organizations and political entities worldwide to create an attractive and comprehensive regulatory framework, explicitly stating desired outcomes and ethical considerations.

While self-regulation mechanisms, guidelines, and white papers exist, they were deemed insufficient for all the reasons mentioned above. Auditing of AI systems should be a people-driven, human-oriented business with people in charge of the auditing process. The widening gap between business and science is pointed out, which is expected to perpetuate by new challenges introduced by AI technology. Scientists develop appropriate algorithms, many times disregarding other dimensions of the technology, while businesses are forced to accept and implement black boxes to stay competitive. There is consensus within some systemic, holistic framing regarding how to assess the viability of an AI regime, its control mechanisms, and ways of keeping such mechanisms aligned with ever-evolving and self-learning systems.

A shortage of scholars is turning to the huge gray area of comprehensive auditing frameworks and processes dedicated to understanding and assessing AI systems given their structure and functioning. Government and major companies have established proxies to study, discuss, and eventually chief the design and regulations of AI systems. A host of questions remains unanswered as to how to audit and access AI systems and how to handle their enormous complexity and always-evolving nature. Extensive literature exists as to what should be considered when auditing AI systems, but the discourse lacks how to practically act on such visions. There are calls for the emergence of a new field, namely, AI auditing with a programmatic overview of topics and methodological avenues to explore those questions. Such field will draw also on the well-established and burgeoning schools of audit and management science.

12 References:

1. Barta, G. (2018). The increasing role of it auditors in financial audit: risks and intelligent answers. [PDF]
2. Belle, V. (2019). The Quest for Interpretable and Responsible Artificial Intelligence. [PDF]
3. Brozović, V. (2019). PRIMJENA UMJETNE INTELIGENCIJE U SEKTORU INVESTICIJSKIH FONDOVA. [PDF]
4. Bubinger, H. & David Dinneen, J. (2021). Actionable Approaches to Promote Ethical AI in Libraries. [PDF]
5. Burger, B., Kanbach, D. K., Kraus, S., Breier, M., & Corvello, V. (2023). On the use of AI-based tools like ChatGPT to support management research. European Journal of Innovation Management, 26(7), 233-241. emerald.com
6. C. Oldhouser, M. (2016). The Effects of Emerging Technologies on Data in Auditing. [PDF]
7. Cui, Z., Jing, X., Zhao, P., Zhang, W., & Chen, J. (2021). A new subspace clustering strategy for AI-based data analysis in IoT system. IEEE Internet of Things Journal, 8(16), 12540-12549. [HTML]
8. Gajjar, N., Rathod, K., & Jani, K. (2022). A systematic literature review on Robotic Process Automation security. [PDF]

9. Ganapathy, V. (2023). AI in auditing: A comprehensive review of applications, benefits and challenges. Shodh Sari-An International Multidisciplinary Journal, 2(4), 328-343. icertpublication.com
10. H. Sarker, I., Janicke, H., Mohammad, N., Watters, P., & Nepal, S. (2023). AI Potentiality and Awareness: A Position Paper from the Perspective of Human-AI Teaming in Cybersecurity. [PDF]
11. Irani, Z., Abril, R. M., Weerakkody, V., Omar, A., & Sivarajah, U. (2023). The impact of legacy systems on digital transformation in European public administration: Lesson learned from a multi case analysis. Government Information Quarterly, 40(1), 101784. sciencedirect.com
12. Khaliq, Z., Umar Farooq, S., & Ashraf Khan, D. (2022). Artificial Intelligence in Software Testing : Impact, Problems, Challenges and Prospect. [PDF]
13. Khanmohammadi, R., M. Ghassemi, M., Verdecchia, K., I. Ghanem, A., Bing, L., J. Chetty, I., Bagher-Ebadian, H., Siddiqui, F., Elshaikh, M., Movsas, B., & Thind, K. (2023). An Introduction to Natural Language Processing Techniques and Framework for Clinical Implementation in Radiation Oncology. [PDF]
14. Kurshan, E., Shen, H., & Chen, J. (2020). Towards Self-Regulating AI: Challenges and Opportunities of AI Model Governance in Financial Services. [PDF]
15. Lal Joshi, P. & Marthandan, G. (2019). The Hype of Big Data Analytics and Auditors. [PDF]
16. Liang, W., Tadesse, G. A., Ho, D., Fei-Fei, L., Zaharia, M., Zhang, C., & Zou, J. (2022). Advances, challenges and opportunities in creating data for trustworthy AI. Nature Machine Intelligence, 4(8), 669-677. google.com
17. Manheim, D., Martin, S., Bailey, M., Samin, M., & Greutzmacher, R. (2024). The Necessity of AI Audit Standards Boards. [PDF]
18. Mökander, J., Morley, J., Taddeo, M., & Floridi, L. (2021). Ethics-based auditing of automated decision-making systems: Nature, scope, and limitations. Science and Engineering Ethics, 27(4), 44. springer.com
19. Mytnyk, B., Tkachyk, O., Shakhovska, N., Fedushko, S., & Syerov, Y. (2023). Application of artificial intelligence for fraudulent banking operations recognition. Big Data and Cognitive Computing, 7(2), 93. mdpi.com
20. Onososen, A. O. & Musonda, I. (2022). Perceived benefits of automation and artificial intelligence in the AEC sector: An interpretive structural modeling approach. Frontiers in built environment. frontiersin.org
21. Pery, A., Rafiei, M., Simon, M., & M. P. van der Aalst, W. (2021). Trustworthy Artificial Intelligence and Process Mining: Challenges and Opportunities. [PDF]
22. Pierre Junior D Aboa, Y. (2014). Continuous Auditing: Technology Involved. [PDF]
23. Shook, J., Smith, R., & Antonio, A. (2018). Transparency and Fairness in Machine Learning Applications. [PDF]
24. Tredinnick, L. (2016). Artificial intelligence and professional roles. [PDF]
25. Whang, S. E., Roh, Y., Song, H., & Lee, J. G. (2023). Data collection and quality challenges in deep learning: A data-centric ai perspective. The VLDB Journal. [PDF]
26. Zhang, L., & Zhang, L. (2022). Artificial intelligence for remote sensing data analysis: A review of challenges and opportunities. IEEE Geoscience and Remote Sensing Magazine, 10(2), 270-294. [HTML]
27. Zhou, C., Liu, X., Yu, C., Tao, Y., & Shao, Y. (2023). Trust in AI-augmented design: Applying structural equation modeling to AI-augmented design acceptance. ncbi.nlm.nih.gov

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Fraud Prediction in E-Commerce Transactions using TabNet with Advanced Data Balancing Techniques

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Abstract:
E-commerce platforms handle substantial financial transactions, making them attractive targets for fraudulent activity. Those activities may include the use of stolen credit cards or the creation of accounts that exploit online systems. These fraudulent techniques are continuously evolving, which makes prediction increasingly challenging. To address this problem, TabNet, a deep learning classification algorithm, has been applied and compared with two standard machine learning algorithms: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), in predicting fraudulent transactions in e-commerce. Moreover, since the dataset utilized in this study is extremely imbalanced, three advanced balancing techniques have been used, i.e., SMOTE, SMOTE-ENN, Borderline -SMOTE. Furthermore, because the accuracy evaluation metric is insufficient for evaluating model performance on an imbalanced dataset, three additional metrics (i.e., recall, specificity, and AUC) have been adopted to evaluate the performance of the classifiers and provide a more comprehensive assessment. Accordingly, TabNet with Borderline-SMOTE approach achieved the best overall performance.

Keywords: Fraud prediction, machine learning, deep learning, classification, SMOTE.

1. Introduction

Recently, the widespread adoption of the internet and e-commerce has driven an enormous rise in electronic transactions. In other words, modern technology advancements have caused people to choose online payment systems for their shopping requirements [1]. At the same time, the growing use of digital devices and e-commerce platforms has led to a substantial rise in cybercrime [2]. The main difficulty of fraud detection arises from the short time period during which acceptance or rejection decisions must be made. Moreover, the use of fraudulent cards creates problems for all parties including cardholders and banks, but merchants bear the greatest impact because they lose more money than the value of their sold items [1].

The term cybercrime describes criminal activities that occur through internet networks while fraud includes deceptive actions that seek to acquire financial or personal advantages, and it can be categorized into two types: offline fraud and online fraud [1]. Accordingly, online fraud represents the most prevalent form of fraud as fraudsters steal digital card data through phishing and skimming methods. While offline fraud occurs when a credit card is stolen physically and used before the owner reports the loss and the bank cancels the card [3]. Those violations result in major damage to the trust between businesses and customers [2]. Therefore, an effective and fast detection of credit-card fraud is essential to preserve user experience and reduce financial losses for online stores [4].

Accordingly, this work aims to enhance transaction security and provide a robust solution for minimizing fraud risk by evaluating a powerful model capable of delivering accurate identification of fraudulent activities in e-commerce transactions. Therefore, a deep learning technique (i.e., TabNet) has been applied and compared to two standard machine learning algorithms (i.e., K-Nearest Neighbors (KNN) and Support Vector Machine (SVM)).

The dataset used in this study is highly imbalanced, which leads to suboptimal classification results [5]. Thus, three advanced resampling techniques have been used to address this problem: Synthetic Minority Over-sampling Technique (SMOTE), SMOTE combined with Edited Nearest Neighbors (SMOTE-ENN) and Borderline-SMOTE. Moreover, while the dataset is imbalanced, the accuracy metric is not sufficient to measure classifier performance, three other metrics were used to assess the real performance of classifiers in predicting fraudulent and not fraudulent cases. These metrics are recall, specificity and area under the ROC curve (AUC).

The rest of the paper is organized as follows: Section 2 reviewed the related literature, Section 3 provides a dataset description, Section 4 outlines the proposed approaches for detecting fraudulent e-commerce transactions, Section 5 presents implementation details and results, and section 6 presents the conclusions and directions for future work.

2. Literature review

The detection of electronic or credit-card fraud has attracted considerable attention of researchers in the last few years. Actually, traditional fraud detection methods have been the foundation of financial institutions' security frameworks for many years. These methods use Information Retrieval, Rule-based methods and professional judgment to detect and prevent fraudulent behavior [6]. Accordingly, Ibrahim et al. [7] developed an e-commerce fraud detection system based on analytical methods and scoring policies to detect outliers. The experimental results demonstrated a considerable performance through 93.3% accuracy and high precision and recall and F1-score values.

However, numerous studies have used machine learning methods to address fraud. For example, Dheepa and Dhanapal [8] created a behavior-based fraud detection system using Support Vector Machines (SVM) which utilized efficient feature extraction and kernel-based adaptability; Their method achieved high accuracy in identifying fraud effectively and it scaled well for processing big transaction volumes. In the same year, Ganji et al. [9] developed Stream Outlier Detection using Reverse Nearest Neighbors (SODRNN) algorithm which uses reverse k-nearest neighbors to detect credit-card fraud. Also, Xuan et al. [10] proposed the Refined Weighted Random Forest (RWRF) model which improves credit-card fraud detection through weighted decision trees to achieve better classification results than standard random forest approaches. In 2019, Porwal and Mukund [4] developed a clustering-based fraud detection system which uses consistency scores to detect outliers effectively without requiring any prior knowledge. The proposed method achieved better results than standard models. More recently, Gölyeri et al. [11] applied decision tree, logistic regression, random forest, and extreme gradient boosting to detect e-commerce fraud, showing how feature selection affects model performance.

Moreover, several researchers used deep learning algorithms to predict credit-card transaction fraud. For instance, Islam, M. et al. [12] used real-world datasets to evaluate AI-based fraud detection techniques by comparing machine learning and deep learning models. The research proved that XGBoost and deep learning models (i.e., LSTM and CNN) outperformed the other approaches. In addition, Pumsirirat and Yan [13] proposed an unsupervised deep learning system which combined Auto-Encoders with Restricted Boltzmann Machines to detect online transaction anomalies. The model achieved excellent results on the European credit-card dataset.

On the other hand, while data balancing problem presents challenges for classifiers in predicting the correct class, some researchers have enhanced the performance of the classifiers in solving the problem by implementing advanced balancing techniques. Consequently, Saputra and Suharjito [6] employed Decision Tree, Naïve Bayes, Random Forest, and Neural Network to detect e-commerce fraud in addition to using SMOTE to handle class imbalance. Their work showed that Neural Network with genetic algorithms obtained the best results compared to other models. Moreover, Vasant et al. [14] created a hybrid fraud detection model which integrated Artificial Neural Networks (ANN) and Deep Neural Networks (DNN), with SMOTE to address class balancing problem. The proposed method yielded superior accuracy and AUC performance than standalone models in providing a secure e-commerce transaction solution.

Furthermore, data availability presents an additional challenge, researchers often face major hurdles when trying to access real financial fraud records. These datasets are usually confidential, or unavailable. Therefore, researchers utilized synthetic data structured to present real-world patterns and complexity.

Accordingly, Raju and Varma [15] developed an e-commerce fraud detection system devoting XGBoost and Stacking Classifier which trained and tested on synthetic data of transactions. Additionally, Mutemi & Bacao [2] also highlighted the increasing reliance on synthetic data due to limited access to real-world datasets related to e-commerce fraud detection.

Thus, in this study, we present a novel application of the TabNet deep learning architecture for fraud detection in e-commerce transactions. To evaluate its effectiveness, we compare TabNet with two widely used machine learning algorithms: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

Additionally, we investigate the impact of advanced data balancing techniques including SMOTE, SMOTE-ENN, and Borderline-SMOTE on enhancing classifier performance.

3. Dataset description

Many studies have employed synthetic data as an effective alternative when real-world datasets are inaccessible [2][15]. Accordingly, while the data related to the credit-card transactions is usually confidential, or unavailable, the dataset used in this study is synthetic (not real). It was obtained from the Kaggle[1] website. Moreover, the dataset consists of 1,472,952 customer transaction records, described by 16 attributes: 9 numerical and 7 categorical. A major challenge with this dataset is its balancing ratio; 1,399,114 records corresponding to non-fraudulent transactions, whereas the remaining 73,838 records belonging to fraudulent ones.

4. Methodology

This work evaluates the performance of one of the relatively new deep learning algorithms (i.e., TabNet) in predicting fraudulent e-commerce transactions. In addition, to strengthen the validity of the evaluation, TabNet classifier performance is compared to two other well-known standard machine learning algorithms (i.e., SVM and KNN). Furthermore, because the dataset employed in this study is highly imbalanced, three advanced balancing techniques were used to address this issue (i.e., SMOTE, Borderline-SMOTE, and SMOTE-ENN).

4.1 TabNet:

TabNet is a deep learning algorithm developed particularly for tabular data. Deep learning uses multi-layered neural networks to extract increasingly abstract features from complex data. Through backpropagation, it fine-tunes internal parameters to improve pattern detection across large datasets [16]. It employs sequential attention mechanisms to select the most relevant features at each decision point. In addition, the design approach of TabNet enhances interpretability and learning efficiency because of its ability to direct model capacity toward the most informative inputs. Furthermore, TabNet achieves better predictions through multiple decision stages that progressively filter out less important features. The structured data handling capabilities of this innovative method improve prediction accuracy while minimizing redundancy, making it a powerful, versatile tool across multiple domains [17].

4.2 Support Vector Machine:

It is a widely used standard machine learning algorithm introduced by Vapnik [18], originally developed to solve classification and regression tasks. It operates by constructing an optimal decision boundary, called a hyperplane, to separate data points of different classes in a high-dimensional space. Moreover, the algorithm maximizes the margin between the data points of each class for better classification performance and generalization [19]. The ability of SVM to generalize well and find optimal solutions made it popular in machine learning and pattern recognition [20].

4.3 K-Nearest Neighbors:

KNN is a supervised machine learning algorithm used for both classification and regression tasks. The algorithm operates by selecting k neighbors to evaluate their similarity to a given point using Euclidean distance. Then, it assigns the class of the new instance according to the majority class of its neighbors. However, the selection of k is critical because small values can lead to noisy predictions, whereas large values may lead to missing important details [21].

4.4 Advanced balancing techniques:

Imbalanced data distribution is common in real-world data. This problem occurs when instances belonging to one class are significantly more than the other class. The majority class comprises most of the data instances, whereas the minority class represents the remaining ones [22]. In this study, SMOTE, SMOTE-ENN and Borderline-SMOTE are utilized to handle the data balancing problem.

4.4.1. Synthetic Minority Oversampling Technique (SMOTE):

[1] 🚨 Fraudulent E-Commerce Transactions 💳

It is an advanced oversampling-based data balancing technique. SMOTE generates new synthetic samples by the interpolation between minority class instances and their closest neighboring points, instead of replicating existing instances. Additionally, the simplicity of SMOTE along with its adaptability across different domains made it a fundamental technique in learning using imbalanced data [23].

4.4.2. SMOTE + Edited Nearest Neighbors (SMOTE-ENN):

It is a hybrid resampling method that combines oversampling and under-sampling. Its process begins by generating synthetic minority class samples using SMOTE. Then, the Edited Nearest Neighbors (ENN) method is applied to eliminate both synthetic and original samples that get misclassified by their nearest neighbors on the dataset [24].

4.4.3. Borderline-SMOTE:

The Borderline-SMOTE algorithm is an advanced oversampling method developed to improve classifiers' performance with imbalanced datasets. Unlike standard SMOTE, Borderline-SMOTE creates synthetic samples only from minority class instances that are near the decision boundary and are most susceptible to be misclassified [25].

4.5 Evaluation metrics:

The class imbalance distribution issue emerged as a major challenge in classification. It adversely affects classifiers' performance and leads to biased prediction results. To address this problem, three advanced data balancing techniques have been applied to improve model reliability and performance. However, the accuracy metric alone does not provide a sufficient evaluation with imbalanced datasets. Therefore, our performance assessment expanded to include recall, specificity, and Area Under the Curve (AUC) to evaluate the performance of each classifier in predicting fraudulent transactions in e-commerce.

Evaluation metrics:

- **Accuracy:** Refers to the proportion of correctly classified fraudulent and non-fraudulent transactions out of the total number of transactions [6].

- **Recall:** Refers to the proportion of actual fraudulent cases that the model successfully predicted [6].

- **Specificity**: Measures the model's ability to correctly identify non-fraudulent transactions [26].

- **Area Under the ROC Curve (AUC):** Refers to the model's performance in distinguishing between fraudulent and non-fraudulent transactions by analyzing the Receiver Operating Characteristic (ROC) curve. The ROC curve shows the relationship between recall and specificity, and how effectively the model detects fraudulent transactions while minimizing false predictions. However, the AUC provides a single numerical value summarizing the classifiers' performance [4].

5. Results:

This section compares the results obtained by a deep learning algorithm (i.e., TabNet), and two standard machine classifiers (i.e., SVM and KNN) in predicting fraudulent transactions in e-commerce. Moreover, the dataset utilized in this study is highly imbalanced. Therefore, three advanced data balancing techniques have been used to solve this issue, which provide three versions of datasets.

5.1 Combinations of TabNet and data balancing techniques

This subsection analyzes the performance of the TabNet classifier, trained and evaluated on three balanced datasets using SMOTE, SMOTE-ENN, and Borderline-SMOTE, respectively. Table 1 presents the values of the evaluation metrics obtained from each combination of classifier and balancing techniques.

	Accuracy	Recall	Specificity	AUC
SMOTE	0.8975	0.8334	**0.9624**	0.9543
SMOTE-ENN	0.9069	0.8712	0.9536	0.9636
BL-SMOTE	**0.9141**	**0.8837**	0.9449	**0.9699**

Table 1. Evaluation metrics values for the TabNet model; The best values are highlighted in bold.

As shown in Table1, the TabNet classifier combined with Borderline-SMOTE outperforms the other approaches. It achieved the best accuracy and highest recall metric value, highlighting its superior ability to effectively predict fraudulent transactions. Moreover, it obtained the best AUC value, which illustrates its strong capacity to distinguish clearly between the two categories. On the other hand, the combination of TabNet with SMOTE yields the best specificity. Figure 1 demonstrates the ROC curves of TabNet across the three balanced datasets, highlighting the Area Under the Curve (AUC) for each.

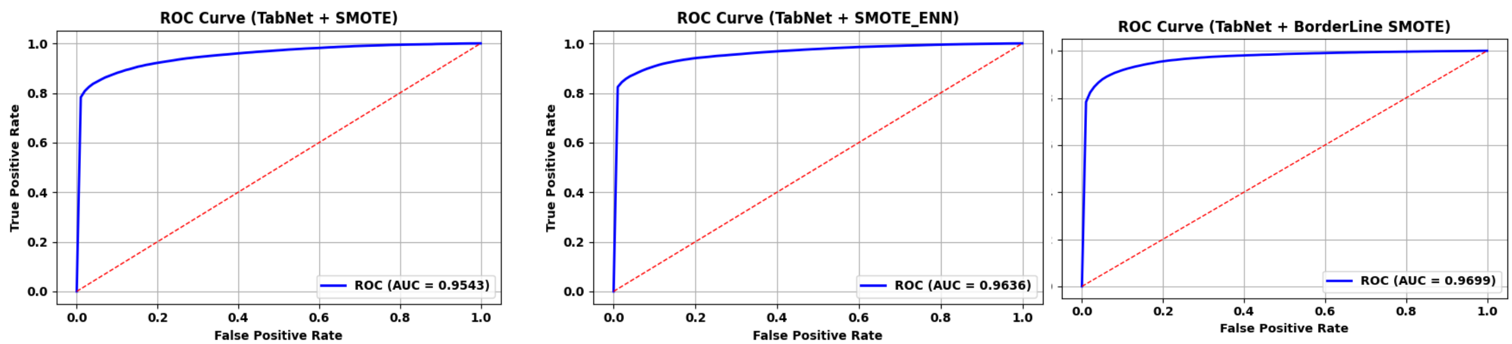


Figure 1: ROC curves for TabNet combined with balancing techniques.

5.2 Combinations of KNN and data balancing techniques

This subsection evaluates the performance of the KNN classifier, which trained and tested on three balanced datasets generated using SMOTE, SMOTE-ENN, and Borderline-SMOTE. Table 2 reports the metric values obtained from KNN combined with each balancing technique.

	Accuracy	Recall	Specificity	AUC
SMOTE	0.8750	0.8262	**0.9243**	0.9280
SMOTE-ENN	0.8808	0.8592	0.9090	0.9394
BL-SMOTE	**0.8901**	**0.8634**	0.9171	**0.9453**

Table 2. Evaluation metrics values for the KNN model; The best values are highlighted in bold.

According to the results of the aforementioned table, KNN with Borderline-SMOTE approach achieved the best results in several metrics. In other words, the conjunction of KNN and Borderline-SMOTE yields the best accuracy, recall and AUC, indicating that it is the superior approach in predicting fraudulent transactions, and in distinguishing between fraudulent and non-fraudulent transactions. Furthermore, when applying SMOTE, it performed the best prediction of non-fraudulent transactions. Figure 2 illustrates the performance of the KNN classifier and in distinguishing between fraudulent and non-fraudulent transactions through AUC curves across three balanced datasets.

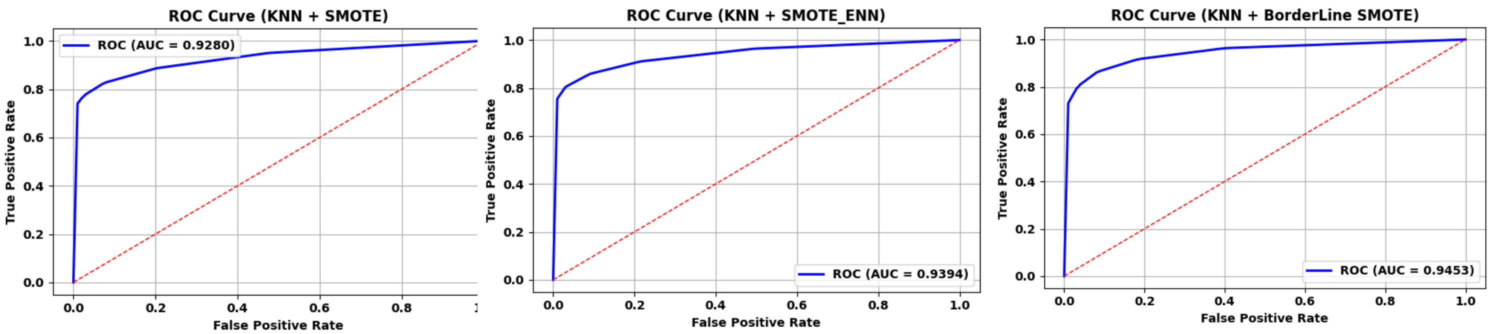


Figure 2: ROC curves for KNN combined with balancing techniques.

5.3 Combinations of SVM and data balancing techniques

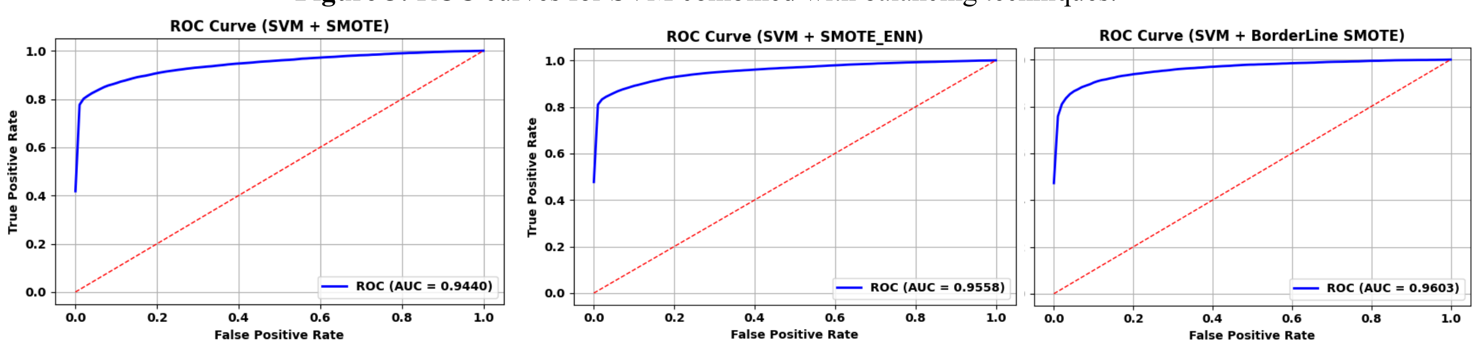
This subsection analyzes the results obtained from the approaches of SVM with balancing techniques in predicting fraudulent transactions in e-commerce.

	Accuracy	Recall	Specificity	AUC
SMOTE	0.8914	0.8171	**0.9667**	0.9440
SMOTE-ENN	0.8986	0.8531	0.9583	0.9558
BL-SMOTE	**0.9063**	**0.8704**	0.9427	**0.9603**

Table 3. Evaluation metrics values for the SVM model; The best values are highlighted in bold.

According to Table 3, the SVM model combined with the Borderline-SMOTE technique delivered the strongest performance in predicting fraud transactions compared to the other combinations. It achieved the highest accuracy, indicating robust overall classification capability, and a high recall reflecting its effectiveness in identifying fraudulent cases. Additionally, it recorded the top AUC score, demonstrating the superior ability to distinguish between fraudulent and legitimate transactions. Moreover, with the combination of SVM and SMOTE balancing technique, it achieved the highest specificity, showing its performance in identifying non-fraudulent transactions. Figure 5 illustrates the ROC curve performance of the SVM model across the three balanced datasets, emphasizing the AUC values for each version.

Figure 3: ROC curves for SVM combined with balancing techniques.



1.1 Results summary:

This section presents a comparative analysis of nine classification approaches. A deep learning algorithm (i.e., TabNet), along with two standard machine learning classifiers (i.e., KNN and SVM), was evaluated. Each classifier is being combined with three data balancing techniques. Moreover, the approaches are assessed using four performance metrics: Accuracy, Recall, Specificity, and AUC to ensure a comprehensive evaluation and determine whether TabNet, which is specifically designed for tabular data, outperforms the traditional algorithms.

With respect to accuracy, Figure 4 illustrates the results obtained by the nine approaches, highlighting that the TabNet model combined with Borderline-SMOTE achieved the highest value compared to the others. Furthermore, as illustrated in Figure 5, TabNet combined with Borderline-SMOTE outperformed the other eight evaluated approaches by achieving the highest recall, indicating its robust performance in correctly identifying actual fraud cases compared to the other approaches. In terms of specificity, Figure 6 demonstrates that the SVM model combined with SMOTE delivered the best performance in accurately identifying non-fraudulent transactions. Additionally, as shown in Figure 7, TabNet combined with Borderline--SMOTE achieved the best AUC, which means this approach demonstrated the strongest performance in differentiating fraudulent from non-fraudulent transactions, while effectively balancing recall and specificity.

As a result of the comparative analysis, TabNet combined with Borderline-SMOTE achieved the highest accuracy, recall and AUC, whereas SVM combined with SMOTE yielded the best specificity, showcasing its effectiveness in correctly identifying non-fraudulent transactions.

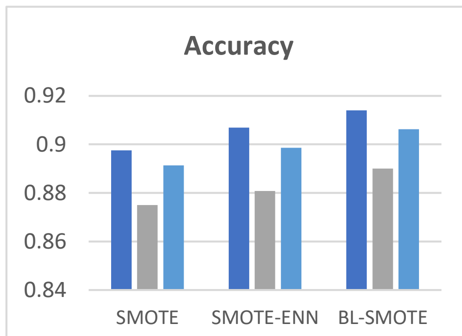


Fig 4. Accuracy values obtained from all approaches (classifiers + balancing techniques).

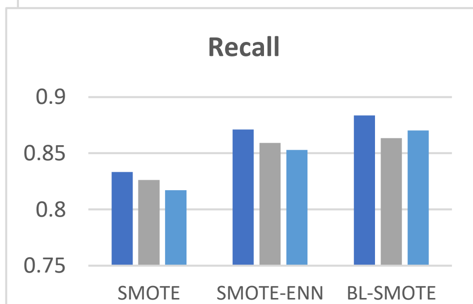


Fig 5. Recall values obtained from all approaches (classifiers + balancing techniques).

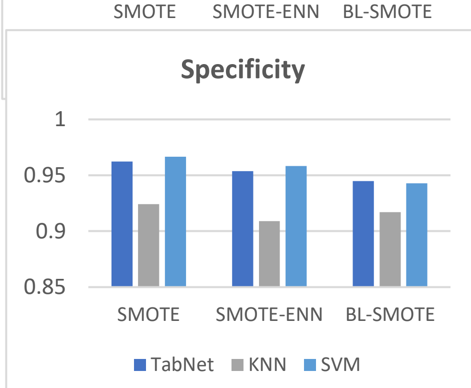


Fig 6. Specificity values obtained from all approaches (classifiers + balancing techniques).

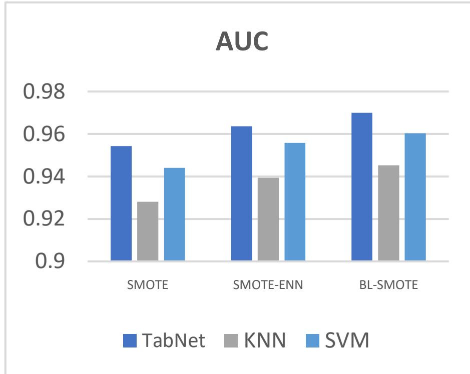


Fig 7. AUC values obtained from all approaches (classifiers + balancing techniques).

1.2 Conclusion and future work:

The rapid expansion of e-commerce has led to a surge in cybercrime, particularly credit-card fraud. However, detecting fraud is a complex task due to the scarcity and evolving nature of fraudulent patterns, which makes training reliable models difficult. The problem worsens as fraudsters consistently develop new techniques to avoid detection systems. As a result, implementing effective mechanisms for fraud detection and prevention is essential to safeguard both businesses and consumers. To address this issue, TabNet, a deep learning algorithm, was employed, and its performance was evaluated against two standard machine learning models (i.e. SVM and KNN). To address the data balancing problem, three advanced resampling techniques (i.e., SMOTE, SMOTE-ENN, and Borderline-SMOTE) were applied. Additionally, since accuracy alone is not sufficient for evaluating model performance on imbalanced datasets, additional metrics including recall, specificity, and AUC were used to provide a more comprehensive assessment. Accordingly, the approach of using TabNet and Borderline-SMOTE balancing techniques showed the best performance in predicting fraudulent transactions in e-commerce. For future work, feature selection methods could be integrated with TabNet. Also, other deep learning models could be evaluated in solving the problem and compared against TabNet.

6. References

1. Shaji, J., & Panchal, D. (2017). Improved fraud detection in e-commerce transactions. 2017 2nd International Conference on Communication Systems, Computing and IT Applications (CSCITA).
2. Mutemi, A., & Bação, F. (2024). E-Commerce fraud detection based on machine learning techniques: Systematic literature review. Big Data Mining and Analytics, 7(2), 419–444.
3. Carta, S., Fenu, G., Reforgiato Recupero, D., & Saia, R. (2019). Fraud detection for E-commerce transactions by employing a prudential Multiple Consensus model. Journal of Information Security and Applications, 46, 92–106.
4. Porwal, U., & Mukund, S. (2019). Credit card fraud detection in e-commerce. In 2019 18th IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom) / 13th IEEE International Conference on Big Data Science and Engineering (BigDataSE) (pp. 280–287). IEEE.
5. Saputra, A., & Suharjito. (2019). Fraud detection using machine learning in e-commerce. International Journal of Advanced Computer Science and Applications, 10(9), 332–338.
6. Bagwe, C. (2024). Fraud detection in financial institutions: AI vs. traditional methods. International Journal of Scientific Research & Engineering Trends, 10(6), Nov–Dec.
7. Ibrahim, B. H., Salihu, H. U., & Aleshinloye, Y. A. (2025). Rule-based approach to e-commerce fraud detection. UNIABUJA Journal of Engineering and Technology (UJET), 2(1), 196–204.

8. Dheepa, V., & Dhanapal, R. (2012). Behavior-based credit card fraud detection using support vector machines. ICTACT Journal on Soft Computing, 2(4), 391–397.
9. Ganji, V. R., & Mannem, S. N. P. (2012). Credit card fraud detection using anti-k nearest neighbor algorithm. International Journal on Computer Science and Engineering (IJCSE), 4(6), 1071–1077.
10. Xuan, S., Liu, G., & Li, Z. (2018). Refined weighted random forest and its application to credit card fraud detection. In X. Chen, A. Sen, W. Li, & M. Thai (Eds.), Computational Data and Social Networks (Vol. 11280, pp. 343–355). Springer.
11. Gölyeri, M., Çelik, S., Bozyiğit, F., & Kılınç, D. (2023). Fraud detection on e-commerce transactions using machine learning techniques. Artificial Intelligence Theory and Applications, 3(1), 45–50.
12. Islam, M. M., Zerine, I., Rahman, M. A., Islam, M. S., & Ahmed, M. Y. (2024). AI-driven fraud detection in financial transactions – Using machine learning and deep learning to detect anomalies and fraudulent activities in banking and e-commerce transactions. International Journal of Communication Networks and Information Security, 16(5), 927–944.
13. Pumsirirat, A., & Yan, L. (2018). Credit card fraud detection using deep learning based on auto-encoder and restricted Boltzmann machine. International Journal of Advanced Computer Science and Applications, 9(1), 18–25.
14. Vasant, M., Ganesan, S., & Kumar, G. (2025). Enhancing e-commerce security: A hybrid machine learning approach to fraud detection. FinTech and Sustainable Innovation, 00(00), 1–9.
15. Raju, G. S., & Varma, V. S. (2025). E-commerce fraud detection based on machine learning techniques. International Journal of Innovative Research in Technology, 11(11), 5252. ISSN: 2349-6002. Retrieved from IJIRT publication
16. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.
17. Arık, S. O., & Pfister, T. (2020). TabNet: Attentive interpretable tabular learning. arXiv preprint arXiv:1908.07442v5.
18. Vapnik, V. N. (1998). The nature of statistical learning theory (2nd ed.). Springer.
19. Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297
20. Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: applications, challenges and trends. Neurocomputing.
21. Halder, R. K., Uddin, M. N., Uddin, M. A., Aryal, S., & Khraisat, A. (2024). Enhancing K-nearest neighbor algorithm: A comprehensive review and performance analysis of modifications. Journal of Big Data, 11, Article 113.
22. Elrahman, S. M. A., & Abraham, A. (2013). A review of class imbalance problem. Journal of Network and Innovative Computing, 1, 332–340.
23. Fernández, A., García, S., Herrera, F., & Chawla, N. V. (2018). SMOTE for learning from imbalanced data: Progress and challenges, marking the 15-year anniversary. Journal of Artificial Intelligence Research, 61, 863–905.
24. Batista, G. E. A. P. A., Prati, R. C., & Monard, M. C. (2004). A study of the behavior of several methods for balancing machine learning training data. ACM SIGKDD Explorations Newsletter, 6(1), 20.
25. Han, H., Wang, W.-Y., & Mao, B.-H. (2005). Borderline-SMOTE: A new over-sampling method in imbalanced data sets learning. In D.-S. Huang, X.-P. Zhang, & G.-B. Huang (Eds.), Advances in Intelligent Computing (pp. 878–887). Springer.
26. Zhang, Z., Yin, H., Rao, S.X. et al. Identifying E-Commerce Fraud Through User Behavior Data: Observations and Insights. Data Sci. Eng. 10, 24–39 (2025). https://doi.org/10.1007/s41019-024-00275-6

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Green Fintech and Carbon Market Integration in Civil Engineering: A Path Toward Sustainable Infrastructure Model

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Abstract
The aims of this paper to focused on the coupling of financial technology (Green Fintech) and sustainable practices is shaped the future of infrastructure development and environmental responsibility. This paper examines the interrelated nature of Green Fintech, Infrastructure, the Carbon Market, and Sustainable infrastructure for the benefit of low-carbon economies. Green Fintech, through mechanisms such as green bond rates, Fintech penetration, and ESG investment indices, drives activity in the Carbon Market by facilitating carbon credit trading, pricing, and emissions certification. methodological this paper adopts qualitative approach and revised previous papers which related, to address the research gap and suggest new integrated model.

1 Introduction

Greenhouse gas emission consider one of the major impact on global climate changes around the world, these Leads to extreme high temperature and increasing seas level (Gambhir et al., 2022; Adamo et al., 2021). in recent response to that challenges on environment, many countries worldwide have incited initiatives to carbon emission reduction.

The urgency of addressing climate change and environmental deterioration has put civil engineering and construction industries on the global lookout for advancements on sustainable development (Ajirotutu et al., 2024). Civil engineering is one of the industries with the highest output of greenhouse gases. Construction and building activities contribute to nearly 39 percent of the global carbon dioxide emissions (IEA 2021). On the other hand, the rapid growth of digital innovation within environmental finance, especially the emergence of Green Fintech and carbon markets, offers a remarkable innovation opportunity (Liu et al., 2023). This paper is concerned with the application of Green Fintech and carbon markets in civil engineering for the advancement of sustainable infrastructure, carbon footprint mitigation, and environmental accountability enforcement.

Green Fintech definition is the development of financial technology innovations for environmental protection (Chueca Vergara and Ferruz Agudo 2021). This includes a various of components, main components are carbon accounting on the blockchain, sustainable investment platforms, and AI-powered carbon foot printing (Chen et al., 2023). In engineering projects, these tools can provide transparency, facilitate the real time monitoring of carbon emissions, and encourage the form of construction projects that utilize smarter, energy-efficient designs with machine learning and advanced analytics. Green Fintech also facilitates access to capital for low-emission construction projects by promoting green bonds and climate-financing crowdfunding and provides a financial incentive to engage in low-carbon construction (Alsmadi et al., 2023; Yip & Bocken, 2018).

The emergence of carbon markets, in conjunction with the Green Fintech movement, facilitates the trading of carbon credits and offsets. These carbon markets operate under the "cap and trade" framework or through voluntary offsetting, enabling enterprises to acquire emission credits that stem from activities aimed at reducing carbon emissions (Lema et al., 2025).

In this context, Green Fintech can act as a bridge between engineering systems and environmental finance (Kaifeng and Chuanzhe 2011). in addition, BIM platforms could tack embodied carbon through tracking smart contracts. Blockchain technology (BT) can help the construction industry to achieve high productivity taking situational instances of Payments in Project Management (PPM), Procurements in Supply Chain

Management (PSCM), and Building Information Modeling (BIM) using Smart Asset Management (SAM) Prakash and Ambekar (2020).

Furthermore, in recent years both regulators and policy makers works together to bring frame to align with this gathering. Governments and organizations are focusing on the role of digital finance and carbon pricing to meet climate commitments under the Paris Agreement (Digitemie et al., 2024). projects which qualifying for public funds or financing from banks are usually demonstrate low carbon impact, matches with sustainable development goals and have high transparency in environment data. (Lagoarde-Segot, 2020).

However, green Fintech and sustainability integration present some challenges. technological barriers consider main challenge to connect both together, also lack of carbon accounting standardized practices and stakeholder's resistance are representing the challenges. thus there are needs for collaboration between education, and policy innovation to unlock the full potential of Green Fintech and carbon market tools in the engineering domain.

This paper investigates the intersection of Green Fintech, carbon markets, and civil engineering, with a focus on enabling sustainable infrastructure. It aims to (1) identify key Green Fintech tools applicable to the engineering sector, (2) evaluate the potential and limitations of carbon market participation by infrastructure projects, and (3) propose a framework for integrating these elements into civil engineering practice. Through this exploration, the study contributes to the growing discourse on climate-smart infrastructure and the role of digital finance in accelerating the transition to a sustainable built environment.

2 Literature Review

sustainability goals considered an essential goal nowadays, as footprint of projects play vitals in environment in general. and creating of carbon credits is methods to reduce the pollutions, these methods need to future direction on changes to an incentives or in taxes, as new future direction to control these impacts integration of green Fintech and carbon markets in civil engineering presents a promising pathway toward sustainable infrastructure (Luo et al., 2021; wang et al., 2022). according to that Van Tam et al., (2024) found that the top-priority strategies for NZCBs included raising awareness, developing project-specific emission reduction roadmaps, and increasing renewable energy utilization. For promoting carbon credits, the prioritized strategies involved tax reduction, integrating emission reduction criteria into tender documents, and awarding technical points to contractors with emission reduction solutions.

Previous studies that integrate green finance and sustainability in general such as udeagha and Muchapondwa, (2023) found that BRICS economics that adopt green Fintech in energy innovations lead to promote environmental sustainability, also Gupta, (2025) suggest that the smart contracts, AI and IoT in Green Fintch has great accelerating moving toward sustainable global economy (Gupta, 2025).

integrated Carbon Markets: these markets works to incorporate the capitals to invest in engineering climate projects, through adopted the carbon taxes funds in new environment projects (Li et al., 2025).

Carbon Credits: it is a measurable criteria used to how can the organization got benefit from footprint, which can lead these organizations to enhance their market values (Zeng et al., 2024).

Green Infrastructure (Gi): adoption of (Gi) in engineering projects can significantly reduce greenhouse gas emissions, improve water quality, and reduce power consumptions, which finally addressing both environmental and infrastructural challenges (Ai and Yan, 2024).

Blended Approaches: Combining natural capital with engineering solutions (green-gray approaches) can enhance water security and reduce costs associated with traditional infrastructure (Vörösmarty et al., 2021).

recent still integration of both green Fintech and carbon markets have challenges and lack implementations, the new technologies such as Fintech can play a potential in future to solve this matter. Addressing these disparities is crucial for achieving sustainable infrastructure on a global scale.

Green Fintech: Emerging Tools for Sustainable Development

sustainable finance and digital innovations convergence together through green financial technology (green Fintech), to facilitating the environmentally responsible economic activities. green Fintech encompasses technologies such as artificial intelligence (AI), Internet of Things (IoT) and blockchain to promote environmental performance across industries (Chen et al., 2023). several previous studies that have indicate the impact of Fintech on green development and sustainability, while studies focused on the impact on carbon emission. Tao et al. (2022) and Cheng et al. (2023) confirm that Fintech technologies reduces greenhouse gas emissions. These applications and tools increasingly being adopted to assess carbon footprints, and green investment projects.

block chain revolution has gained attention in the various fields in industries, in climate finance space specially, making it suitable for carbon tracking and green bond verification. Xu,w et al. (2023) highlighted that blockchain platforms allow for monitoring of emissions through adoption of smart contracts in construction industry that struggle with carbon accountability. in other hand, such AI platforms are emerging to optimize energy efficiency in infrastructure, predict environmental risks, and automate sustainability metrics (Zhang et al., 2022).

Era of finch focused on how adopt technology in finance, while green Fintech represent new applications and technologies helps on control emission in environment, while integrate these new applications in finance to control projects emission represents in nascent stage. Yip and Ochinanwata et al., (2024) highlighted, the institutional barriers, lack of digital transformation infrastructure slow down the pace of innovation diffusion.

Carbon markets are designed to reduce greenhouse gas emissions through market-based incentives. They allow entities to buy and sell carbon credits, each representing one metric ton of CO_2-equivalent emissions (Nevzorova, 2024). The two main types of carbon markets are compliance markets (regulated by governments) and voluntary markets (driven by corporate or consumer demand) (Ahonenet al., 2022). These mechanisms are becoming increasingly relevant for the construction and civil engineering industries, which are seeking cost-effective pathways to decarbonization.

Policy, Standards, and Global Frameworks

International policy frameworks such as the Paris Agreement and the United Nations Sustainable Development Goals (SDGs) have laid the groundwork for a shift toward climate-resilient infrastructure. National governments and multilateral development banks are increasingly embedding carbon reduction targets into public infrastructure funding criteria. Ozili (2022) notes that green finance mechanisms, including climate bonds and blended finance models, are being adapted for infrastructure development, creating opportunities for civil engineering firms that align with environmental benchmarks.

However, the regulatory landscape for Green Fintech and carbon markets remains fragmented. A study by Hou et al. (2022) finds that while countries such as China, the EU, and the US have made strides in developing digital finance standards for sustainability, there is little cohesion in how carbon emissions from infrastructure are measured or priced globally. This makes it difficult for engineering firms to navigate or leverage carbon markets efficiently.

Recent shifts in policy and public awareness are pushing the industry to adopt greener practices, including lifecycle assessments (LCAs), circular construction techniques, and low-carbon building materials (Liu et al., 2021). The integration of digital technologies into civil engineering commonly referred to as "smart infrastructure" has become a key driver of sustainability. Tools like Building Information Modeling (BIM), Geographic Information Systems (GIS), and digital twins enable more accurate modeling of environmental impacts and support better decision-making (Wang et al., 2022).

In this context, Green Fintech can act as a bridge between engineering systems and environmental finance (Kaifeng and Chuanzhe 2011). For example, a blockchain-integrated BIM platform could automatically track embodied carbon and trigger smart contracts for issuing carbon credits based on verified reductions. Studies by Prakash and Ambekar (2020). suggest that integrating such technologies could drastically enhance accountability and incentivize sustainability in infrastructure projects.

New technologies such as block chain and smart contacts can enhance secure and provide trustable tracking and trading of carbon credits, and decreasing fraud (Gulati et al., 2025; Li et al., 2025). while yet most of implementation still invalidate in real construction projects (Rodrigo et al., 2020). Besides, (Cheng et al 2023) identify the impact of Fintech on carbon emissions by examining China's. This results found that Fintech and carbon emissions are part of a complicated ecology integration influenced by various economic and societal factors.

literature models reveal that external environmental and policy, managerial support and technological significantly impact blockchain uptake in construction sector organizations. behind that, Smart contract systems leading to information accuracy, trading carbon credits workflows, and supply chain transparency though linking these to carbon credit issuance remains a research frontier. while reviews in Fintech for carbon credit markets detect methods for future price prediction and emissions forecasts, but mostly targeting finance professionals not civil infrastructure contexts (Gopal and Pitts 2025).

3 research Gaps & Opportunities

Lack of Sector Specific Applications: Green Fintech especially blockchain, smart contracts, and tokenization is revolutionizing carbon markets by enhancing transparency and reducing transaction costs. There is little to no tailored application of these Fintech tools specifically to civil engineering projects, such as infrastructure retrofitting, green buildings, or sustainable materials. Engineering firms lack accessible platforms or use-cases to actively participate in carbon credit trading or integrate them into project planning (Vilkov and Tian 2023).

Poor Integration Between Engineering Design & Carbon Finance: Lifecycle analysis tools exist in civil engineering, and carbon finance models exist in Fintech, but they operate in silos. There is no framework to integrate lifecycle carbon emissions with Fintech tools (e.g., carbon token valuation, forecasted pricing) directly into BIM or engineering design workflows. Designers and project managers cannot factor carbon finance into early decision-making, missing economic incentives for greener solutions (Karakosta and Papathanasiou 2024).

according to lack of empirical projects that applied green Fintech in sustainable civil engineering projects, without empirical data the effectiveness and accuracy still remain unproven (Mammadov, W., et al. 2024). Regulatory and policy support for green Fintech integration in projects still weak, there are no frameworks that support or incentivize civil engineering firms to adopt Fintech-enabled carbon accounting or participate in voluntary carbon markets. while there are lack of studies that on construction project adoption of carbon credits in Fintech.

Although the body of literature has examined the impacts of green Fintech, evidence on how green Fintech affects projects carbon abatement remains under-explored and unnourished.

4 Suggested model

integration of green Fintech and carbon markets in civil engineering projects infrastructure will provide a controllable system where easy to tracking, according to the study gap, these paper suggests the following model under path name, Integrated Green Fintech- Carbon Market Framework (IGFCM) for sustainable Infrastructure projects.

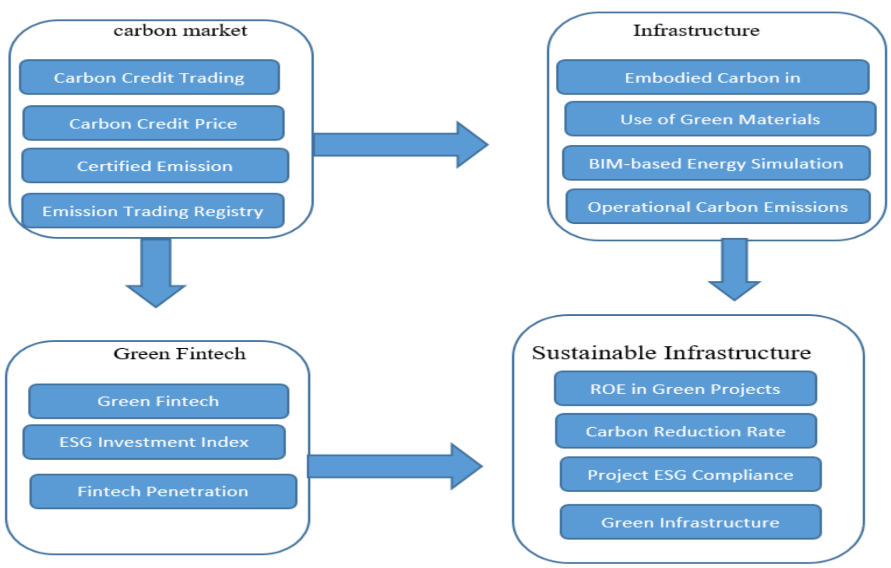

Figure 1: Integrated Green Fintech- Carbon Market Framework (IGFCM)

Then this study suggests regulatory to adopt platforms in civil engineering projects that can tracking emission and carbon, while these platforms connected with financial systems to calculate or standardize scale for each project or constructor, these points can be benefited in financial incentives.

5 Conclusion

This paper provides insight on how to combining the Green Fintech solutions into carbon markets, offers transformative potential for civil engineering projects. This study began with a robust quantitative approach to show the integration of green Fintech and carbon emission of engineering project. After all, this technology and applications have proven to be transformative.

Technologies such as blockchain, artificial intelligence (AI), digital accounting carbon platforms and carbon credit trading systems, can be better measures in civil engineering projects. through these technologies could be easier to measure, report, and verify emissions. This digital-financial synergy not only supports the decarbonization of infrastructure projects but also aligns them with global climate goals and ESG frameworks.

The paper discussed how Green Fintech Emerging Tools for Sustainable Development, Carbon Markets Mechanisms and Opportunities, Policy, Standards, and Global Frameworks and how Civil Engineering contribute the Sustainability Transition. While the Research Gaps and Opportunities generates to suggest a measurable framework to integrate green Fintech and emission (carbon market) impact on sustainable infrastructure.

6 References

1. Adamo, N., Al-Ansari, N., & Sissakian, V. (2021). Review of climate change impacts on human environment: past, present and future projections. *Engineering*, *13*(11), 605-630.
2. Ahonen, H. M., Kessler, J., Michaelowa, A., Espelage, A., & Hoch, S. (2022). Governance of fragmented compliance and voluntary carbon markets under the Paris Agreement. Politics and governance, 10(1), 4759.
3. Ai, K., & Yan, X. (2024). Can green infrastructure investment reduce urban carbon emissions: Empirical evidence from China. Land, 13(2), 226.
4. Ajirotutu, R. O., Adeyemi, A. B., Ifechukwu, G. O., Iwuanyanwu, O., Ohakawa, T. C., & Garba, B. M. P. (2024). Future cities and sustainable development: Integrating renewable energy, advanced materials, and civil engineering for urban resilience. International Journal of Sustainable Urban Development, 3.
5. Alsmadi, A. A., Al-Okaily, M., Alrawashdeh, N., Al-Gasaymeh, A., Moh'd Al-hazimeh, A., & Zakari, A. (2023). A bibliometric analysis of green bonds and sustainable green energy: evidence from the last fifteen years (2007–2022). Sustainability, 15(7), 5778.
6. Chen, H. (2023). Fintech and investment risk of digital finance: mediating role of clean energy and green bonds through the dynamics of spill over. Environmental Science and Pollution Research, 30(34), 82286-82296.
7. Cheng, X., Yao, D., Qian, Y., Wang, B., & Zhang, D. (2023). How does fintech influence carbon emissions: evidence from China's prefecture-level cities. International Review of Financial Analysis, 87, 102655.
8. Cheng, X., Yao, D., Qian, Y., Wang, B., & Zhang, D. (2023). How does fintech influence carbon emissions: evidence from China's prefecture-level cities. International Review of Financial Analysis, 87, 102655.
9. Chueca Vergara, C., & Ferruz Agudo, L. (2021). Fintech and sustainability: do they affect each other?. Sustainability, 13(13), 7012.
10. Digitemie, W. N., & Ekemezie, I. O. (2024). Assessing the role of carbon pricing in global climate change mitigation strategies. Magna Scientia Advanced Research and Reviews, 10(2), 022-031.
11. Gambhir, A., George, M., McJeon, H., Arnell, N. W., Bernie, D., Mittal, S., ... & Monteith, S. (2022). Near-term transition and longer-term physical climate risks of greenhouse gas emissions pathways. Nature Climate Change, 12(1), 88-96.

12. Gopal, S., & Pitts, J. (2025). The Intersection of Carbon Pricing, Fintech, and Blockchain Technology. In The FinTech Revolution: Bridging Geospatial Data Science, AI, and Sustainability (pp. 317-343). Cham: Springer Nature Switzerland.
13. Gulati, S., Arora, A., Singh, S., & Goel, P. K. (2025). Blockchain and IoT for Secure Carbon Credit Transactions: A Decentralized and Transparent Approach. In Advanced Systems for Monitoring Carbon Sequestration (pp. 87-106). IGI Global Scientific Publishing.
14. Gupta, D. S. (2025). Sustainable Digital Banking: Exploring The Role of Fintech in Promoting Green Finance and Sustainable Development Goals. Journal of Information Systems Engineering and Management, 10(3).
15. Hou, W., Shi, Q., & Guo, L. (2022). Impacts of COVID-19 pandemic on foreign trade intermodal transport accessibility: Evidence from the Yangtze River Delta region of mainland China. Transportation Research Part A: Policy and Practice, 165, 419-438.
16. Kaifeng, L., & Chuanzhe, L. (2011). Construction of carbon finance system and promotion of environmental finance innovation in China. Energy Procedia, 5, 1065-1072.
17. Karakosta, C., & Papathanasiou, J. (2024). Climate-Driven Sustainable Energy Investments: Key Decision Factors for a Low-Carbon Transition Using a Multi-Criteria Approach. Energies, 17(21), 5515.
18. Lagoarde-Segot, T. (2020). Financing the sustainable development goals. Sustainability, 12(7), 2775.
19. Lema, R., Vargas, L. B., Gonzalez, A. D., Lachman, J., Maes-Anastasi, A., Kumar, P., ... & Mensing, N. (2025). Smallholder Farmers and the Voluntary Carbon Market: A Balancing Act: Navigating Pricing, Co-Benefits, and Challenges.
20. Li, C., Su, X., Fan, C., Wang, J., & Wang, X. (2025). A Sustainable Circular Framework for Financing Infrastructure Climate Adaptation: Integrated Carbon Markets. arXiv preprint arXiv:2501.08004.
21. Li, X., Jiang, M., Lin, C., Chen, R., Weng, M., & Jim, C. Y. (2025). Integrated BIM-IoT platform for carbon emission assessment and tracking in prefabricated building materialization. Resources, Conservation and Recycling, 215, 108122.
22. Liu, J., Zhang, Y., & Kuang, J. (2023). Fintech development and green innovation: Evidence from China. Energy Policy, 183, 113827.
23. Liu, X., Bao, Y., Zhang, Y., & Li, J. (2022). Decoupling analysis on China's civil aviation carbon emissions from transportation revenue: a three-dimension decomposition framework. Sustainable Production and Consumption, 32, 718-730.
24. Luo, W., Zhang, Y., Gao, Y., Liu, Y., Shi, C., & Wang, Y. (2021). Life cycle carbon cost of buildings under carbon trading and carbon tax system in China. Sustainable Cities and Society, 66, 102509.
25. Mammadov, E., Asgarov, A., & Mammadova, A. (2024). Applications of IoT in Civil Engineering: From Smart Cities to Smart Infrastructure. Luminis Applied Science and Engineering, 1(1), 13-28.
26. Nevzorova, T. (2024). Carbon market for climate projects in Russia: an overview of nature-based and technological carbon offsets. Gases, 4(3), 153-173.
27. Ochinanwata, C., Igwe, P. A., & Radicic, D. (2024). The institutional impact on the digital platform ecosystem and innovation. International Journal of Entrepreneurial Behavior & Research, 30(2-3), 687-708.
28. Ozili, P. K. (2022). Green finance research around the world: a review of literature. International Journal of Green Economics, 16(1), 56-75.
29. Prakash, A., & Ambekar, S. (2020). Digital transformation using blockchain technology in the construction industry. Journal of information technology case and application research, 22(4), 256-278.
30. Rodrigo, M. N. N., Perera, S., Senaratne, S., & Jin, X. (2020). Potential application of blockchain technology for embodied carbon estimating in construction supply chains. Buildings, 10(8), 140.
31. Tao, R., Su, C. W., Naqvi, B., & Rizvi, S. K. A. (2022). Can Fintech development pave the way for a transition towards low-carbon economy: A global perspective. Technological Forecasting and Social Change, 174, 121278.
32. Udeagha, M. C., & Muchapondwa, E. (2023). Green finance, fintech, and environmental sustainability: fresh policy insights from the BRICS nations. International Journal of Sustainable Development & World Ecology, 30(6), 633-649.

33. Van Tam, N., Toan, N. Q., & Ngoc, P. H. (2024). Key strategies for achieving net-zero carbon buildings and promoting carbon credits in construction markets: a case of an emerging economy. Energy for Sustainable Development, 81, 101488.
34. Vilkov, A., & Tian, G. (2023). Blockchain's scope and purpose in carbon markets: A systematic literature review. Sustainability, 15(11), 8495.
35. Vörösmarty, C. J., Stewart-Koster, B., Green, P. A., Boone, E. L., Flörke, M., Fischer, G., ... & Stifel, D. (2021). A green-gray path to global water security and sustainable infrastructure. Global Environmental Change, 70, 102344.
36. Wang, J., Pan, K., Wang, C., Liu, W., Wei, J., Guo, K., & Liu, Z. (2022). Integrated carbon emissions and carbon costs for bridge construction projects using carbon trading and tax systems—taking beijing as an example. Applied Sciences, 12(20), 10589.
37. Wang, W., Guo, H., Li, X., Tang, S., Xia, J., & Lv, Z. (2022). Deep learning for assessment of environmental satisfaction using BIM big data in energy efficient building digital twins. Sustainable Energy Technologies and Assessments, 50, 101897.
38. Xu, J., Chen, F., Zhang, W., Liu, Y., & Li, T. (2023). Analysis of the carbon emission reduction effect of Fintech and the transmission channel of green finance. Finance Research Letters, 56, 104127.
39. Xu, W., Yan, W., Song, B., & He, J. (2023). Blockchain adoption and strategic contracting in a green supply chain considering market segmentation. Industrial Management & Data Systems, 123(10), 2704-2732.
40. Yip, C. C., Marsono, A. K., Wong, J. Y., & Lee, S. C. (2018). Seismic performance of scaled IBS block column for static nonlinear monotonic pushover experimental analysis. Jurnal Teknologi (Sciences & Engineering), 80(1).
41. Zeng, Q., Xu, H., Xu, N., Salim, F., Gao, J., & Chen, H. (2024). Engineering Carbon Credits Towards A Responsible FinTech Era: The Practices, Implications, and Future. arXiv preprint arXiv:2501.14750.
42. Zhang, D., Maslej, N., Brynjolfsson, E., Etchemendy, J., Lyons, T., Manyika, J., ... & Perrault, R. (2022). The AI index 2022 annual report. arXiv preprint arXiv:2205.03468.

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Mitigating Cyber Risk and Current Trends in Modern Authentication Techniques for Businesses

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Abstract
Cyber risk and data breaches for organizations increasingly arise from outdated password practices, influenced by human behavior, mistakes, and the reliance on information that individuals must remember. Cybercriminals and hackers exploit vulnerabilities in password security and the tendency of users to reuse passwords across various platforms, including work and personal websites, as well as for multiple purposes. Leaders in the IT industry and Chief Information Officers have advocated for organizations and users to eliminate traditional password security measures in favor of more robust authentication methods, such as biometric and multifactor approaches. These advanced security techniques offer companies and users enhanced opportunities to safeguard themselves against cyber threats and data breaches. However, user resistance and a lack of familiarity with contemporary authentication methods pose significant challenges to the adoption of passwordless solutions
This paper will examine various aspects of contemporary passwordless authentication techniques. Firstly, it will discuss the recent trends in shifting away from exclusively password-based security systems and analyze what modern authentication solutions offer to both businesses and users, including multifactor authentication (MFA), biometric logins, and hardware security keys. Secondly, it will address the challenges that organizations encounter in the implementation and adoption of these modern methods. Thirdly, it will explore the opportunities for enhancing education and awareness among users regarding the advantages of transitioning from passwords to modern authentication factors, thereby safeguarding themselves against cyber risks. Lastly, this paper will review case studies illustrating how modern authentication methods could have averted substantial financial and health losses for prominent companies.

Keywords—Cyber Risk, Cyber Threat, Biometric, Multifactor Authentication (MFA), Passwords, Data Breach

1 Introduction

Usernames and passwords often serve as the initial access point for individuals logging into systems for both professional and personal use. Whether it is for banking, healthcare, government services, or social media, users are increasingly encouraged to manage a significant portion of their lives online. Traditionally, passwords have been utilized as a means of safeguarding security for both organizations and individuals. Despite receiving guidance to select strong, unique, and complex passwords, individuals frequently opt for passwords that expose themselves and their organizations to considerable cyber threats, thereby heightening the risk of data breaches. Passwords are commonly compromised due to users relying on easily identifiable information (such as their names, birth dates, home addresses, and phone numbers), writing down their passwords, reusing them across various platforms, sharing them within their organizations, or selecting passwords that are simple for cybercriminals to decipher [1]. A study conducted by Verizon Wireless revealed that in 2024 alone, over 2.8 billion passwords were made available for purchase or free distribution in criminal forums [2]. Furthermore, the same Verizon study indicated that research on password datasets demonstrated that only 3% of the total unique passwords fulfill complexity criteria.

Recently, the personal genetics company 23andMe declared bankruptcy in the spring of 2025 due to significant financial difficulties and a series of cyber-attacks. A cybercriminal exploited users' tendency to reuse usernames and passwords to gain unauthorized access to user accounts [3]. As a result, the cybercriminal disclosed the display name, gender, birth year, and certain information regarding genetic ancestry results for more than four million 23andMe users in 2023. In February 2024, UnitedHealth Group fell victim to hackers who exploited the absence of multifactor authentication (MFA) measures [4]. The repercussions of this attack were anticipated to cost UnitedHealth over $2 billion to rectify.

Regardless of prompts, reminders, and suggestions: "Humans are bad at choosing strong passwords, we frequently reuse them and we are victims of Social Engineering fairly consistently" [2]. Multifactor authentication faces opposition as it is viewed as slow and is not well comprehended [4].

By adopting contemporary authentication techniques that do not depend exclusively on passwords or entirely eliminate their use, organizations and individuals can safeguard their data and personal information, thereby mitigating the risk of cyber-attacks or data breaches within the workplace. Contemporary authentication techniques, including multifactor authentication, biometric logins, and hardware security key protection, offer numerous opportunities to transition from "something the user knows" (i.e., their memorized password) to "something the user has" (i.e., their mobile device for verification or access) or "something the user is" (i.e., their fingerprint or facial recognition), as illustrated in Figure 1 [1]. These latter two categories of information and authentication strategies significantly increase the difficulty for cybercriminals to obtain access [5]

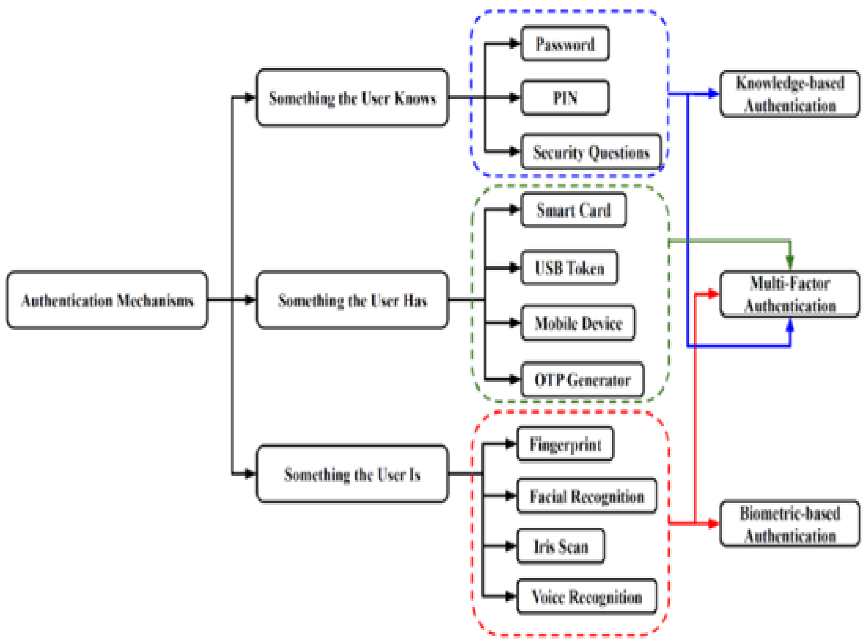

Figure 1: Albesher, A. S., Alkhaldi, A., & Aljughaiman, A. (2024). Toward secure mobile applications through proper authentication mechanisms. *PLoS One, 19*(12)

Despite the challenges associated with transitioning users and organizations to contemporary authentication methods, the escalating threats and attacks related to cyber risks underscore the necessity for more sophisticated solutions. Furthermore, the concept of passwordless authentication is becoming increasingly familiar as public cloud services, mobile providers, and applications, such as those offered by Amazon, Apple, and Google, readily provide these alternatives. This allows the public to authenticate their login and activities using biometric methods like fingerprints or facial recognition [6]. Organizations have the potential to capitalize on the practices that users already engage in across various aspects of their lives. However, the broader adoption and implementation of modern authentication techniques necessitate enhanced education regarding the convenience and security of passwordless options, user-friendly training, and dedicated time to assist users during the initial setup of these advanced methods.

2 Trends And the Shift Toward Stronger Authentication

Numerous companies in the present day are enhancing their cybersecurity measures in response to the increasing frequency of cyberattacks observed over the last decade. Research indicates that enhancing password protection techniques that extend beyond the conventional username and password framework is effective in thwarting unauthorized access. As cyberattacks evolve in sophistication, depending solely on passwords is insufficient to safeguard company data [7]. Although the basic username and password method remain prevalent, many organizations are starting to implement more secure authentication strategies. Password managers represent another tool that provides a level of password protection. Rather than reusing identical passwords or attempting to recall multiple passwords for various logins, a password manager consolidates them all under a single master password. However, this approach has faced criticism, as compromising the master password would also jeopardize all other stored passwords. These trends illustrate the transition towards more robust and convenient methods of data protection. While there are numerous strategies to enhance a company's cybersecurity, three methods have been identified as particularly effective: multifactor authentication, biometric authentication, and hardware security keys.

Multifactor authentication is rapidly becoming one of the most widely adopted security measures across various industries, necessitating that users confirm their identity through two or more steps during the login process. Google first implemented this method in 2011 and has recently made it a requirement for all customers accessing Google Cloud, aiming to safeguard sensitive information [8]. Typically, this procedure entails obtaining a verification code or notification sent to the registered phone number or email for login purposes. The intent of this additional step is to mitigate the risk of unauthorized access, even in cases where the password may have been compromised.

Biometric authentication enables users to access their accounts through distinctive physical characteristics, such as fingerprints or facial features. This technology gained popularity following Apple's launch of the Touch ID feature on iPhones in 2013, which permitted users to log in with their finger rather than relying on traditional passwords or codes. The facial recognition systems employed by numerous companies, including Apple, are engineered to thwart prevalent spoofing methods. These systems can identify three-dimensional faces, reject two-dimensional images, and require that the user's eyes remain open for access [9]. Additionally, fingerprint scanners possess the capability to sense body heat and authentic skin, making it challenging for individuals to gain unauthorized access using replicas.

Hardware security keys are tangible devices utilized for logging in, serving either as a substitute for or an enhancement to the conventional password. These security keys typically take the form of USB devices or Near-Field Communication (NFC) enabled cards, which can be either inserted into or tapped against a device. A prominent example of this effective security approach is the YubiKey, widely adopted by numerous major corporations, including Google. In fact, Google reported in 2017 that after mandating all employees to utilize the security key, there have been no successful phishing attempts on employee accounts [10]. This method adds an additional layer of security, as it necessitates physical possession of the security key for login. Hardware security keys are regarded as one of the most reliable options for sectors that manage sensitive data, such as finance, technology, and human resources [11].

As cyberattacks grow increasingly sophisticated, it is imperative for companies to proactively implement advanced security measures to safeguard against both current and emerging threats. The transition towards more robust authentication methods signifies a wider acknowledgment that digital security has transitioned from being optional to becoming essential for a successful business and fostering customer loyalty. Organizations that allocate resources to these technologies illustrate their dedication to maintaining customer trust by ensuring the protection of their data. Although there are numerous strategies to enhance an organization's cybersecurity, these authentication methods have consistently demonstrated their effectiveness in decreasing the frequency of attacks across various industries, as evidenced in Figure 2 [12].

Department	MFA Adoption (%)	Phishing Incidents Reduced (%)
HR	85%	72%
Finance	92%	78%
IT	95%	85%

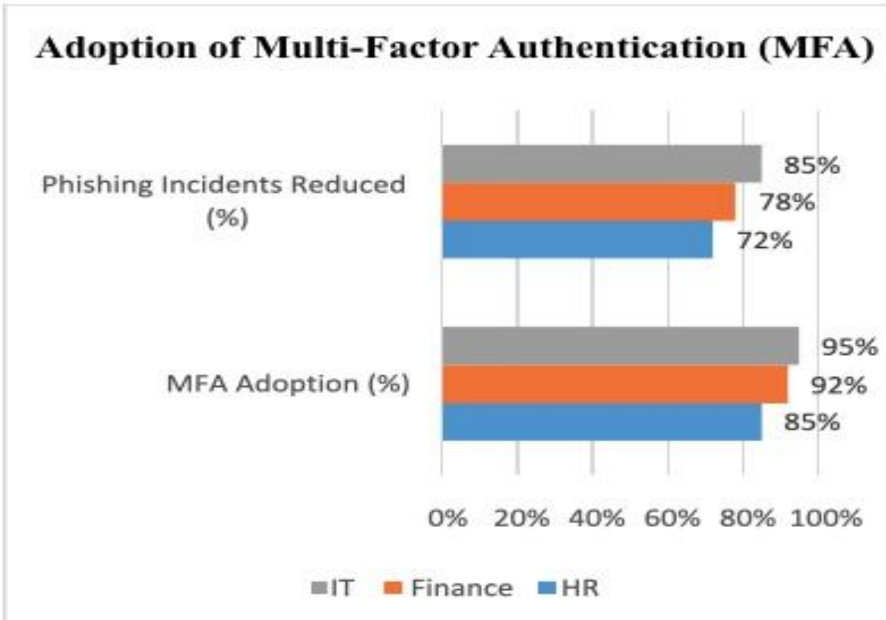

Figure 2: Shaheen et al. (2025). Data privacy in HR: Securing employee information in U.S enterprises using Oracle HCM Cloud. *International Journal of Research Radicals in Multidisciplinary Fields, 3*(2)

3 Challenges And What Is Holding Back Modern Authentication

Despite the increasing recognition of the shortcomings associated with password-based security, the adoption of contemporary authentication techniques, including biometric authentication, multi-factor authentication (MFA), and hardware security keys, presents a significant challenge for organizations regarding risk-based access. These challenges stem not only from user behavior but also from technical constraints, the preparedness of infrastructure, financial considerations, and cultural obstacles.

One of the most urgent challenges is the disparity between awareness and implementation. Organizations may advocate for MFA or passwordless systems; however, the absence of enforcement mechanisms and adequate infrastructure frequently results in these solutions being underutilized. For instance, credential abuse remains one of the primary threat vectors, not solely due to weak passwords, but also because MFA is applied inconsistently across various systems and user groups [2]. This lack of consistency enables attackers to take advantage of systems where protections are either weak or absent.

In addition to enforcement deficiencies, user resistance continues to be a significant obstacle. Although users may recognize that fingerprint scanners or verification codes offer enhanced security, many view these systems as inconvenient or perplexing. Studies indicate that in developing regions, particularly where cybersecurity awareness is limited, such resistance can be even more pronounced [13]. Consequently, this results in low adoption rates, even when systems are designed to support modern authentication methods [5]..

The integration of technology presents a considerable challenge. Numerous legacy systems were not originally designed to accommodate biometric data, adaptive authentication methods (which modify verification criteria based on user behavior or context), or token-based login processes such as hardware security keys. In cloud-based settings, identity verification must be synchronized across multiple platforms and endpoints, frequently necessitating custom development and collaboration with vendors [15, 14].

The financial implications of upgrading identity frameworks represent another significant hurdle, particularly for small and medium-sized enterprises. Costs encompass software purchases, hardware provisioning, employee training, and compliance management. These expenses can appear daunting, even in light of the long-term security advantages [15; 5].

Additionally, there are pressing issues regarding user privacy and data ethics. Unlike passwords, biometric identifiers cannot be altered once they have been compromised. Users are becoming increasingly apprehensive about how their facial scans, fingerprints, or behavioral data are stored and who has access to this information. In the absence of well-defined policies and secure data management practices, organizations risk undermining user trust [13].

Additionally, some tools marketed as "secure by design," Furthermore, certain tools promoted as "secure by design," like password managers, are frequently misinterpreted. Users might assume that keeping passwords in a single vault suffices, failing to recognize that without Multi-Factor Authentication (MFA), the vault itself turns into a single point of failure [1]. Awareness regarding these tools is scarce, particularly in organizations lacking specialized cybersecurity training.

The implementation of zero trust frameworks introduces both cultural and technical obstacles. These frameworks necessitate ongoing verification and detailed access control, which can hinder productivity if not executed correctly. Numerous companies are ill-equipped for the mindset shift required from implicit trust to continuous verification and neglect to provide the essential operational support [16].

Even well-structured authentication systems can be disregarded if the user experience is inadequate. Multi-layered logins, frequent prompts, or poorly integrated biometric processes can irritate users and compel them to find alternative solutions. In such scenarios, usability itself becomes a security vulnerability [15, 14].

In conclusion, moving towards modern authentication is not simply a technological enhancement; it requires comprehensive changes across the organization in training, infrastructure, and policy. For success, businesses must view the transition as both a cultural and operational transformation, as well as a technical upgrade..

4 People Drive Adoption Of Modern Authentication Methods

There are numerous opportunities for the increased adoption of contemporary authentication security methods, including MFA, biometric authentication, and hardware security keys among both users and organizations. Nevertheless, it is crucial to remember that the adoption and implementation hinge not solely on technology but also on human factors. Individuals are the primary contributors to successful cyberattacks, encompassing both cybercriminals and the millions of users with weak passwords. Furthermore, it is individuals who influence the utilization of security methods and determine which ones prevail in both domestic and professional environments. Enhancing workplace training, broadening educational and awareness initiatives, and lowering barriers to adoption begins with prioritizing people in the practices of implementation and adoption.

Users who adopt advanced security tools such as biometric and multifactor authentication frequently express feelings of trust, usefulness, and ease of use regarding these methods. This indicates that companies should take into account human behavior, attitudes, and emotions when disseminating information about non-password methods, as well as assisting individuals in comprehending the rationale behind more modern authentication techniques. Merely presenting facts and information may not motivate individuals to take action; rather, their emotional responses to a method are significant. Additionally, the simplicity of adoption will enhance how users perceive the integration of new methods. Research indicates that fingerprint, voice, and facial recognition options, which are now widely available on mobile devices and applications, have contributed to improved usability due to the rapid access and significant convenience they offer during login processes.

Raising awareness about contemporary authentication techniques and implementing extensive educational initiatives in workplaces and communities presents a significant opportunity for businesses to assist users in adopting more secure tools. When users possess a deeper understanding of these methods, coupled with a positive training experience, it fosters a more secure cyber environment [17]. Users can feel empowered to identify and effectively respond to cyber threats, as well as adopt superior authentication security practices that do not expose them to vulnerabilities [18]. By dedicating time to enhance digital literacy and educating users about security methods, the incidence of human error that leads to cyberattacks can be significantly reduced.

Moreover, beyond increased awareness, training, and education, research indicates that users require direction on what they can discard and “unlearn.” Users have been conditioned to rely on outdated or ineffective practices, such as passwords, making it challenging to abandon what they learned during their initial technological encounters. By demonstrating, rather than merely informing, users about real-world security breach incidents—particularly in finance or health—they may be more inclined to unlearn and adopt modern authentication techniques [18]. Rather than clinging to obsolete practices out of fear, users may be motivated to take action based on their newfound knowledge.

Finally, there exists a chance to further diminish obstacles to the adoption of contemporary authentication techniques by enhancing biometric and multifactor technologies to thwart bypassing methods [5]. Although numerous platforms and mobile applications incorporate user-friendly facial recognition, for instance, or multifactor authentication within their systems, users still possess various means to circumvent these measures and may choose to bypass them. Ongoing enhancements to intuitive interfaces that cater to diverse levels of digital literacy can significantly contribute to ensuring accessibility and user-friendliness [5]. Certain application developers advocate that multifactor authentication should be mandatory to safeguard both users and organizations [2].

5 The Cost of Weak Authentication

To enhance the understanding of the importance of secure authentication methods, it is beneficial to analyze several recent incidents involving major corporations. These incidents provide crucial insights for businesses regarding the necessity of safeguarding their systems and data.

In 2016, the Hollywood Presbyterian Medical Center in Los Angeles was among the numerous hospitals targeted in a ransomware attack [19]. Cybercriminals successfully installed a virus on the hospital's systems, encrypting their files. To regain access, the hospital was compelled to pay hackers a ransom of $17,000 in Bitcoin. Although it is reported that the breach began when an employee opened a phishing email, the absence of multifactor authentication enabled the hackers to completely compromise the hospital's systems.

In early 2024, cellular service provider AT&T and health insurance provider UnitedHealth Group experienced significant data breaches around the same time, also due to the lack of multifactor authentication. Hackers managed to penetrate one of AT&T’s third-party platforms using stolen credentials. To avert the leakage of customer data, they reportedly paid a ransom of $370,000 and incurred a $130 million loss in market value as a result of the incident. Similarly, UnitedHealth’s systems were breached through a comparable method, leading to widespread disruption of their healthcare services and jeopardizing the data and lives of many patients. The company disclosed that it paid a ransom of $22 million to prevent any data leaks [4]. Both occurrences underscore the vulnerabilities associated with traditional login methods and illustrate how effective modern secure authentication methods could have been in averting these crises.

One of the notable events that has transpired in recent years is the cyberattack executed by Salt Typhoon, a notorious Chinese hacking group. In late 2024, this group successfully infiltrated the systems of several U.S. cellular service providers, gaining access to sensitive customer data, including phone calls and text messages [20]. The companies affected include prominent names such as AT&T, T-Mobile, Verizon, and Consolidated Communications, all of which have been established in the industry for over two decades. Although they were compromised through advanced attacks, analysts suggest that these incidents might have been averted with the implementation of secure authentication methods.

These real-world instances of major corporations suffering significant losses underscore the necessity for every business to invest in cybersecurity measures to reduce the likelihood of an attack. From employees falling victim to phishing emails and the lack of multifactor authentication to vulnerabilities within infrastructure, each scenario illustrates how a single weak point can result in substantial financial loss, data breaches, or operational disruptions. Companies that do not evolve and embrace modern authentication techniques face risks that extend beyond mere inconvenience; they jeopardize their trust, reputation, and long-term viability. Moving forward, multifactor authentication, biometric authentication, and hardware security keys should be regarded as essential elements of conducting business in the digital era.

6 Conclusion

As cyber threats continue to rise, the dangers associated with outdated password-based authentication methods become increasingly pronounced. This paper has explored the significant transition towards contemporary authentication technologies, such as multifactor authentication, biometric verification, hardware security keys, and various passwordless solutions, which are vital for bolstering cybersecurity.

Current trends indicate that numerous leading organizations are embracing these tools to remain ahead of emerging threats. Nevertheless, the implementation process is fraught with challenges. Technical limitations, integration difficulties with legacy systems, budgetary constraints, user resistance, and privacy issues persist in obstructing widespread adoption. Despite these hurdles, there are considerable opportunities to enhance adoption through user-centered design, focused training, and extensive public education initiatives.

Real-world case studies illustrate both the costs of inaction and the advantages of implementing modern security measures. High-profile breaches reveal how inadequate, or nonexistent authentication protocols can result in substantial financial, operational, and reputational harm. In contrast, when effectively executed, modern authentication can successfully thwart sophisticated attacks and safeguard sensitive systems.

Ultimately, enhancing authentication transcends mere technical upgrades. It represents a strategic necessity. Moving forward, organizations must embrace a layered and user-aware approach to authentication that integrates technology, policy, and education. The journey towards stronger cybersecurity commences with re-evaluating how users access systems and investing in secure, scalable, and resilient authentication practices suitable for the digital era.

7 References

1. Albesher, A. S., Alkhaldi, A., & Aljughaiman, A. (2024). Toward secure mobile applications through proper authentication mechanisms. PLoS One, 19(12)https://doi.org/10.1371/journal.pone.0315201
2. Verizon, "Data Breach Investigations Report" [Online] Available: https://www.verizon.com/business/resources/reports/2025-dbir-data-breach-investigations-report.pdf [Accessed 05 03 2015]
3. R. Holthouse, S. Owens, and S. Bhunia, The 23andMe Data Breach: Analyzing Credential Stuffing Attacks, Security Vulnerabilities, and Mitigation Strategies, Dept. of Computer Science and Software Engineering, Miami Univ., Oxford, OH, USA.
4. Rundle, J., & Stupp, C. (2024). Data Breaches Highlight Lack of Basic Cyber Controls; AT&T, UnitedHealth Group join a growing list of companies with hacks traced to the absence of one particular security measure: multifactor authentication. WSJ Pro.Cyber Security
5. Irfan, R., Shah, M., & Sinan, G. M. (2025). Strengthening Cybersecurity Resilience: An Investigation of Customers' Adoption of Emerging Security Tools in Mobile Banking Apps. Computers, 14(4), 129. https://doi.org/10.3390/computers14040129
6. I. Gordin, A. Graur, S. Vlad, and C. I. Adomniței, Moving forward passwordless authentication: Challenges and implementations for the private cloud, Ștefan cel Mare Univ. Suceava, Romania.
7. Mapgaonkar, D. (2024). Digital authentication: 4 steps to move beyond passwords. WSJ Risk & Compliance Journal, https://deloitte.wsj.com/riskandcompliance/digital-authentication-4-steps-to-move-beyond-passwords-d526e404
8. Upadhyay, M. (2024). Mandatory MFA is coming to Google Cloud: Here's what you need to know. Google, https://cloud.google.com/blog/products/identity-security/mandatory-mfa-is-coming-to-google-cloud-heres-what-you-need-to-know
9. Apple. (2023). About Touch ID advanced security technology. Apple, https://support.apple.com/en-us/105095
10. Krebs, B. (2018). Google: Security keys neutralized employee phishing. KrebsOnSecurity, https://krebsonsecurity.com/2018/07/google-security-keys-neutralized-employee-phishing/
11. Lang, J. (2016). Security keys: Practical cryptographic second factors for the modern web. Google, https://www.researchgate.net/publication/306373685_Security_Keys_Practical_Cryptographic_Second_Factors_for_the_Modern_Web

12. Shaheen, N., Jaiswal, S., Chinta, U., Singh, N., Goel, O., & Chhapola, A. (2025). Data privacy in HR: Securing employee information in U.S enterprises using Oracle HCM Cloud. International Journal of Research Radicals in Multidisciplinary Fields, 3(2), https://www.researchgate.net/publication/390040166_Data_Privacy_in_HR_Securing_Employee_Information_in_US_Enterprises_using_Oracle_HCM_Cloud
13. Kovalan, K., Omar, S. Z., Tang, L., Bolong, J., Abdullah, R., Ghazali, A. H. A., & Pitchan, M. A. (2021). A systematic literature review of the types of authentication safety practices among internet users. International Journal of Advanced Computer Science and Applications, 12(7), 500–506. https://www.proquest.com/docview/2655113137
14. Anitha, S., & Jayarekha, P. (2021). MultiStage authentication to enhance security of virtual machines in cloud environment. International Journal of Computer Applications, 174(10), 1–5. https://www.proquest.com/docview/2655113601
15. Mostafa, R., El-Alfy, E., & Alsulaiman, M. (2023). Strengthening cloud security. International Journal of Computer Applications, 176(2), 20–25. https://www.proquest.com/docview/2904646301
16. Kang, E., Mowbray, M., & Watanabe, Y. (2023). Theory and application of zero trust security: A brief survey. International Journal of Computer Applications, 175(3), 10–15. https://www.proquest.com/docview/2876465838
17. Zwilling, M.; Klien, G.; Lesjak, D.;Wiechetek, Ł.; Cetin, F.; Basim, H.N. Cyber security awareness, knowledge and behavior: A comparative study. J. Comput. Inf. Syst. 2022, 62, 82–97. [CrossRef]
18. Gundu, T. (2024). Learn, Unlearn and Relearn: Adaptive Cybersecurity Culture Model. Academic Conferences International Limited
19. Yadron, D. (2016). Los Angeles hospital paid $17,000 in bitcoin to ransomware hackers. The Guardian, https://www.theguardian.com/technology/2016/feb/17/los-angeles-hospital-hacked-ransom-bitcoin-hollywood-presbyterian-medical-center
20. Jaikaran, C. (2025). Salt Typhoon hacks of telecommunications companies and federal response implications. Library of Congress. https://www.congress.gov/crs-product/IF12798

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Creativity, Motivation, and Social Impact: Exploring Social Innovation at Al-Zaytoonah University of Jordan

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Abstract.
This study investigates the interplay of university support, creativity, and intrinsic motivation in fostering social innovation among students at Al-Zaytoonah University of Jordan. Utilizing a quantitative research design, a cross-sectional survey was conducted with 309 undergraduate and postgraduate students. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to examine the relationships between university support, creativity, motivation, and social innovation engagement. Findings reveal that university support and creativity significantly enhance students' intrinsic motivation, which in turn strongly predicts their engagement in social innovation. Motivation fully mediates the relationship between both university support and creativity and social innovation outcomes. These results underscore the critical role of institutional resources and creative environments in cultivating motivated students who actively contribute to societal change. The study offers insights into developing university policies that foster innovative and sustainable learning ecosystems.

Keywords: Social Innovation · University Support · Creativeness · Motivation · Al-Zaytoonah University of Jordan

1 Introduction

The rapid changes that are taking place around the world due to social, political, and economic factors is creating new challenges in societies that radically need innovation, that goes beyond the conventional way of solving problems. In this case, social innovations have been the subject of considerable interest from both researchers and policy makers as they seek to have a lasting constructive impact on communities (Mulgan et al., 2007). There is no doubt that higher education and particularly universities sit at the epicenter in driving this type of innovation where intellectual and human resources are abundant. At universities, students are no longer empowered to just absorb academic content; they actively engage in solving issues with the concern of changing and improving the global community in which they reside through the exercise of leadership, creativity, and social action skill sets (Bazan et al., 2020). Focus on the theme of providing a stimulating university environment to actively engage students in addressing social challenges has also been emphasized in earlier works (Cazarez, 2022; Bacq & Janssen, 2011).

Therefore, the goal of the present research is to address the main aspects that will enhance the ability to create and initiate socially oriented projects among university students. The importance of this research derives from the need to better understand the psychological and institutional factors that underpin social innovation and detail how universities construct environments that are likely to motivate students to support, through their activities, the construction of an inclusive and sustainable world (Bryant-Scott, 2024).

Although there is increasing recognition of the role of universities in fostering social innovation, there is still a limited understanding of how systemic support impacts students' innovative actions through internal pathways like intrinsic motivation. It has been shown that institutional support has some level of importance; however, innovation outcomes may be comparatively greater when there is interaction with internal factors such as personal motivation and creativity (Chen, et al., 2024). Most prior studies have focused on the direct impact of university support on entrepreneurial or innovative activity, ignoring the mediation of psychological factors like passion, engagement, and self-determined motivation (Jiang et al., 2023). Furthermore, very few studies have examined the relationship between university support and individual traits such as creativity and morality, which are crucial for socially innovative outcomes resulting from institutional actions (Setiamurti & Kurniawati, 2022).

As noted in systematic reviews, there is a scarcity of models which encompass both institutional and individual-level elements to explain the innovation outcomes, which stifles the usability of existing models in educational settings (Li et al., 2025). Hence, this research seeks to fill the identified gap by examining the influence of university support and moral identity of students on social innovation with intrinsic motivation as a mediating factor. The purpose of the study is to formulate an integrated model that could help shape policies in higher education directed toward fostering innovative, comprehensively motivated learning ecosystems (Svennevik, 2022). The remaining of this article will discuss relevant literature in section 2, afterward section 3 will discuss the theoretical framework of this study. The methodology (in section 4), will present research design, scales, and data collection. The results of this study will be demonstrated in section 5 and discussed in section 6. Finally, Section 7 will present research implications, limitations, and conclusions.

2 Literature Review

University support is increasingly viewed as a primary factor in motivating students to participate in social innovation. Comprehensive support from a university, such as structured mentorships, incubators, funding, and curricula focused on real-world problem solving, creates an environment that enables students' internal and external motivations to flourish (Suresh, 2015). Institutional support does not only enhance students' confidence and willingness to pursue innovation, but it also promotes the engagement in projects with societal impact (Al-Jubari et al., 2019). As an example, Hoang et al. (2020) shows that access to university-sponsored resources for entrepreneurial and social activities motivated students to pursue and actualize social innovations. Also, (Bazan et al., 2020) showed that a perceived supportive culture within higher education institutions significantly increases students' intentions and participation in social entrepreneurial activities. This demonstrates that university support is not limited to academic teaching; it also comprises provision of critical mental and physical resource building support that enable students to actively and positively impact the world. Here, motivation is both an outcome of support and a driving factor for continued participation in sustaining innovative social projects. Therefore, to guarantee that motivation is sustained and innovation is relentless, universities have to make changes to their support systems in relation to the ever-shifting student requirements and societal demands (Ruan et al., 2023).

The importance of creativeness, a student's ability to generate original and valuable ideas, has emerged as a significant factor of student motivation in social innovation contexts. Students who possess high levels of creative self-efficacy appear to be more motivated to pursue novel social solutions and overcome complex societal challenges. As highlighted by (Cunha et al., 2022), creativity influences motivation to engage in social innovation, acting primarily through the mediating pathway of self-beliefs. Universities that foster interdisciplinary collaboration and teamwork promote higher levels of motivation and creativity, which then helps in addressing real-world challenges as described by (Aranha et al., 2017). The relationship (da Silva Santos, 2024) identified between creative learning environments and the sustained motivational capacity to launch social initiatives was underscored by (Cunha et al., 2022) when demonstrating that motivation to socialize peaks with ideation and perseverance in civic engagement when enhanced by creativity-boosting interventions. Motivational resilience grounded in creative capacity as described by (Jeong & Alhanaee, 2020) allows students to withstand repeated failures while remaining committed to social change. Together, this body of research underscores the importance of creativeness as a critical factor in nurturing sustainable motivation for social innovation within the university student population.

Motivation is increasingly considered the psychological factor that interlinks university support, creativity, and social innovations that stem from them. University supports such as mentorship access, funding, and innovation spaces have been noted to work best with students who are already motivated to implement ideas (Anjum et al., 2020). (Aggarwal & Manchanda, 2023) illustrated that it's the motivational states, and not resources alone, which dictate the persistence of students to pursue social innovation. (Cunha et al., 2022) evidenced that motivation fully mediates the relationship between cognitive inputs (support and creativity) and social innovation behavior, thus making it a crucial pivot in successful innovation models. (Yang, 2021) found that students possessing high motivation coupled with institutional support were more resilient and more committed to long-term social innovation. Furthermore, (Puente et al., 2021) demonstrated that motivational recognition, workshops, or feedback could enhance the conversion of university support and creativity into tangible social change. The right blend of motivational factors and institutional support enables students not just to start, but also to sustain solutions for social issues within their communities.

3 Theoretical Framework

Self-Determination Theory (SDT) is one of the most accepted theories of motivation in the social sciences and rests on the fulfillment of three basic psychological needs, which are autonomy, competence, and relatedness. The satisfaction of these needs increases the likelihood of intrinsically motivated behaviors, greater well-being, and increased engagement in activities. The importance of SDT theory continues to be supported in diverse fields. For example, (Palacio et al. 2024) showed that autonomy-supportive climates within higher education significantly improve student engagement and academic performance. In the same way, (Howard et al. 2024) showed a strong association of perceived competence with sustained health behaviors and self-directed learning correlates. In the workplace context, (Autin et al. 2022) pointed out that relatedness, in the form of being valued and connected to coworkers, enhances employee retention, job satisfaction, and innovative work behavior. All these examples reinforce the relevance of SDT to aid in the design and implementation of educational, health, and organizational strategies that seek to foster intrinsic motivation and sustainable favorable results.

Social Cognitive Theory (SCT) is one of the many theories developed by Albert Bandura. SCT particularly focuses on an individual's learning process. It aims to understand the learning and maintenance of behavior through a person's individual characteristics, specific actions, and their surroundings. SCT's relevance continues to be validated across several fields. For example, (Warner & Schwarzer, 2024) demonstrate that self-efficacy was a stronger predictor of healthy behavior and long-term commitment to holistic wellness. In the classroom, (Feraco et al., 2023) urged educators to harness academic self-efficacy to promote deeper engagement and self-regulated learning among students. In addition, modeling, social support, and feedback, which fall under environmental influence, have been shown to sculpt innovative behaviors in organizational contexts. These findings further sustain the theory's relevance toward developing strategies aimed at improvement, which not only focus on individuals but also emphasize the design of their environments to enhance growth and innovation (Bandura, 2023).

4 University Support

Comprehensive support systems established by universities cultivate students' motivation in academic, personal, and career-related areas. (Ryan et al., 2021) noted motivation is enhanced through institutional support systems that provide adequate academic guidance, mentorship, research opportunities, counseling, and career guidance. (Zhang et al., 2021; Rashed et al., 2025) provided more recent findings stating motivation and performance levels are greatly influenced by an individual's self-efficacy, autonomy, and goal commitment, all of which are maximized when adequate institutional support is provided. Moreover, educational systems that emphasize a student-centered approach and a holistic view of learning construct systems that address and fulfill students' intrinsic psychological needs, as outlined in Self-Determination Theory (SDT) (Ryan & Deci, 2024). This is important in regard to the encouragement of student participation in innovation, leadership, and active community engagement programs that strengthen self-identity, hence, intrinsic motivation (Alonso et al., 2023). The collective findings bolster the theory that comprehensive university support systems greatly enhance students' motivation, serving as a core driver of development, both academically and socially (Okada, 2023). Building on this discussion, we propose the following hypothesis:
H1: University support has a positive effect on students' motivation.

5 Students and Creativity

Using creativity effectively is critical when examining its effect on student motivation in both academic and non-academic spheres. When students exercise their creative skills through self-expression, ideation, and problem-solving, they are more likely to attain intrinsic rewards (Amabile & Mueller, 2024). The intrinsic rewards include autonomy and connection to their learning objectives. Research suggests that motivated, creative students are likely to engage in and pursue novel learning opportunities and learn strategies to tackle them due to the self-efficacy bolstered by the creativity (Zielińska et al., 2021). Self Determination Theory has explained that motivation is maintained when learners feel they have autonomy and competence the two of which are enhanced with strong motivational engagement (Ryan & Deci, 2024). Moreover, students who perceive themselves as creative learners tend to take responsibility for their learning, engage unconventional methods, and create meaningful goals. Collectively, these behaviors advance deeper motivation and academic persistence (Tirado et al., 2022).

Thus, creativity also motivates and sustains something that drives motivation, supporting the hypothesis that creativity has a positive impact on students' motivation while they undertake classroom tasks and activities. Continuing from this discussion, we propose the following hypothesis:
H2: Students' creativity has a positive effect on students' motivation.

6 Students and Motivation

The motivation that students have greatly impacts their level of interaction with social innovations. Highly motivated individuals are more likely to encounter challenges, work through complex problems, and pursue meaningful socially driven objectives. Students who are motivated intensely, especially by intrinsic factors, are more likely to take the initiative to address societal problems and devise innovative solutions to meet them (Ryan et al., 2021). Recent empirical studies show that active social innovation, particularly in campus environments, is much more likely to be undertaken by students with a sense of competence, autonomy, and purpose, and is offered within a context that values civic engagement and interdisciplinary collaboration (Puente et al., 2021). Motivation not only facilitates participation but also helps sustain students' commitment through the often prolonged and ambiguous social innovation process (Wang & Horta, 2024). According to the Self-Determination Theory, motivation resulting from fulfilling students' basic psychological needs is converted to action when it is sustained is frequently with socially positive outcomes (Ryan & Deci, 2024). Motivated students are capable of developing empathy, social awareness, and the requisite social leadership skills needed for effective social innovation (Monirs & Geberemeskel, 2024). Thus, it seems logical to assume that motivation has a positive influence on students' participation in social innovation activities both at the intention and behavioral levels. Given this discussion, we put forth the following hypothesis:
H3: Students' motivation positively influences their social innovation

7 The Mediating Role of Students' Motivation

The motivational processes influencing a university student's engagement in social innovation have received increasing attention, particularly as a mediation factor between university support and participation outcomes. Although institutional support in the form of mentorships, funding, innovation labs, and community engagement programs has the potential to enhance student outcomes on the merits of psychology, specifically motivation, the outcomes remain limited of their intrinsic value (Ryan et al., 2021). Providing optimal environments that cultivate autonomy, competence, and relatedness strengthens intrinsic motivation, which willingly pushes students toward socially innovative practices (Ryan & Deci, 2024). There is empirical evidence confirming that motivational factors are essential regardless of the nature of university support, and without these processes, the support will not translate to pro-active, creative, and socially responsible action (Solórzano et al., 2022). To illustrate, motivated students receive supportive scaffolds from the university, which empowers them to purposefully tackle societal challenges. Motivation thereby becomes the explanatory mediator that externalizes institutional support and internalizes the students' drive for social innovation (Wu et al., 2023). Such evidence supports the hypothesis that motivation mediates the impact of university support on social innovation outcomes. In light of the earlier conversation, we propose the following hypothesis:
H4: Students' motivation mediates the relationship between university support and social innovation

Furthermore, motivation is essential in conjunction with creativity for students to generate social innovation. Even though students who are creative can generate new ideas and alternative solutions for intricate social challenges, often, it is their motivation that decides whether such ideas are pursued and turned into impactful initiatives (Amabile & Mueller, 2024). In accordance with Self-Determination Theory, creativity can work in students' favor by enhancing their intrinsic motivation through meeting their need for competence and autonomy, thus increasing the probability of social meaningful engagement (Ryan & Deci, 2024). Recently, empirical research has affirmed that motivation acts as a mediator that channels students' creative potential towards social innovation outcomes (Wang, & Chang, 2022). A case in point is a student with an innovative idea for addressing a certain problem at the community level. In the absence of intrinsic motivation be it personal interest or a profound sense of purpose this idea is not likely to mature into real-world innovation (Villanueva-Paredes et al., 2024). Thus, motivation sustains the work and investment needed to implement purposeful social change. This is consistent with the hypothesis that students' motivation acts as a mediator in the relationship between creativity and social innovation, thereby rendering it instrumental in the process of converting creative thought into social action. From the earlier discussion, we propose the following hypothesis:

H5: Students' motivation mediates the relationship between creativity and social innovation.

Based on the previous arguments, this study developed the following conceptual framework to investigate the social innovation engagement (Fig. 1).

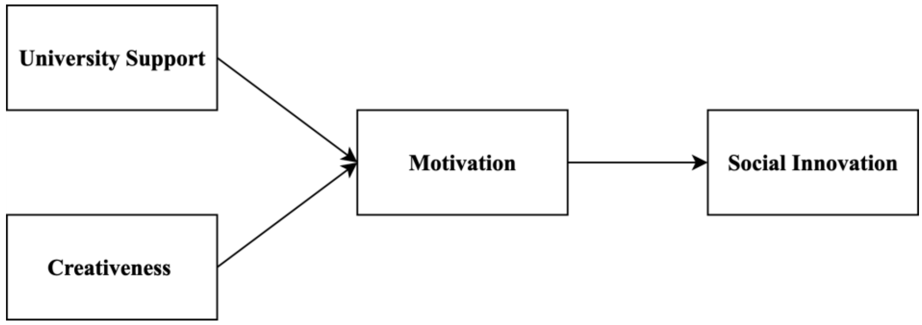

Fig. 1. Conceptual Framework of the Study (developed by authors)

8 Methodology

In this research, a quantitative research design will be employed, as it aims to identify the factors influencing social innovation engagement among students at Al-Zaytoonah University of Jordan. In order to examine the relationships between the variables of this study, a cross-sectional survey was carried out on the study variables: university support, students' creativity, motivation, and engagement in social innovation. Furthermore, the Partial Least Squares Structural Equation Modeling (PLS-SEM) is being used to determine the relationship between the study variables.

The target population of this study includes undergraduate and post-graduate students of Al-Zaytoonah University of Jordan enrolled in the academic year of 2024/2025. The convenience sampling method was applied in selecting the study participants, given that it is practical and convenient in the university context. The aim was to collect a sample of about 300 students as the sample needed to be at least 10 times the number of structural paths in the model (Hair et al., 2017). They had to be active student participants, and they were made to read the purpose of the study and the voluntary nature of the study.

The design of the survey tool was based on validated scales used in earlier literature to ensure reliability and validity of collected data. All the items are measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). University support was measured based on a 3-item scale adapted from Salamzadeg et al. (2022), which determines how much the university can offer, train, or give encouraging support to engage in social innovation. The creativity of students was assessed through a 3-item scale featuring the ability of students to develop novel and beneficial ideas was adapted from (Cunha et al., 2022). A 3-item scale adapted and modified from Wang et al. (2022) based intrinsic motivation to the process of innovation was used in evaluating the degree of motivation. In the end, a 3 item scale on measuring students active engagement in social innovation was borrowed and modified from (based on Cunha et al., 2022). All the scales were translated and back-translated into the Arabic language guarantee linguistic accuracy. A pilot test was done at the scale of 30 students to evaluate the clarity and reliability of the instrument and Cronbach alpha values were more than 0.7 in all constructs showing the reliability of the instrument satisfactory (Hair et al., 2019).

Variable	Category	Frequency (n)	Percentage (%)
Age Group	18–22 years	160	51.8%
	23–27 years	128	41.4%
	28–32 years	18	5.8%
	33 years and above	3	1.0%
Gender	Male	145	46.9%
	Female	164	53.1%
Level of Education	Bachelor's degree	232	75.1%
	Master's degree	77	24.9%

Field of Study	Business and Economic Sciences	146	47.3%
	Law and Legal Studies	42	13.6%
	Pharmaceutical Sciences	36	11.7%
	Engineering	48	15.5%
	Technology	20	6.5%
	Literature and Arts	17	5.5%
Previous Volunteer or Social Work Experience	Yes	211	68.3%
	No	98	31.7%
Total		309	100.0%

The size of the study sample was 309 people and their demographic profile is summarized in the following way. As per age demographics, most respondents (51.8 percent) were aged between 18 and 22 years with 41.4 percent falling between 23 and 27 years. A smaller percent of the participants fell between the age of 28-32 (5.8%), with only 1.0 percent being age 33 years and above. In terms of gender, the sample was relatively even; although there were more females: 53.1 percent of the sample reported female gender and 46.9 percent reported male gender. Regarding the educational level, the majority of the participants performed or graduated with a bachelor degree (75.1), and 24.9 were at the master degree level. Regarding the field of study, Business and Economic Sciences had almost half (47.3%) of the respondents, thus being the best-represented area. The sample was dominated by 15.5 percent engineering, 13.6 percent Law and Legal Studies, 11.7 percent Pharmaceutical Sciences, 6.5 percent Technology, and 5.5 percent Literature and Arts. Finally, a strong majority of the respondents (68.3%) stated absolutely having prior volunteer or social work experience, whereas 31.7% of participants said that they had no such experience. These demographic patterns are valuable clues in the context of study population structure.

9 Research Analysis and Results

The Measurement Model

To determine the structural relationships, it is important to make sure that the measurement model is sufficiently adequate in terms of reliability and validity of the constructs. According to Table 2, all outer loadings (OL) items on all constructs exceeded the recommended standard of 0.7, thus revealing that items sufficiently illustrate the corresponding constructs (Hair et al., 2017). The values of VIF, which varied between 1.468 and 2.950, were less than the standard of 5, thus signifying that there should be no notable multicollinearity among the items (Hair et al., 2019). All constructs Cronbach's alpha values were larger than 0.7 and values of composite reliability (rho_c) were larger than 0.7, which satisfies the minimum criterion of 0.7 (Fornell & Larcker, 1981). The convergent validity was sufficient; it was indicated by Average Variance Extracted (AVE) values of 0.687 to 0.789, which are more than sufficient for 0.5 related to the construct explaining variance of its items (Hair et al., 2017).

Table 2: Quality Criteria

Variable	Item	OL	VIF	a	rho_c	AVE
Creativeness	CR1	0.845	1.890	0.866	0.918	0.789
	CR2	0.901	2.558			
	CR3	0.918	2.950			
Motivation	MO1	0.869	2.104	0.840	0.904	0.758
	MO2	0.890	2.328			
	MO3	0.852	1.756			
Social Innovation	SI1	0.867	1.651	0.776	0.868	0.687
	SI2	0.876	1.889			
	SI3	0.736	1.468			
University Support	US2	0.880	2.056	0.838	0.902	0.755
	US3	0.868	1.937			

US1	0.859	1.914

The Fornell-Larcker criterion was used to determine the discriminant validity. The inter-construct correlations were lower than the square root of the AVE of the respective constructs, which shows that each of the constructs is unique (Fornell & Larcker, 1981). This yet confirms that the constructs of Creativeness, Motivation, Social Innovation, and University Support are empirically distinct and assists in proving the strength of the measurement model (Table 3).

Moreover, the model fit indices also provide a reflection of overall quality of structural model. The SRMR value is below the recommended and accepted measure (0.08) of 0.686, which shows they are adequate (Hu & Bentler, 1999). The Normed Fit Index (NFI) figure (0.912) reach the desirable norm (at least 0.9), indicating the model fit (Bentler & Bonett, 1980). Explanatory capability of structural model was assessed by use of R square values. Motivation as a mediating variable had R-square 0.545 (adjusted R-square 0.542), so 54.5% of the variation of Motivation is described by Creativeness and University Support and this is a moderately strong effect (Cohen, 1988). The R-square of Social Innovation was 0.652 (adjusted R-square 0.651), which implies that 65.2% of the determination of the Social Innovation engagement is inspired by Motivation, Creativeness, and University Support, which depicts a robust explanatory power (Hair et al., 2017).

Table 3: Fornell-Larcker criterion

Variables	CR	MO	SI	US
CR	0.889			
MO	0.615	0.870		
SI	0.614	0.807	0.829	
US	0.548	0.679	0.642	0.869

The Structural Model

The findings of the hypothesis testing through PLS-SEM reveal the significance of the study variables. Table 4 demonstrates the analysis results, including path coefficients, T-values, and P-values, which show all direct and indirect relationships are supported with a level of significance of 0.05. Precisely, the interrelationship between University Support and Motivation was found to be significantly positive (ß= 0.488, T = 10.596, P = 0.000). This finding means that the resources offered by universities, including financial resources, mentorship opportunities and facilities, greatly influence the desire of the students to take part in social innovation initiatives. This fact is supported by the recent findings related to the importance of the institutional support that provides the environment that encourages the innovation-related motivation by establishing the enabling environment (Alzoubi et al., 2022). Colleges that promote social innovation programs create a sense of purpose and motive in students, further increasing their determination.

Moreover, a significant positive coefficient of (ß= 0.347, T = 8.799, P = 0.000) was obtained which shows the relationship between Creativeness and Motivation. According to this finding, it can be stated that creative skills of students play an important role in their social innovation motivation. Creative people, who are capable of creating new ideas, are also more likely to be motivated to start improvements to the issues of society, because creativity shows a proactive approach to solving a problem (Shalley et al., 2023). This finding again reminds the need to foster creativity to increase motivational levels in institutions of learning. The coefficient of path from Motivation to Social Innovation engagement was very strong with the value of (ß= 0.807, T = 26.028, P = 0.000). This close relationship brings attention to the fact that motivation acts as a key factor that influences students to undertake social innovation projects actively. Well-motivated students tend to become involved in the initiatives that solve social tasks, either by choosing a community project or a sustainable innovation, supporting the recent claim that the motivation type intrinsic is a vital antecedent of innovative actions (Chen et al., 2024). A high coefficient highlights the fact that motivation is a drive to take part in social innovation.

Table 4: Hypothesis Testing

Hypothesis	Path	Coefficient	T value	P value
H1	US -> MO	0.488	10.596	0.000
H2	CR -> MO	0.347	8.799	0.000
H3	MO -> SI	0.807	26.028	0.000
H4	US -> MO -> SI	0.394	10.234	0.000

H5	CR -> MO -> SI	0.280	7.518	0.000

The indirect effect of University Support on Social Innovation through Motivation was significant with the coefficient estimate of (ß= 0.394, T = 10.234, P = 0.000). The finding provides support for the confirmation of the mediation role of Motivation between the variables of University Support and Social Innovation engagement. The enthusiasm of the students during this process is boosted by the support they receive from the university, which further leads to the motivation of these young people to engage in social innovation. This mediation effect is congruent with the current studies that showed the significance of motivation as an agent by which the institutional resources are converted into innovative results (Hair et al., 2022). The indirect effect of Creativeness is proved to be significant, with a value of (ß= 0.280, T = 7.518, P = 0.000) that is the indirect effect via Motivation. The given finding possesses the following implication: Motivation mediates the connection between the level of creativeness and that of the engagement of students in social innovation. A higher level of interest to engage in social innovation results in the higher level of student engagement in this kind of activity because creative students are encouraged to become a part of the innovation. This finding is consistent with the modern research with the connection between creativity and innovation based on motivation processes (Shalley et al., 2023).

To conclude, the findings support the idea that both the University Support and Creativeness have a significant influence on Motivation, which has a strong impact in predicting engagement on Social Innovation. The measurement and structural model are illustrated in Fig. 2.

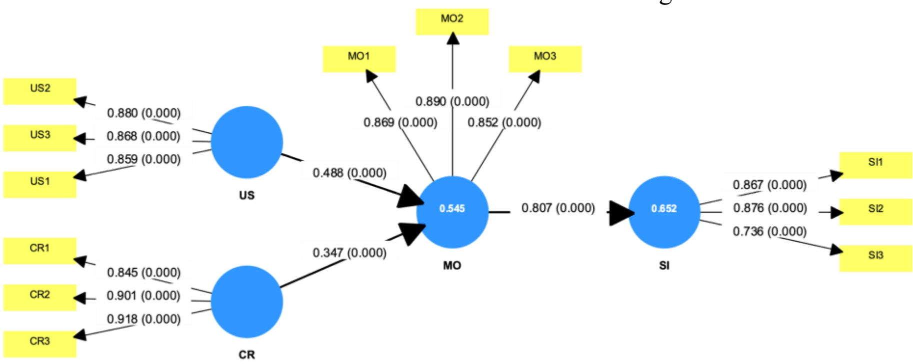

Fig. 2. Hypothesis Testing Results (source: SmartPLS 4.1)

10 Discussion

The current research strongly extends our knowledge about how university support and creativity of students can enhance participation in social innovation, and motivation is an important intervening variable. University support which is characterized as the mentioning, financing, and incubators, as well as the curricula allied to viable real-life problem-solving, in turn, appears to be an effective antecedent of student motivation. Its analysis illustrates that the overall effect is significant and positive, which means that resourceful institutional environments and conducive academic culture play a crucial role in instilling confidence and motivation among the students in undertaking socially innovative projects. This finding aligns with SDT, according to which environments in which the psychological needs of autonomy, competence, and relatedness are met have a greater likelihood of fostering intrinsic motivation, as well as prolonged engagement on the part of students (Ryan & Deci, 2020). The present study builds on this frame-work by showing that the support provided in universities does not only increase motivation but with this increase in motivation, also provides greater participation of students in social innovation to an actual effect. Such results are supported by prior evidence, in which the researchers also emphasized the role of institutional scaffolding in the teacher (Al-Jubari et al., 2019; Suresh, 2015).

In the same manner, the research establishes that student creativity has a major positive in-fluence on motivation. Creative self-efficacy supports students to enable them to develop innovative responses to difficult problems in society and this boosts their intrinsic motivation to create and sustain social innovation projects (Cunha et al., 2022). This underling connection is further explained by SCT which pays attention to the interactions of the self-efficacy, support of the environment and motivated behavior (Bandura, 1986). Universities that facilitate with interdisciplinary cooperation and creative learning circumstances do not only help to advance the creative capabilities in students but also improve their motivational resilience earlier than hardship (Jeong & Alhanaee, 2020). In this way, it is critical to instill creativity into the academic environment to provide students with the required attitude and skills to solve or attempt to resolve acute societal problems.

The most interesting conclusion of the paper is a very high direct impact of motiva-tion on social innovation engagement. This strong relationship emphasizes moti-vation as the pivot between institutional and self-driven elements and tangible social products. When students are highly motivated, they are more likely to start, engage and continue the lifespan of a social innovation project, which is a show of a sense of purpose, competence and civic belonging (Puente et al., 2021; Ryan et al., 2021). Also, mediation analyses indicate that motivation mediate completely the effects of university support and creativity on social innovation. These findings support the in-ference that although access to resources and creating potential are requisites, they are not sufficient alone to promote social innovation; rather it is motivation internalized that would convert potential into action (Amabile & Mueller, 2024; Wang & Chang, 2022).

The structural model that was used in this research obtained 65.2 percent of the social innovation engagement variance; therefore, it was highly explanatory. This sug moves that interaction of the factors of university support, creativity, and motivation creates an encompassing framework of explanations on the contribution of the students to social innovation. Nonetheless, the relevance of these results can be constrained by the institutional and cultural variation which makes it necessary to conduct additional studies in various settings. The conclusions provided indicate the scope of future research, which may include other mediating and moderating variables and focus on longitudinal research that can provide a deeper insight into how social innovation in higher education is possible with dynamic processes happening at the levels of individual institutions.

11 Implications

This study has major implications both in theory and practice of higher education. Theoretically, the research benefits the introduction of the Self-Determination Theory and the Social Cognitive Theory by explaining the mediating role of intrinsic motivation in the social innovation of the relationship between institutional and individ-ual factors. Blending these theories gives the research a comprehensive model as it reconciles the psychological and the environmental determinants, which had not been achieved in previous bodies of literature where influences had been too direct (Li at al., 2025). As it applies to future research, the model can be used in testing further mediators including moral identity or prosocial motivation to improve our understanding of social innovation processes further.

The researchers practically demonstrate the relevance of the role of a university as a source of social innovation. Institutions, such as Al-Zaytoonah University, can complement their support systems by investing in mentorship activities, innovation labs and inter-disciplinary curricula activities, which can encourage creativity and motivation. As an example, students can be empowered to transform their creativity into solutions by creating rooms where collaborative ideation can take place and funds on the types of social projects that students want to implement. Educational policymakers need to focus more on SDT-consistent student-centered policies to make sure that the existing support mechanisms help cultivate autonomy, competence, and related. These efforts will be able to enhance the dedication of students towards social issues to achieve the aim of sustainable development. Additionally, the paper also emphasizes the importance of universities implementing creativity-enhancing interventions (e.g. workshops or learning challenges) in order to support the innovative abilities of students (Villanueva-Paredes et al., 2024). The faculty development programs must also be able to educate the educator on how to instill a creative and inspiring environment because this is what is important to keep student involved in social innovation.

12 Conclusions

This study underscores the vital roles of university support, creativity, and intrinsic motivation in promoting social innovation among students at Al-Zaytoonah University of Jordan. By integrating SDT and SCT theories, the research demonstrates that institutional resources—such as mentorship, funding, and innovation-focused curricula—significantly enhance students' intrinsic motivation. Additionally, creativity fosters a proactive approach to problem-solving and strengthens the link between motivation and social innovation engagement. The findings indicate that motivation mediates the relationship between university support and creativity in social innovation engagement. This integrated model provides a framework for how universities can effectively empower students to address societal challenges. While the research reflects broader calls for higher education institutions to serve as catalysts for sustainable development, its limitations—such as reliance on convenience sampling—suggest the need for further studies to validate these findings in diverse contexts. Future research could also explore additional mediators and employ longitudinal designs to better understand social innovation dynamics. This study contributes to advancing our understanding of how higher education can cultivate socially innovative leaders, thereby enhancing both academic discourse and practical approaches to sustainable development.

In spite of its contributions, this study is faced with a number of limitations. First, convenience sampling might reduce the extent of generalizability of results because the sample might not reflect actual diversity of student in Al-Zaytoonah University or other institutions. The research in the future is to use random or stratified sample to make it more representative. Second, the cross-sectional notion does not allow to interpret the causality or to trace changes over time. The use of longitudinal studies may allow gaining better understanding of the role of university support and creativity in relation to motivation and social innovation in long-term. Third, the paper only considered using intrinsic motivation as a mediator and may have missed other psychological variables, extrinsic motivation or moral identity being the ones also contributing to it. Lastly, the study was performed in terms of a particular cultural and institutional environment, which can restrict the possibility of its generalization to the other contexts. This can be eliminated by carrying out comparative research among various universities and nations.

13 References

1. Aggarwal, A., & Manchanda, P. (2023). A moderated mediation model linking prosocial motivation and social entrepreneurial intention. *International Journal of Entrepreneurial Venturing*, *15*(5), 445-467.
2. Al-Jubari, I., Hassan, A., & Liñán, F. (2019). Entrepreneurial intention among university students in Malaysia: integrating self-determination theory and the theory of planned behavior. *International entrepreneurship and management journal*, *15*(4), 1323-1342.
3. Alonso, R. K., Velez, A., & Martinez-Monteagudo, M. C. (2023). Interventions for the development of intrinsic motivation in university online education: systematic review—enhancing the 4th sustainable development goal. *Sustainability*, *15*(13), 9862.
4. Amabile, T. M. (1993). Motivational synergy: Toward new conceptualizations of intrinsic and extrinsic motivation in the workplace. *Human Resource Management Review, 3*(3), 185–201.
5. Amabile, T. M., & Mueller, J. S. (2024). Studying creativity, its processes, and its antecedents: An exploration of the componential theory of creativity. In *Handbook of organizational creativity* (pp. 33-64). Psychology Press.
6. Anjum, T., Farrukh, M., Heidler, P., & Díaz Tautiva, J. A. (2020). Entrepreneurial intention: Creativity, entrepreneurship, and university support. Journal of Open Innovation: Technology, Market, and Complexity, 7(1), 11.
7. Aranha, E. A., Garcia, N. A. P., & Dos Santos, P. H. (2017). Fostering entrepreneurship, creativity and innovation in cities. *International Business Research*, *10*(4), 92-103.
8. Autin, K. L., Herdt, M. E., Garcia, R. G., & Ezema, G. N. (2022). Basic psychological need satisfaction, autonomous motivation, and meaningful work: A self-determination theory perspective. *Journal of Career Assessment*, *30*(1), 78-93.
9. Bacq, S., & Janssen, F. (2011). The multiple faces of social entrepreneurship: A review of definitional issues based on geographical and thematic criteria. Entrepreneurship & Regional Development, 23(5-6), 373-403.
10. Bandura, A. (2023). Cultivate self-efficacy for personal and organizational effectiveness. *Principles of Organizational Behavior: The Handbook of Evidence-Based Management 3rd Edition*, 113-135.
11. Bazan, C., Gaultois, H., Shaikh, A., Gillespie, K., Frederick, S., Amjad, A., ... & Belal, N. (2020). A systematic literature review of the influence of the university's environment and support system on the precursors of social entrepreneurial intention of students. *Journal of Innovation and Entrepreneurship*, *9*(1), 4.
12. Bazan, C., Ruiz, M., & Martínez, E. (2020). Universities as drivers of social innovation: The role of social entrepreneurship education. Journal of Social Entrepreneurship, 11(3), 253-270. https://doi.org/10.1080/19420676.2019.1705732

13. Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588–606.
14. Bryant-Scott, K. (2024). How Social Innovation is Being Conceptualized by Administrators and Students at a Large Public University (Doctoral dissertation).
15. Cazarez, D. C. M. (2022). Exploring influences on the choice of fields of study in higher education: Evidence from Mexico. International Journal of Educational Development, 93, 102643.Westley, F., & Antadze, N. (2022). Making a difference: Strategies for social innovation. Stanford Social Innovation Review.
16. Chen, H., Chen, X., & Pan, Y. (2024). Exploring the Mediating Role of Intrinsic Motivation Between Innovation Support and Innovative Behavior: An Empirical Study Based on a Design Thinking Course. International Journal of Learning, Teaching and Educational Research, 23(6), 32-55.
17. Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
18. Cunha, J., Ferreira, C., Araújo, M., & Nunes, M. L. (2022). The mediating role of entrepreneurial intention between creativity and social innovation tendency. *Social Enterprise Journal*, *18*(2), 383-405.
19. Cunha, J., Ferreira, C., Araújo, M., & Nunes, M. L. (2022). The mediating role of entrepreneurial intention between creativity and social innovation tendency. *Social Enterprise Journal*, *18*(2), 383-405.
20. Cunha, J., Ferreira, C., Araújo, M., & Nunes, M. L. (2022). The mediating role of entrepreneurial intention between creativity and social innovation tendency. *Social Enterprise Journal*, *18*(2), 383-405.
21. da Silva Santos, B. M. D. (2024). The Influence of a Creative School Environment on Students' Motivation (Master's thesis, Universidade NOVA de Lisboa (Portugal)).
22. Feraco, T., Resnati, D., Fregonese, D., Spoto, A., & Meneghetti, C. (2023). An integrated model of school students' academic achievement and life satisfaction. Linking soft skills, extracurricular activities, self-regulated learning, motivation, and emotions. *European Journal of Psychology of Education*, *38*(1), 109-130.
23. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.
24. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.
25. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.
26. Hoang, G., Le, T. T. T., Tran, A. K. T., & Du, T. (2020). Entrepreneurship education and entrepreneurial intentions of university students in Vietnam: the mediating roles of self-efficacy and learning orientation. Education+ Training, 63(1), 115-133.
27. Howard, J. L., Slemp, G. R., & Wang, X. (2024). Need support and need thwarting: A meta-analysis of autonomy, competence, and relatedness supportive and thwarting behaviors in student populations. *Personality and Social Psychology Bulletin*, 01461672231225364.
28. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.
29. Jeong, S. S., & Alhanaee, D. W. T. A. (2020). Prosocial motivation as a driver of social innovation in the UAE. *Social Science Quarterly*, *101*(7), 2450-2464.
30. Jiang, S., Wang, J., Zhang, R., & Liu, O. (2023). Innovation climate for individual motivation and innovation performance: Is innovative behavior a missing link?. Journal of Innovation & Knowledge, 8(4), 100440.
31. Li, Q., Zhang, Z., & Xiao, S. (2025). A psychological perspective on entrepreneurship and innovation in universities: The role of educators and tutors in enhancing motivation, interest, and academic success. *Acta Psychologica*, *255*, 104870.
32. MONIR, M. M. S., & GEBEREMESKEL, A. N. (2024). FACTORS INFLUENCING INDIAN UNIVERSITY STUDENTS'ENGAGEMENT IN SOCIAL ENTREPRENEURSHIP. *Ecoforum Journal*, *13*(3).
33. Mulgan, G., Tucker, S., Ali, R., & Sanders, B. (2007). Social innovation: what it is, why it matters and how it can be accelerated.
34. Okada, R. (2023). Effects of perceived autonomy support on academic achievement and motivation among higher education students: A meta-analysis. *Japanese Psychological Research*, *65*(3), 230-242.

35. Palacio, E. S., Prieto, J. L., Duarte, M. M., & Ruiz, J. F. (2024). Impact of an intervention program based on self-determination theory on basic psychological needs, intention to be physically active and life satisfaction of high school students: A longitudinal study. *Retos: nuevas tendencias en educación física, deporte y recreación*, (56), 228-237.
36. Puente, C., Fabra, M. E., Mason, C., Puente-Rueda, C., Saenz-Nuno, M. A., & Vinuales, R. (2021). Role of the universities as drivers of social innovation. *Sustainability*, *13*(24), 13727.
37. Rashed, R. Q. G., Abubakar, A. A., Madani, O., & Al-Mamary, Y. H. (2025). Enhancing Student Engagement and Motivation for Sustainable Education: The Role of Internship and Institutional Support. *Sustainability*, *17*(12), 5291.
38. Ruan, P., Dong, H., & Liu, X. (2023). Innovation and Entrepreneurship Education for All: Why is It Possible and How is It Feasible?. *Journal of East China Normal University (Educational Sciences)*, *41*(9), 100.
39. Ryan, R. M., & Deci, E. L. (2024). Self-determination theory. In *Encyclopedia of quality of life and well-being research* (pp. 6229-6235). Cham: Springer International Publishing.
40. Ryan, R. M., Deci, E. L., Vansteenkiste, M., & Soenens, B. (2021). Building a science of motivated persons: Self-determination theory's empirical approach to human experience and the regulation of behavior. *Motivation science*, *7*(2), 97.
41. Salamzadeh, Y., Sangosanya, T.A., Salamzadeh, A. and Braga, V. (2022), "Entrepreneurial universities and social capital: The moderating role of entrepreneurial intention in the Malaysian context", The International Journal of Management Education, Vol. 20 No. 1, 100609, doi: 10.1016/j.ijme. 2022.100609
42. Setiamurti, A., & Kurniawati, F. (2024). Fostering creativity in higher education institution: a systematic review (2018–2022). Open Education Studies, 6(1), 20220221.
43. Solórzano-García, M., Navio-Marco, J., & Laguia, A. (2022). The influence of intrinsic motivation and contextual factors on MOOC students' social entrepreneurial intentions. *Interactive Learning Environments*, *30*(9), 1768-1780.
44. Suresh, S. (2015). Research Universities, Innovation, and Growth. *Research-Technology Management*, *58*(6), 19-23.
45. Svennevik, E. (2022). Social innovation-as-practice: establishing a social innovation program at a university. Management & Marketing, 17(1).
46. Tirado-Morueta, R., Ceada-Garrido, Y., Barragán, A. J., Enrique, J. M., & Andujar, J. M. (2022). Factors explaining students' engagement and self-reported outcomes in a project-based learning case. *The Journal of educaTional research*, *115*(6), 333-348.
47. Villanueva-Paredes, G. X., Juarez-Alvarez, C. R., Cuya-Zevallos, C., Mamani-Machaca, E. S., & Esquicha-Tejada, J. D. (2024). Enhancing social innovation through design thinking, challenge-based learning, and collaboration in university students. *Sustainability*, *16*(23), 10471.
48. Wang, H., Jiang, X., Wu, W., & Tang, Y. (2022). The effect of social innovation education on sustainability learning outcomes: The roles of intrinsic learning motivation and prosocial motivation. *International Journal of Sustainability in Higher Education*.
49. Wang, R. N., & Chang, Y. C. (2022). Effect of Intrinsic Motivation on Junior High School Students' Creativity: Mediating Role of Cognitive Flexibility. *International Journal of Educational Methodology*, *8*(2), 297-312.
50. Wang, Y., & Horta, H. (2024). Teaching and learning social innovation and entrepreneurship in higher education: a scoping review. *Journal of Social Entrepreneurship*, 1-30.
51. Warner, L. M., & Schwarzer, R. (2024). Self-efficacy and health. In *Handbook of concepts in health, health behavior and environmental health* (pp. 1-26). Singapore: Springer Nature Singapore.
52. Wu, Y. J., Goh, M., & Mai, Y. (2023). Social innovation and higher education: evolution and future promise. *Humanities and Social Sciences Communications*, *10*(1), 1-14.
53. Yang, J. (2021). The Effect of Perceived Social Support on Entrepreneurial Motivation of Korean, Chinese and Japanese University Students: Focused on mediator of Entrepreneurial Self-Efficacy. *대한경영학회지*, *34*(11), 1933-1954.
54. Zhang, J., Gu, X., Zhang, X., Lee, J., Chang, M., & Zhang, T. (2021). Longitudinal effects of motivation and physical activity on depressive symptoms among college students. *International Journal of Environmental Research and Public Health*, *18*(10), 5121.
55. Zielińska, A., Lebuda, I., Jankowska, D. M., & Karwowski, M. (2021). Self-regulation in creative learning: Agentic perspective. *Creativity. Theories–Research-Applications*, *8*(1), 52-71

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The Impact of Intellectual Capital on Sustainability Analytics Adoption in Manufacturing Companies

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Abstract
This study examines the impact of intellectual capital on the adoption of sustainability analytics in manufacturing companies. As organizations increasingly face pressure to enhance environmental, social, and governance (ESG) performance, sustainability analytics has emerged as a strategic tool to guide decision-making and improve operational efficiency. The research adopts a quantitative methodology, collecting data from managers and specialists in manufacturing firms through structured questionnaires. Intellectual capital is analyzed through its three main components: human capital, structural capital, and relational capital, assessing how each contributes to the effective integration of sustainability analytics. The findings reveal a significant and positive relationship between intellectual capital and the adoption of sustainability analytics, with human capital exerting the most substantial influence. The study concludes that leveraging intellectual capital is essential for driving data-informed sustainability strategies in the manufacturing sector. Recommendations are provided for enhancing knowledge-sharing systems and investing in employee capabilities to foster sustainable innovation.

Keywords: Intellectual Capital, Sustainability Analytics, Manufacturing Companies, Human Capital, Structural Capital, Relational Capital, ESG, Innovation

1 Introduction

With the onset of digitalization and growing environmental awareness, manufacturing companies are coming under mounting pressure to embrace sustainability in business. This has triggered the evolution of sustainability analytics, a data-driven approach that allows organizations to quantify, track, and improve their environmental, social, and economic performance (Ojokoh et al., 2020). Sustainability analytics is one of the most visible agenda tools used by organizations in addressing global sustainability agendas, regulative pressures, and stakeholder expectations (Vale et al., 2022). However, its effective implementation, to a very large extent, hinges on an organization's intellectual capital (IC)—a highly valued intangible asset made up of human know-how, systemized structural knowledge, and interdependent networks. Despite intellectual capital being firmly anchored as a generator of innovation and competitiveness, there is less studied application in harnessing its function to enable sustainability analytics among manufacturing firms (Alvino & Di Vaio, 2019).

Intellectual capital is the enabler for empowering the potential of an organization in leveraging data-driven sustainability practices. Human capital, being employees' competences, technical skills, and solution-finding capabilities, play an important role towards enabling the optimal utilization of sustainability analytics tools (Yusoff et al., 2019). Workers' expertise in data interpretation, artificial intelligence, and big data analytics gives companies the ability to extract meaningful information to be used in making smart decisions regarding sustainability initiatives (Delmas et al., 2013). Similarly, structural capital, such as databases, IT infrastructure, and internal processes, provides the foundation on which sustainability analytics can be embedded in business decision-making systems (Malik et al., 2020). Without highly advanced data systems and analytical capabilities within an organization, it will not be able to exploit the full potential of sustainability analytics (Delmas et al., 2013). Further, relational capital, i.e., a company's stakeholder, customer, regulator, and industry peer relationship, promotes collaboration and helps in adherence to sustainability practices (Alvino & Di Vaio, 2019). Through the enablement of relational capital, firms can align sustainability practices with industry practices and expectations (Jabbour & Jabbour, 2016).

Sustainability concerns are industry-specific. Companies must reconcile economic development and environmental sustainability in such a way that their activities not only please regulators but also generate profits. Transparency through sustainability reporting is being demanded by governments, investors, and consumers alike, which is fueling the need for robust data analytics capabilities (Vale et al., 2022). Strategic leveraging of intellectual capital holds the promise of enhancing the sustainability performance of organizations and attaining sustainable long-term competitive success (Alvino & Di Vaio, 2019). The majority of the organizations, nonetheless, are faced with the challenge of low stakeholder sustainability-oriented intellectual capital awareness, thereby inhibiting its diffusion and utilization (Alvino & Di Vaio, 2019). Such challenges raise significant questions as to how firms can leverage their knowledge assets to render sustainability analytics effective and enhance their sustainability performance.

This study aims to fill this gap in knowledge by examining the role of intellectual capital in the adoption of sustainability analytics by manufacturing firms. More precisely, this research aims to identify how human, structural, and relational capital facilitate effective use of data-based sustainability metrics (Yusliza et al., 2020). Through examining synergetic interdependencies between these IC dimensions, this research will make valuable contributions to business managers, policymakers, and academics (Ojokoh et al., 2020). Through understanding how IC can be connected with sustainability analytics, companies can develop means of enhancing their environmental performance, resource productivity, and sustainability reporting (Jabbour & Jabbour, 2016).

2 Literature Review

Human Capital and Sustainability Analytics Adoption

Human capital is the most important driver of effective implementation of sustainability analytics by manufacturing firms. Different studies highlight the importance of the awareness, innovation, and sensitivity of employees towards the environment in bridging gaps between sustainability objectives and quantifiable data-driven action. For instance, Malik et al. (2020) showed how green human resource management with the development of human capital makes the adoption of sustainability practices feasible. Those employees who have analytical skills, sustainability knowledge, and problem-solving skills are more likely to manage high-end analysis tools and draw insightful conclusions out of complex data (Yusoff et al., 2019).

Yusliza et al. (2020) confirmed this relationship by building a structural model that established the direct relationship of green intellectual capitals, one of which is human capital, and sustainable firm performance. Similarly, Iqbal et al. (2023) also outlined that human capital triggers green product innovation and process innovation, both of which are significantly dependent on the ability to read and implement sustainability programs.

Another notable contribution is provided by Akmalia and Muharam (2024), who reasserted that although structural capital contributed the most to sustainable growth among Indonesian companies, human capital remained significant in underpinning knowledge-based sustainability strategies. Grant (1996) and Nonaka and Takeuchi (1995) are some of the theoretical authors presenting evidence for these findings, claiming that knowledge in individuals is the foundation of innovation and strategic change. Tonial et al. (2019) supplemented this by demonstrating that worker knowledge promotes data collection, reporting precision, and sustainability innovation when connected to organizational strategy.

Structural Capital and Sustainability Analytics Adoption

Structural capital in the form of internal processes, databases, IT infrastructure, and innovation habits is also critical in leveraging sustainability analytics within business functions. It facilitates the technical infrastructure needed to ensure production companies effectively receive, process, and examine the data for sustainability. Bontis et al. (2000) pointed out that information technologies and structurally ordered knowledge systems are facilitators to capitalize on data-driven strategies into sustainability strategy initiatives. Companies possessing greater structural capital are best equipped to exploit real-time sustainability dashboards, monitoring of resources by IoT, and analytics-based prediction tools.

Malik et al. (2020) set that structural elements such as green policies and eco-centric databases are key to guaranteeing the success of sustainability performance if they are incorporated into the business's digital transformation strategy. Ojokoh et al. (2020) also clarified that after manufacturing firms adopt big data and artificial intelligence platforms with robust structural designs, sustainability analytics implementation is more manageable and affordable.

Delmas et al. (2013) argued that strong structural capital enables firms to comply with environmental regulation through internal reporting and monitoring. In the same vein, Tonial et al. (2019) illustrated with their case study of a Brazilian company that digital infrastructure and knowledge repositories enable the institutionalization of sustainability practices.

Rashid et al. (2024) placed great importance on green supply chain management and analytics-driven decision-making supported by convergent IT infrastructure. Therefore, the success in implementing sustainability analytics entirely depends upon the structural capital maturity of a firm. In the lack of robust digital and procedural setup, sustainability programs tend to be under-leveraged and unstructured.

Relational Capital and Sustainability Analytics Adoption

Relational capital or a firm's external relations with external players like customers, suppliers, government agencies, and industry networks is central to the adoption of sustainability analytics. The relations create an enabling environment of mutual knowledge, co-innovation, and collective practices of sustainability. Past research supports the argument that relational capital is an enabler for the reception of sustainability norms and external knowledge into the firm and, in the end, the firm's ability to apply and digest data-driven sustainability tools improves.

For example, Zahoor and Gerged (2021) ensured to have a constructive effect of great relational capital upon the environmental performance of SMEs in emerging markets by incorporating the environmental knowledge along with communicating the stakeholders. Similarly, Yu et al. (2020) ensured that stakeholder engagement has immediate effects on strategic alignment and execution of sustainability analytics, especially when firms are considering responding to mutual sustainability expectations. Such interactions provide the potential for trust development and collaborative learning environments essential to advanced analytics tool adoption.

In addition, empirical evidence by Van Zyl (2023) determined that relational capital enables corporate reporting and disclosure, enabling real-time synchronizing of sustainability data with strategic goals. Relatively mature relational networks within corporates get more visibility of sustainability initiatives, regulatory requirements, and environmental agendas at an industry level. This enables customization and deployment of analytics-driven solutions at high velocity. Likewise, Jain and Jamal (2022) also centered on the aspect that green data-sharing culture results from long-term supply chain collaboration through traceability and sustainability adoption of analytics in supply chains.

Sustainability Analytics Adoption and Innovation Performance

Recent research has given clear indications of the association between the adoption of sustainability analytics and manufacturing firm innovation performance. Because sustainability analytics is based on big data, artificial intelligence, and digital technology, it allows innovative products, achieves process efficiency, and helps create green products. Rashid et al. (2024) contended that business companies leveraging analytics are able to better predict environmental trends and optimize operations, sparking ongoing innovation in supply chain management and product innovation. In a similar perspective, Ojokoh et al. (2020) indicated that the real-time monitoring of data by leveraging AI technologies enhances the adaptive potential of companies to environmental pressures, sparking innovative manufacturing solutions.

A number of empirical studies have confirmed that analytics enables the attainment of eco-innovation and differentiation of products. Awadallah and Elnady (2020) confirmed that sustainability analytics enables decision-making based on evidence, which leads to the optimal R&D activity and green product innovation design. Malik et al. (2020) also confirmed that a mix of digital analytics and human and structural capital maintains innovation. This was corroborated by Yusliza et al. (2020), whose study indicated that firms with data platforms to aid sustainability will likely embrace green processes and technology.

Sustainability Analytics Adoption and Competitive Advantage

Use of sustainability analytics (SA) in business strategy has emerged as a key driver to attain competitive advantage in manufacturing. Because sustainability has emerged as a necessity to enable building stakeholder trust and regulatory compliance, organizations leveraging advanced analytics tools derive strategic advantage through value-optimizing operations, increased transparency, and enabling green innovation. There is existing literature that justified the positive correlation of SA implementation with competitiveness positioning, where emphasis has been provided to how evidence-based best practices enable firms to react to environmental pressures and remain sensitive to global sustainability objectives (Rashid et al., 2024).

For instance, Rashid et al. (2024) remark that BDA and AI highly rely on competitive advantage via real-time decision-making and supporting green product innovation among producers. Similarly, Ojokoh et al. (2020) believe that AI technologies are greener with greater reliability in sustainability reports and hence discriminate against firms that compete in highly environmentally oriented markets.

Awadallah and Elnady (2020) also contribute that investment in analytics capability and digital infrastructure enhances the value of environmental monitoring and compliance and provides manufacturers with reputational advantage and access to environmentally sensitive markets. Vale et al. (2022) also attest that intellectual capital utilization with sustainability analytics promotes operational understanding and increases the adaptive capability of a firm operating in ever-changing regulatory environments.

Sustainability Analytics Adoption and Competitive Advantage

Sustainability analytics (SA) is a competitive corporate strategy for companies that want to be leaders in a changing, green economy business environment. By incorporating advanced data analysis in sustainability programs, companies are able to monitor environmental, social, and economic performance in real time, identify operating inefficiencies, and innovate on the edge. In business, where regulatory adherence, resource optimization, and environment upkeep are overriding concerns, the adoption of sustainability analytics is no longer a strategic choice but a competitive imperative.

There is literature that supports the sustenance of sustainability analytics adoption in enhancing competitive strength. Rashid et al. (2024) confirmed that the implementation of big data analytics by manufacturing firms and the utilization of artificial intelligence in their green supply chain attained high market competitiveness via operations effectiveness, cost reduction, and enhanced sustainability performance. Similarly, Ojokoh et al. (2020) observed that sustainability efforts that are data-based lead to greater stakeholder trust and better environmental disclosure that impact positively on customer loyalty and brand differentiation.

Awadallah and Elnady (2020) also argued further that sustainability analytics enables organizations to respond better to external regulatory pressure while enhancing in-house processes such as resource deployment and strategic management. This two-pronged effect—externally legitimacy, internally efficiency—makes SA an important asset to be used in long-term competitiveness. Moreover, Malik et al. (2020) instituted that firms that utilize green intellectual capital and data analytics can better align innovation strategies and environmental objectives, thus yielding long-term value and sustainability for competitive markets.

3 Methodology

Data Collection Method and Questionnaire Distribution

For the purpose of collecting data and information, two sources were adopted, namely:

First, secondary sources: The study relied on secondary sources with the aim of building a theoretical framework that includes the study variables through relevant Arabic and foreign references and books, in addition to bulletins, websites, books, magazines, research, and previous studies in a manner consistent with the study topic.

Second, primary sources: Primary sources were relied upon by preparing a special and validated questionnaire. It was distributed to the study sample to obtain data related to the study and its problem according to the five-point Likert scale. The questionnaire included all dimensions of the study, questions, and hypotheses of the study, and for the purpose of addressing the analytical aspects.

Descriptive Analysis

Human Capital (Independent Variable) Means ranged from 3.94 to 4.08, with a mean of 4.01 and a standard deviation of 0.84, indicating a strong perceived capability among employees regarding sustainability-related skills. The highest-rated item was "Knowledge sharing among employees enhances our sustainability efforts" (M = 4.08, SD = 0.90), reflecting the value of collaborative learning. The lowest mean (M = 3.94) was associated with technical skills in using big data and artificial intelligence, indicating potential room for skill development. Overall, human capital appears to be a strong asset within organizations when it comes to driving sustainability analytics. For more information, the following table shows the rest of the Descriptive Analysis.

Table 1: Descriptive statistics

Constructs	N	Min	Max	Mean	Std.Deviation
Human Capital (IV)					
1. Our employees have strong analytical and problem-solving skills relevant to sustainability	200	1.00	5.00	3.9900	.93502
2. Staff are trained to use data analytics tools for sustainability monitoring	200	1.00	5.00	3.9950	.92153
3. Employees possess adequate knowledge about sustainability goals and standards.	200	1.00	5.00	4.0000	.92427
4. We have a skilled workforce capable of using big data and AI in sustainability applications.	200	1.00	5.00	3.9450	.95211
5. Our organization invests in continuous learning related to sustainability analytics.	200	1.00	5.00	4.0700	.87689
6. Knowledge sharing among employees enhances our sustainability efforts.				4.0750	.90191
Average	200	1.00	5.00	4.0125	.84240
Structural Capital (IV)					
. Our organization has an integrated database system supporting sustainability reporting	200	1.00	5.00	3.9250	.78898
We use IT systems effectively to collect and analyze sustainability-related data	200	1.00	5.00	3.9600	.81345
Our internal procedures promote the use of data in environmental performance evaluation.	200	1.00	5.00	3.9200	.83492
4. We have a well-documented process for tracking sustainability KPIs.	200	1.00	5.00	3.9550	.85241
5. Our sustainability analytics tools are regularly updated to meet regulatory standards.	200	1.00	5.00	3.9150	.81307
6. Digital infrastructure in our organization facilitates effective sustainability practices.	200	1.00	5.00	3.5200	.91311
Average	200	1.00	5.00	3.8658	.74248
Relational Capital (IV)					
1. We collaborate with stakeholders (e.g., customers, suppliers) on sustainability initiatives.	200	1.00	5.00	3.5550	.88934
2. Our company shares environmental performance data with partners.	200	1.00	5.00	3.4300	.94847
3. We receive support from government bodies regarding sustainability policies.	200	1.00	5.00	3.5250	.91847
4. Our networks enhance our ability to adopt sustainability analytics.	200	1.00	5.00	3.5300	.89054
5. Partnerships contribute positively to our sustainability goals.	200	1.00	5.00	3.6050	.91277
6. Our stakeholders actively participate in our sustainability plans.	200	1.00	5.00	2.4050	.96208
Average	200	1.00	5.00	3.3417	.61089
Sustainability Analytics Adoption (DV)					
1. We have adopted analytics tools to track and report sustainability performance.	200	1.00	5.00	2.4200	.92622

2. Our decisions are based on data generated from sustainability analytics.	200	1.00	5.00	2.2300	.92269
3. We use real-time data analysis to reduce environmental impact.	200	1.00	5.00	2.5000	.96157
4. Sustainability analytics is integrated into our business strategy.	200	1.00	5.00	2.3700	1.01402
5. Big data and AI are used to identify sustainability-related risks and opportunities.	200	1.00	5.00	4.1200	.71284
6. Our analytics platform supports our sustainability reporting obligations.	200	1.00	5.00	4.1550	.72360
Average	200	1.00	5.00	2.9658	.59010
Innovation Performance (DV)					
1. Sustainability analytics has led to the development of innovative products or processes.	200	1.00	5.00	4.2000	.68729
2. We have introduced new eco-friendly products in recent years.	200	1.00	5.00	4.1900	.66036
3. Data-driven sustainability practices have improved operational efficiency.	200	1.00	5.00	4.3350	.70374
4. Our sustainability initiatives drive technological innovation.	200	1.00	5.00	3.8300	.85131
5. Analytics help us identify areas for green innovation.	200	1.00	5.00	3.7950	.86992
6. Our innovation performance has improved due to our sustainability focus.	200	1.00	5.00	3.8800	.86565
Average	200	1.00	5.00	4.0383	.58568
Competitive Advantage (DV)					
1. Sustainability analytics has strengthened our competitive position.	200	1.00	5.00	3.8350	.91760
2. We have achieved cost reductions through sustainability analytics.	200	1.00	5.00	3.7150	.89318
3. Our reputation has improved due to the use of sustainability analytics.	200	1.00	5.00	4.4500	.54680
4. Data-driven sustainability strategies help us outperform competitors.	200	1.00	5.00	4.4750	.55761
5. Sustainability practices give us a market advantage.	200	1.00	5.00	4.4400	.58146
6. Our analytics use aligns with customer demands and expectations.	200	1.00	5.00	4.4250	.57097
Average	200	1.00	5.00	4.2233	.40942

4 Data Analyses

Failure to fulfill the assumptions required for regression analysis negatively affects the results of hypothesis testing, as an incorrect correlation appears between the study variables. Accordingly, some of the tests required by regression analysis were conducted, as they required the fulfillment of three conditions: first, that the sample be chosen randomly, second, that the data follow a normal distribution, and third, that there be no autocorrelation problem between the independent variables.

The first condition was met when selecting the study sample, as a random sample was chosen. This was achieved when selecting the study sample, where a simple random sample was chosen to represent the study population. As for the second condition related to the normal distribution of the data, the sampling distribution approaches the normal distribution when the sample size is larger than (30) observations. To confirm this, the Smirnov test was used, which is considered one of the most widely used tests. The values in this test show that the data follows a normal distribution when they are greater than (0.05).

Table 2: normal distribution

	Sample Kolmogorov	p-value	Result
Human Capital	.861	.211	normal
Relational Capital	.923	.198	normal
Structural Capital	.953	.157	normal

The data follows a normal distribution for the study variables and their dimensions, as the statistical significance value of the test was greater than (5%) and not significant at the level of (0.05) for all study variables. Based on the above, we conclude that the study data follows a normal distribution.

The First Main Hypothesis

To test the first main hypothesis, simple linear regression analysis was performed.

The first main hypothesis of the study was as follows **"Human capital positively affects the adoption of sustainability analytics among manufacturing companies"**

Table 3: result of the First Main Hypothesis

Independent variable	"t" value	"t" sig	B	R	R2	"F" value	"F" sig
Human capital	14.119	.000	.492	.708	.502	199.346	.000

The table (3) shows that there is a statistically significant effect (Human capital) in (adoption of sustainability analytics where the correlation coefficient reached ((R=0.708), which indicates the existence of a statistically significant correlation between the independent variable Human capital in adoption of sustainability analytics. It has been shown that the value of the coefficient of determination (R2 = 0.502, which indicates that Human capital explained (50.2%) of the variance occurring in adoption of sustainability analytics, while the remainder is due to other variables that were not included in the model. The value of (F = 199.34) was at a confidence level equal to (sig = 000). This confirms the significance of the regression at a significance level of 0.05 > (α). It appears from the coefficients table that the value of (B) reached (.492) and that the value of (t) was (14.119) with a statistical significance of (0.000), which indicates the presence of a significant effect.

The second main hypothesis of the study was as follows **"Relational capital significantly affects facilitating the adoption of sustainability analytics among manufacturing companies."**

Table 4: result of the second Main Hypothesis

Independent variable	"t" value	"t" sig	B	R	R2	"F" value	"F" sig
Relational capital	.639	.409	.492	.659	.434	151.742	.000

The table 4 shows that there is a statistically significant effect (Relational capital) in (adoption of sustainability analytics where the correlation coefficient reached (R=0.639), which indicates the existence of a statistically significant correlation between the independent variable Relational capital in adoption of sustainability analytics. It has been shown that the value of the coefficient of determination (R2 = 0.409), which indicates that Relational capital explained (40.9%) of the variance occurring in adoption of sustainability analytics, while the remainder is due to other variables that were not included in the model. The value of (F = 151.742) was at a confidence level equal to (sig = 000). This confirms the significance of the regression at a significance level of 0.05 > (α).It appears from the coefficients table that the value of (B) reached (.492) and that the value of (t) was (12.318) with a statistical significance of (0.000), which indicates the presence of a significant effect.

The third main hypothesis of the study was as follows:**" Structural capital facilitates successful adoption of sustainability analytics among manufacturing organizations"**

Table 5 result of the third Main Hypothesis

Independent variable	"t" value	"t" sig	B	R	R2	"F" value	"F" sig
Structural capital	11.699	.000	.613	.659	.434	136.874	.000

The table 5 shows that there is a statistically significant effect (Structural capital) in (adoption of sustainability analytics where the correlation coefficient reached (R=0.659), which indicates the existence of a statistically significant correlation between the independent variable Structural capital in adoption of sustainability analytics. It has been shown that the value of the coefficient of determination (R2 = 0.464), which indicates that Structural capital explained (46.4%) of the variance occurring in adoption of sustainability analytics, while the remainder is due to other variables that were not included in the model. The value of (F = 136.874) was at a confidence level equal to (sig = 000). This confirms the significance of the regression at a significance level of 0.05 > (α). It appears from the coefficients table that the value of (B) reached (.613) and that the value of (t) was (11.699) with a statistical significance of (0.000), which indicates the presence of a significant effect.

The fourth main hypothesis of the study was as follows:**" Sustainability analytics adoption positively affects organizational performance, i.e., innovation performance and competitive advantage"**

Table 6: result of the fourth Main Hypothesis

dependent variable	"t" value	"t" sig	B	R	R2	"F" value	"F" sig
organizational performance	-4.755	.000	.318	.320	.102	22.605	.000
competitive advantage"	8.554	.000	0.718	.519	.270	73.172	.000

The table 6 shows that there is a statistically significant effect (Sustainability analytics adoption) in (organizational performance)where the correlation coefficient reached (R=0.32), which indicates the existence of a statistically significant correlation between the independent variable Sustainability analytics adoption in adoption of organizational performance. It has been shown that the value of the coefficient of determination (R2 = 0.102), which indicates that adoption of sustainability analytics explained (10.2%) of the variance occurring in organizational performance, while the remainder is due to other variables that were not included in the model. The value of (F = 22.602) was at a confidence level equal to (sig = 000). This confirms the significance of the regression at a significance level of 0.05 > (α). It appears from the coefficients table that the value of (B) reached (.318) and that the value of (t) was (-4.755) with a statistical significance of (0.000), which indicates the presence of a significant effect.

5 Discussion

The findings strongly support a significant and positive influence of human capital on the adoption of sustainability analytics. The correlation coefficient (R = 0.708) indicates a high degree of association, while the coefficient of determination (R^2 = 0.502) reveals that 50.2% of the variance in the adoption of sustainability analytics can be explained by human capital alone. The standardized coefficient (B = 0.492) and the high t-value (14.119, p = 0.000) confirm this strong predictive relationship.

The analysis also demonstrates a statistically significant impact of relational capital on the adoption of sustainability analytics, with a correlation coefficient of R = 0.639 and R^2 = 0.409. This means that 40.9% of the variance in adoption is attributable to relational capital. The regression coefficient (B = 0.492), supported by a t-value of 12.318 (p = 0.000), further confirms the positive association.

The study confirms that structural capital has a significant and positive effect on the adoption of sustainability analytics. The results show a correlation coefficient of R = 0.659 and $R^2 = 0.464$, indicating that 46.4% of the variation in adoption can be explained by structural capital. The regression coefficient (B = 0.613) and the corresponding t-value (11.699, p = 0.000) validate this relationship.

The study found a statistically significant but relatively modest relationship between the adoption of sustainability analytics and innovation performance, with R = 0.320 and $R^2 = 0.102$. This indicates that 10.2% of the variance in innovation performance is explained by sustainability analytics adoption. The regression coefficient (B = 0.318), along with a negative t-value (-4.755, p = 0.000), still affirms the presence of a meaningful connection.

Finally, the results clearly demonstrate that the adoption of sustainability analytics significantly enhances competitive advantage, with a correlation coefficient of R = 0.519 and $R^2 = 0.270$. This means that 27% of the variability in competitive advantage is accounted for by sustainability analytics adoption. The regression coefficient (B = 0.718) and t-value (8.554, p = 0.000) strongly support this conclusion.

This finding indicates that manufacturing firms using sustainability analytics are more likely to achieve differentiation, efficiency, and responsiveness in their markets. By leveraging analytics to inform strategic decisions, optimize operations, and reduce environmental impact, these firms can gain a substantial edge over competitors.

The comparative analysis reveals strong consistency between this study's results and a substantial body of existing research. The study reinforces the significance of intellectual capital dimensions in facilitating sustainability initiatives and highlights the mediating role of sustainability analytics in enhancing organizational performance. While there are some contextual variations, particularly regarding the influence of human capital, the general alignment with previous findings confirms the robustness and relevance of the study's conclusions for both academic and practical applications.

6 Research Implications

Theoretical Implications

This study makes a significant theoretical contribution by integrating the Intellectual Capital framework with the concept of Sustainability Analytics within the context of manufacturing firms. The results reinforce and extend the Resource-Based Theory (RBT) by demonstrating that intangible assets—such as human, relational, and structural capital—are critical enablers of sustainability analytics adoption. Furthermore, the study confirms that the adoption of such analytics leads to improved innovation performance and competitive advantage, suggesting that intellectual capital is not only a resource but also a strategic capability that enhances organizational sustainability.

Practical Implications

From a managerial perspective, the study emphasizes the need for investment in human capital development, particularly through training programs focused on data literacy, environmental awareness, and analytics tools. Firms should prioritize recruiting and retaining talent with the technical and strategic skills needed to implement sustainability analytics effectively. The findings also suggest that building and maintaining strong external relationships—with suppliers, customers, and stakeholders—is essential for supporting sustainability objectives. Organizations should engage in strategic partnerships and knowledge-sharing initiatives to enhance relational capital.

7 Conclusion

This study aimed to investigate the role of intellectual capital—specifically human, relational, and structural capital—in driving the adoption of sustainability analytics within manufacturing companies, and to assess how such adoption influences innovation performance and competitive advantage.

The results, derived from quantitative analysis using linear regression, revealed strong empirical support for the proposed model. All three components of intellectual capital were found to have a significant and positive impact on the adoption of sustainability analytics. Among them, human capital emerged as the most influential, followed by structural and relational capital. These findings highlight the critical importance of investing in knowledge, systems, and external relationships to support sustainable digital transformation.

In addition, the study demonstrated that sustainability analytics adoption contributes positively to organizational outcomes—namely innovation performance and competitive advantage. Although the relationship with innovation was moderate, the impact on competitive advantage was stronger, suggesting that firms leveraging analytics to support sustainability are better positioned to enhance their market performance and strategic positioning.

8 References

1. Akmalia, N., & Muharam, H. (2024). Intellectual capital and companies' sustainable growth: Evidence from Indonesia. *Journal of Sustainability Management, 18*(1), 45–58.
2. Alvino, F., & Di Vaio, A. (2019). Intellectual capital and sustainable development: A systematic literature review. Journal of Intellectual Capital. https://doi.org/10.1108/JIC-11-2019-0259
3. Awadallah, N. A., & Elnady, M. A. (2020). The Impact of Artificial Intelligence and Big Data on Sustainable Development. Sadat Academy for Management Sciences, Egypt.
4. Bontis, N., Dragonetti, N. C., Jacobsen, K., & Roos, G. (2000). The knowledge toolbox: A review of the tools available to measure and manage intangible resources. European Management Journal, 18(5), 575–592.
5. Delmas, M., Etzion, D., & Nairn-Birch, N. (2013). Triangulating Environmental Performance: What Do Corporate Social Responsibility Ratings Really Capture? Academy of Management Perspectives, 27(3), 255–267.
6. Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(S2), 109–122.
7. Iqbal, M. A. B., Zafar, R., Imran, M., Khan, W. A., Batool, S., & Sadiq, W. (2023). Impact of green intellectual capital on corporate sustainability with mediating role of green innovation. Russian Law Journal, 11(3), 2707–2713. https://doi.org/10.17589/2309-8678-2023-11-3-2707-2713
8. Jabbour, C. J. C., & Jabbour, A. B. L. D. S. (2016). Green human resource management and green supply chain management: Linking two emerging agendas. Journal of Cleaner Production, 112, 1824–1833.
9. Jain, A., & Jamal, A. (2022). The role of relational capital in enabling green analytics practices across manufacturing supply chains. Journal of Cleaner Production, 345, 130826.
10. Malik, S., Cao, Y., Mughal, Y. H., Kundi, G. M., Mughal, M. H., & Ramayah, T. (2020). Pathways towards sustainability in organizations: Empirical evidence on the role of green human resource management practices and green intellectual capital. Sustainability, 12(8), 3228. https://doi.org/10.3390/su12083228
11. Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford University Press.
12. Ojokoh, B. A., Samuel, O. W., Omisore, O. M., Sarumi, O. A., Idowu, P. A., Chimusa, E. R., et al. (2020). Big data, analytics, and artificial intelligence for sustainability. Scientific African, 9(e00551). https://doi.org/10.1016/j.sciaf.2020.e00551
13. Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2024). Big data analytics–artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms. Journal of Science and Technology Policy Management, https://doi.org/10.1108/JSTPM-04-2023-0050
14. Tonial, G., Cassol, A., Selig, P. M., & Giugliani, E. (2019). Intellectual capital management and sustainability activities in Brazilian organizations: A case study. In Sustainability and Organizational Change Management (pp. 99–116). Springer. https://doi.org/10.1007/978-3-319-79051-0_7
15. Vale, J., Miranda, R., Azevedo, G., & Tavares, M. C. (2022). The impact of sustainable intellectual capital on sustainable performance: A case study. Sustainability, 14(8), 4382. https://doi.org/10.3390/su14084382
16. Yusliza, M.-Y., Yong, J. Y., Tanveer, M. I., Ramayah, T., Noor Faezah, J., & Muhammad, Z. (2020). A structural model of the impact of green intellectual capital on sustainable performance. Journal of Cleaner Production, 249, 119334. https://doi.org/10.1016/j.jclepro.2019.119334
17. Yusoff, R. M., Jusoh, R., Mohd Noor, N. F., & Harun, A. (2019). Intellectual capital and sustainability in manufacturing companies: Evidence from Malaysia. Journal of Cleaner Production, 226, 1178–1190. https://doi.org/10.1016/j.jclepro.2019.04.127
18. Zahoor, N., & Gerged, A. M. (2021). Relational capital, environmental knowledge integration, and environmental performance of SMEs in emerging markets. Business Strategy and the Environment. https://doi.org/10.1002/bse.2872

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The long run cointegration Relationship among Macroeconomic Variable and Total Investment In Jordan

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Abstract
This study aimed to identify the cointegration relationship among macroeconomic variables (economic growth rate, inflation rate, income and profit tax rate, budget deficit after grants, balance of payments deficit) and investment volume in Jordan using time series data from 1990 to 2025 and Autoregressive Distributed Lag Model (ARDL) will be used to analyze the cointegration relationship between selected economic indicators. The results show that there existence of both long-term and short-term relationships between the selected macroeconomic indicators and the investment volume in Jordan. The policy makers must pay more attention to the importance of size of investment in Jordan, Intensifying the efforts by the relevant authorities to facilitate the process of obtaining approvals and licenses, and providing greater incentives for investors, in order to create a secure investment environment, encourage investment, and increase its rates.

1 Introduction

The world today faces many successive changes that affect the economy in one way or another, in addition to the environmental and political disasters that the world is witnessing, which have impacted the macroeconomic indicators of countries. As a result, the economy under these changes has become a single interconnected entity that influences and is influenced by these changes. Consequently, macroeconomic indicators reflect the economic outlook and are considered an essential part of economic data. Economic analysts also resort to using these indicators to interpret the standards and potential of current and future investments (Bekhet and Al-smadi, 2015)

Investment is considered one of the main economic factors that contribute to the performance and stability of the Jordanian economy and can positively contribute to the utilization of available resources, as well as economic and social growth. Consequently, it helps increase production and productivity levels, as investment contributes to improving the economic situation and is an important factor for development and driving the Jordanian economy. Therefore, governments seek, through a series of economic reforms, to provide a stimulating and suitable environment for investment and to facilitate procedures and policies related to investment in order to achieve economic advancement (Bekhet and Al-smadi, 2015; Bekhet and Al-smadi, 2017). Hence, this study was conducted to identify the impact of selected macroeconomic indicators on the growth of investment size in Jordan.

The problem of the study lies in the weak overall investment in Jordan, which is mainly due to the nature of the changes associated with the selected macroeconomic indicators (economic growth rate, inflation rate, income and profit tax rate, budget deficit after grants GDR%, balance of payments deficit).

The Jordanian economy faces many difficult challenges such as unemployment, inflation, and budget deficits, among many others, all of which negatively affect the Jordanian economy as a whole. Since macroeconomic indicators play a major role in encouraging or limiting these investments, this study attempts to clarify the nature and direction of the causal relationship between macroeconomic indicators and the growth of Jordanian investment.

2 Literature Review and Hypotheses

The main objective of the current study is to measuring the relationship between selected macroeconomic indicators and the volume of investment in Jordan in the short and long term. However, several empirical studies have examined the relationship between macroeconomic indicators and the volume of investment, the study of Megaravalli, & Sampagnaro (2018) aimed to examine the long-term and short-term relationships between India, China, and the Japanese stock markets, as well as key macroeconomic variables such as exchange rates and inflation (based on the Consumer Price Index in the economies of India, China, and Japan). Monthly time series data from January 2008 to November 2016 were used. Unit root tests, cointegration tests, and Granger causality tests were conducted. The study's results indicate that the exchange rate has a positive and significant long-term effect on stock markets, while inflation has a negative and insignificant long-term effect. In the short term, there is no statistically significant relationship between macroeconomic variables and stock markets.

Abidin, & Haseeb (2018) his study aimed to investigate the impact of macroeconomic indicators such as GDP per capita, inflation, and the real exchange rate. A panel time series from 1990-2017 was applied. The gravity model approach was used as a theoretical support. The results of the fixed and random effects show that all the variables are statistically significant. However, variables such as the real exchange rate, inflation, and distance were found to be negatively significant, meaning that as these variables increase, the total bilateral trade between Malaysia and the GCC countries will decrease. Also, Nyangarika et al. (2019) this study aimed to investigate the impact of oil price shocks on Russian economic indicators using time series data for the period 1991-2016 to cover all oil price shocks. An autoregressive vector and the Dickey-Fuller test were used to examine the long-term and short-term relationships between the variables. The results show that one of the most important external influencing factors is the global oil price, and there is a significant long-term positive relationship between oil prices and the dynamics of Russian GDP.

Javid, M. (2019) This study aimed to investigate the relationship between investment in infrastructure and economic growth at both the aggregate and sectoral levels, namely the industry, agriculture, and services sectors of Pakistan during the period from 1972 to 2015. It also compares the analysis of different compositions of infrastructure investments, including public versus private investment and investment in infrastructure in sub-sectors such as energy, roads, and telecommunications. The Fully Modified Ordinary Least Squares (FMOLS) method was used to address the issue of reverse causality. The main conclusion of this study is that both public and private infrastructure investments have positive but different effects on economic growth.

Ćorić, & Šimić (2021) this paper examines the long-term relationship between economic disasters and aggregate investment. We analyze data for a large number of developing and developed countries after World War II. The panel data analysis conducted indicates a negative effect of the likelihood of economic disasters on total investment. Also, Gavurova, et al (2021) this study aimed to investigate the relationships between macroeconomic indicators related to tourism and their impact on the economies of countries. The dataset consists of eight macroeconomic indicators, including four GDP-related indicators, two employment indicators, one investment indicator, and one expenditure indicator. The observed period covers the years from 1995 to 2019. Euclidean distance is used to assess the similarity between countries, and cluster analysis is applied to group them accordingly. Several patterns emerge from the analysis results. First, countries behave differently regarding the two sets of indicators, with Mexico ranking first. Second, some countries experienced significant changes during the observed period, with Greece at the extremes for GDP indicators and Hungary for the other economic indicators.

In order to achieve the objectives of the study and address its questions leading to a solution to the study problem, the following main hypothesis was formulated:

1. There is no statistically significant effect at the significance level ($\alpha \leq 0.05$) in measuring the relationship between selected macroeconomic indicators and the volume of investment in Jordan in the long term.
2. There is no statistically significant effect at the significance level ($\alpha \leq 0.05$) in measuring the relationship between selected macroeconomic indicators and the volume of investment in Jordan in the short term.

3 METHOD

The study relied on the descriptive analytical approach by describing the phenomenon under investigation, represented by the macroeconomic indicators, and analyzing the obtained data, including (economic growth rate GDP, inflation rate INF, and income and profit tax rate T, budget deficit after grants BD, balance of payments deficit BOP, and total public debt TIN) and the growth of the Jordanian investment volume. The current study measures Jordan's macroeconomic indicators and the growth of investment in Jordan based on data issued by the Central Bank of Jordan.

In previous years, many prior studies discussed the relationship between selected macroeconomic indicators GDP, INF, T, BD, BOP and investment size (Tin) (Bahriddinovich, 2020; Al-smadi, and Al-smadi, 2024). In this study, the research model will be built based on prior studies that relied on economic theories. However, the study model can be constructed as shown in Equation No. (1)

LTINt =α +β1LGDPt+β2LINFt+β3LTt+β4LBDt+β5LBOPt+Ɛt……………………………(1)

Where, α is intercept; βIS (1,5) are Variable coefficients; natural logarithms is L; and tƐ Random error TIN is Investment size; GDP is Economic growth rate; INF is Inflation rate; T is Income and profit tax rate; BD is Budget deficit after grants and BOP is Balance of payments deficit.

In this study, time series data from 1990 to 2025 will be used to analyze the cointegration relationship between selected economic indicators (GDP, INF, T, BD, BOP) and the investment volume TIN in Jordan. The following data were collected: GDP, INF, T, BD, BOP) from the Central Bank, and data related to investment volume (TIN) from the Ministry of Investment, as shown in the following table 1.

Table 1. Is Sources of study variables.

Variables	sources
TIN	Ministry of Investment https://www.moin.gov.jo
GDP	Central Bank :https://www.cbj.gov.jo/
INF	Central Bank :https://www.cbj.gov.jo/
T	Central Bank :https://www.cbj.gov.jo/
BD,	Central Bank :https://www.cbj.gov.jo/
BOP	Central Bank :https://www.cbj.gov.jo/

Based on the above discussion, this study examines the long and short term relationship among the variables (GDP, Inflation, Trade, Budget Deficit, Balance of Payments) in Jordan by using Autoregressive Distributed Lag Model (ARDL) (Al-smadi, and Al-smadi, 2024; Bekhet and Al-smadi, 2015)., as shown in equation number (2).

$$\Delta LTIN_t = \mu_1 + \sum_{j=1}^{k} \beta_{11}\Delta LTIN_{t-j} + \sum_{j=0}^{k} \beta_{12}\Delta LGDP_{t-j} + \sum_{j=0}^{k} \beta_{13}\Delta LINF_{t-j} + \sum_{j=0}^{k} \beta_{14}\Delta LT_{t-j} + \sum_{j=0}^{k} \beta_{15}\Delta LBD_{t-j} + \sum_{j=0}^{k} \beta_{16}\Delta LBOP_{t-j} + \eta_{11}LTIN_{t-1} + \eta_{12}LGDP_{t-1} + \eta_{13}LINF_{t-1} + + \eta_{14}LT_{t-1} + \eta_{15}LBD_{t-1} + \eta_{16}LBOP_{t-1+}\varepsilon_t \quad (2)$$

Where μ is intercept, βijs = (i, j = 1, ...) are short-term relationship coefficients and Ƞijs = (i, j = 1, ...) are the long-term relationship coefficients and εt is represent the error term.

4 RESULTS

In this part, the impact of selected macroeconomic indicators (GDP, T, BD, BOP, INF) and the volume of investment in Jordan (TIN) for the period 1990-2025 was analyzed. The results of the statistical analysis and hypothesis testing were presented by following the following statistical procedures: First: descriptive analysis of the variables, Second: unit root test, Third: co-integration test, Fourth: analysis of the long-term and short-term relationship between the variables, Fifth: stability analysis.

The independent variables of the selected economic indicators (GDP, T, BD, BOP, INF) and the investment volume in Jordan (TIN) were measured during the selected period (1990-2025). The first procedure in this section is the descriptive statistical analysis of the data by calculating the mean and standard deviation of the data, as shown in Table (2).

Table (2). Descriptive statistical analysis

indicators	TIN	GDP	T	BD	BOP	INF
Mean	21.38	22.10	0.134	-1064.8	-426.33	3.674
Median	23.34	23.00	0.139	-737.5	-298.45	3.320
Maximum	21.85	22.19	0.207	841.60	422.10	16.19

indicators	TIN	GDP	T	BD	BOP	INF
Minimum	19.38	21.73	0.067	-3354.9	-2282.4	-0.876
Std. Dev.	0.695	0.82	0.028	1152.6	523.90	3.685
Skewness	0.398	-0.03	0.041	-0.3267	-1.5564	1.809
Kurtosis	1.994	1.52	3.222	1.8988	3.9731	3.847
Jarque-Bera	2.194	2.92	0.075	2.1861	4.7106	3.119
Probability	0.333	0.23	0.963	0.3351	0.2400	0.124

Source: Output of the Eviews 7.2 econometric software

Table 2 show that the mean of the dependent variable, Investment Size TIN, is 21.38 (with a standard deviation of 0.6959), the minimum value is 19.38, and the maximum value is 21.859. The highest value among the independent variables is the Gross Domestic Product (GDP), with a mean of 23.10356 and a standard deviation of 0.821. Also Table 2 show that the results of the J.B test confirm that all selected variables (GDP, T, BD, BOP, INF) are normally distributed, which means that there is no problem of multicollinearity and no dispersion in the data (Gujarati, 2021).

The result of stationarity in time series is one of the important aspects of analysis that relies on temporal data, particularly financial and economic data. This is because non-stationary data produces incorrect or misleading results, which is called spurious regression. There are statistical methods used to test data stationarity, the most important of which is the unit root test, which aims to examine the properties of the time series for each variable (Gujarati, 2021). To test the stationarity of time series, the most important unit root test used is the Augmented Dickey-Fuller (ADF) test, as shown in Table 3.

Table 3. Unit root test result Augmented Dickey-Fuller (ADF) test

Regressor	I(0)	I(1)
TIN	-2.425763	4.818766*
GDP	-1.854567	-3.906338**
T	-3.997470	-8.90344*
BD	-1.646876	-5.448223*
BOP	-1.654070	-5.576050*
INF	-4.947654	-8.042392*

Notes: (1) * and ** denotes statistically significance at 1%, 5% levels.
Source: Output of the Eviews 7.2 econometric software

In this section, the cointegration model was used, as this test aims to determine whether there is cointegration among the study variables. The existence of cointegration between the study variables indicates that there is a long-term relationship between them (Bekhet and Smadi 2016; Bekhet and Mugableh 2012). A decision regarding the presence of cointegration among the study variables can be made based on comparing the calculated value of (F value) with the Pesaran 2001 table. If the calculated F value is higher than the I(1), this indicates that there is a cointegration relationship between the study variables; whereas if the calculated F value is lower than the I(0) table value, this means that there is no cointegration relationship between the study variables, as shown in Table 4.

Table 4. Cointegration between the study variables

Models	F-statistic	Bound Critical Values	Decisions
		1% → I(0): 2.61 , I(1): 3.86 **5%** → I(0): 3.50 , I(1): 5.12	
TIN	4.91	2.61, 3.86, 3.50, 5.12	Cointegration
GDP	4.87	2.61, 3.86, 3.50, 5.12	Cointegration
T	3.79	2.61, 3.86, 3.50, 5.12	Cointegration
BD	4.82	2.61, 3.86, 3.50, 5.12	Cointegration

Models	F-statistic	Bound Critical Values	Decisions
BOP	4.47	2.61, 3.86, 3.50, 5.12	Cointegration
INF	4.11	2.61, 3.86, 3.50, 5.12	Cointegration

Source: Output of the Eviews 7.2 econometric software

In this section, the long-term relationship between macroeconomic variables (GDP, T, BD, BOP, INF) and the volume of investment in Jordan (TIN) was analyzed using the ARDL model, which allows examining the explanatory variables for long-term dynamics across all the study variables. Table (5) shows the long-term relationship between the study variables.

Table 5. Long-term relationship

Regressor	Coefficient	Prob
C	5.8308	0.000*
GDP	.98973	0.001*
T	-8.1708	0.00*
BD	-19460.0	0.004*
BOP	-9574.8	0.003*
INF	-9.4807	0.002*

Notes: (1) * denotes statistically significance at 1% levels.
Source: Output of the Eviews 7.2 econometric software

The results in the long-term relationship analysis between the size of investment (TIN) and the selected macroeconomic indicators (GDP, T, BD, BOP, INF) showed that there is a long-term relationship among the study variables. There is a significant positive relationship with the investment size indicator (TIN) and GDP. This means that working on investment laws and regulations and making them characterized by clarity, transparency, and attractiveness leads to the availability of a suitable investment environment and improves economic conditions. Generally, this will necessarily lead to an improvement in the level of economic growth, which will positively reflect on the increase in investment size (Al-Quraan, 2020).

In addition, the results showed that there is a significant negative relationship between the size of investment (TIN) and each of (T, BD, BOP, INF). This is consistent with economic theories and previous studies, such as the study by Qadi (2006), which suggested an inverse relationship between the size of investment (TIN) and the income and profit tax index (T). This means that the higher the tax rate on income and profits, the higher the costs associated with investing, which leads to a decrease in the size of investment. The results also showed that there is a significant negative relationship between the size of investment (TIN) and the inflation rate (INF), as these results are consistent with economic theories and previous studies, such as the study by Fatkhurrozi, (2024), which assumed the existence of an inverse relationship between the size of investment (TIN) and the inflation rate (INF), indicating that as the inflation rate rises, it leads to a decrease in the size of investment.

The results in of the short-term relationship between selected macroeconomic indicators (GDP, T, BD, BOP, INF) and the investment volume in Jordan (TIN) in table 6 that showed there is a short-term relationship between the study variables .

Table 6 short-term relationship

Regressor	Coefficient	Prob
C	6.7308	0.000*
GDP	.88973	0.003*
T	-6.5608	0.00*
BD	- 414630	0.002*

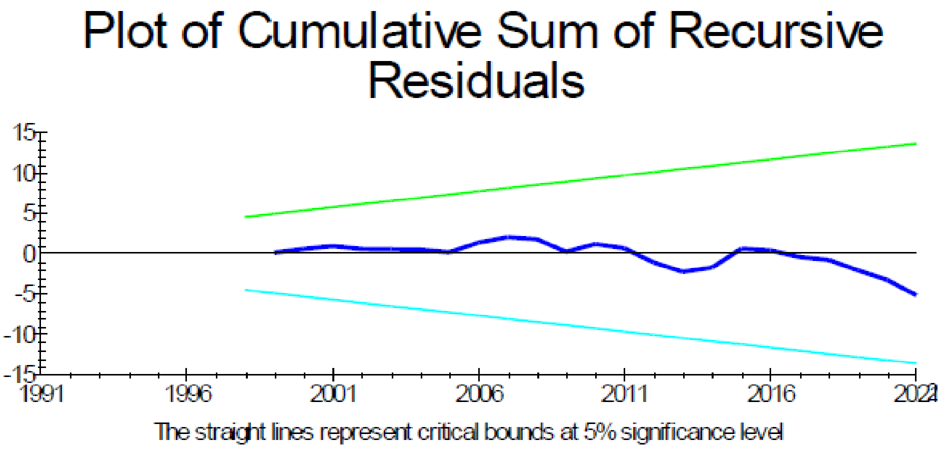
Regressor	Coefficient	Prob
BOP	-803208	0.001*
INF	-9.4009	0.004*
ECM (-1)	-0.80	0.000

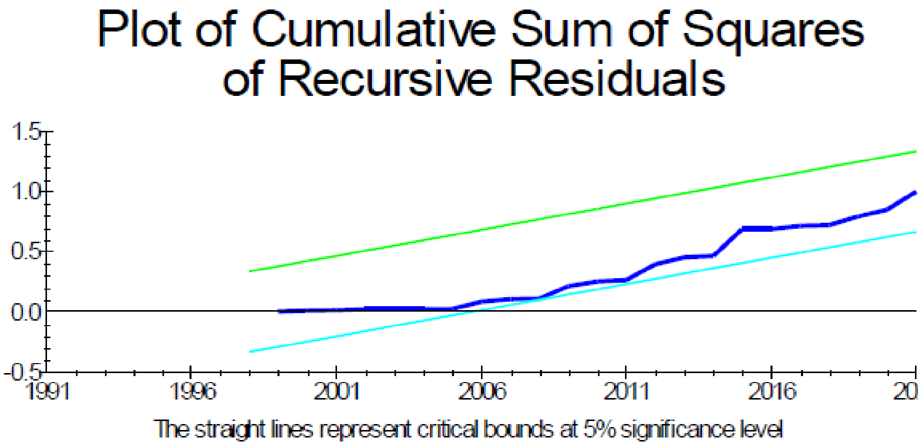
Notes: (1) * denotes statistically significance at 1% levels.
Source: Output of the Eviews 7.2 econometric software

Table 6 shows there is a significant positive relationship between the Investment Size Index (TIN) and Gross Domestic Product (GDP), which means that working on the laws and regulations governing investment and making them characterized by clarity, transparency, and attractiveness leads to a suitable investment environment and improves economic conditions. In general, this will necessarily lead to an improvement in the level of economic growth, which will positively reflect on the increase in investment size (Al-Quraan, 2020). The results of this study are consistent with the results of many previous studies, such as the study by Bekhet and Smadi (2016), which showed the existence of a short-term relationship between investment size and economic growth.

In addition, the results showed that there is a significant negative relationship between the size of investment (TIN) and each of (T, BD, BOP, INF). This is consistent with economic theories and previous studies such as the study by Qadi (2006), which suggested a negative relationship between the size of investment (TIN) and the tax rate index (T). This means that the higher the tax rate, the higher the costs associated with investments, which leads to a decrease in the size of investment. Also, the results shown in Table 6 indicate that the ECM (-1) is 0.80, which means that this model will achieve equilibrium from the short term to the long term at a rate of 80%. In other words, the long-term relationship corrected itself quickly within one year.

However, the Cumulative Sum of Recursive Residuals (CUSUM) test was used in the time series to ensure the long-term stability of the variables. The results showed that the data for the variables are stable in the long term, which means that all the variables in the study are stable in the long term, confirming the presence of cointegration among the study variables. These results are consistent with similar previous studies, such as the study by Bekhet and Smadi (2016).





5 Conclusion

This study aimed to identify the common integration among macroeconomic variables (economic growth rate GDP, inflation rate INF, income and profit tax rate T, budget deficit after grants BD, balance of payments deficit BOP, and investment volume in Jordan Tin), and to measure the indicators of the Jordanian economy and investment in a realistic manner based on statistical data related to the variables covered in this study.

Based on the analysis results showed there existence of both long-term and short-term relationships between the selected macroeconomic indicators (GDP, T, BD, BOP, INF) and the investment volume in Jordan (TIN). Thus, the results indicated the existence of a statistically significant effect between macroeconomic indicators (economic growth rate, inflation rate, income and profit tax, budget deficit after grants, balance of payments deficit) and the volume of investment in Jordan over the long term. The results of the first hypothesis showed a significant positive relationship between the economic growth rate and the volume of investment in Jordan. This result can be interpreted to mean that the economic growth rate positively affects the volume of investment, as higher growth rates act as a key factor in attracting and drawing investments, which ultimately leads to the prosperity and advancement of the national economy.

Also, the results showed a significant negative relationship between (inflation rate, income and profit tax, budget deficit after grants, and balance of payments deficit) and the size of investment in Jordan in the long term. This is interpreted to mean that these indicators have a negative impact on the level of investment, meaning that these indicators lead to an unstable environment for attracting investments, which consequently weakens the national economy. From this point of view, the policy makers must pay more attention to the importance of size of investment in Jordan, Intensifying the efforts by the relevant authorities to facilitate the process of obtaining approvals and licenses, and providing greater incentives for investors, in order to create a secure investment environment, encourage investment, and increase its rates. Also, giving more attention to laws and regulations that encourage the attraction of investments, whether local or foreign, as they have a clear impact on improving economic conditions, which in turn reflects on the overall standard of living.

6 References

1. Bekhet, H. A., & Al-Smadi, R. W. (2015). Determinants of Jordanian foreign direct investment inflows: Bounds testing approach. Economic Modelling, 46, 27-35.
2. Bekhet, H. A., & Al-Smadi, R. W. (2017). Exploring the long-run and short-run elasticities between FDI inflow and its determinants in Jordan. International Journal of Business and Globalisation, 18(3), 337-362.
3. Megaravalli, A. V., & Sampagnaro, G. (2018). Macroeconomic indicators and their impact on stock markets in ASIAN 3: A pooled mean group approach. Cogent Economics & Finance, 6(1), 1432450.

4. Zainal Abidin, I. S., & Haseeb, M. (2018). Malaysia-Gcc bilateral trade, macroeconomic indicators and islamic finance linkages: A gravity model approach. Academy of Accounting and Financial Studies Journal, 22(SI), 1-7.
5. Nyangarika, A. M., Mikhaylov, A., & Richter, U. H. (2019). Influence oil price towards macroeconomic indicators in Russia. International Journal of Energy Economics and Policy, 9(1), 123-129.
6. Javid, M. (2019). Public and private infrastructure investment and economic growth in Pakistan: An aggregate and disaggregate analysis. Sustainability, 11(12), 3359.
7. Ćorić, B., & Šimić, V. (2021). Economic disasters and aggregate investment. Empirical economics, 61(6), 3087-3124.
8. Gavurova, B., Belas, J., Valášková, K., Rigelský, M., & Ivankova, V. (2021). Relations between infrastructure innovations and tourism spending in developed countries: A macroeconomic perspective. Technological and Economic Development of Economy.
9. Bahriddinovich, M. S. (2021). The Spiritual Heritage of Abu Hafs Umar Suhrawardi and it's significance for the Contemporary World. Central Asian Journal of Social Sciences and History, 2(3), 53-60.
10. Al-Smadi, R. W., & Al-Smadi, A. W. (2024). The relationship between foreign direct investment and financial inclusion in MENA countries: Evidence from the General Method of Moments. Investment Management & Financial Innovations, 21(2), 144.
11. Gujarati, D. N. (2021). Essentials of econometrics. Sage Publications.
12. Bekhet, H. A., & Al-Smadi, R. W. (2016). The dynamic causality between FDI inflow and its determinants in Jordan. International Journal of Economics and Business Research, 11(1), 26-47.
13. Bekhet, H. A., & Mugableh, M. I. (2012). Investigating equilibrium relationship between macroeconomic variables and Malaysian stock market index through bounds tests approach. International Journal of Economics and finance, 4(10), 69-81.
14. Al Quraan, Q. R. (2020). General sales tax and economic growth in small open developing countries: Evidence from jordan. Montenegrin Journal of Economics, 16(3), 7-15.
15. Fatkhurrozi, T. (2024). Islamic Capital Market Investment Alternatives Facing the 2024 Election Year. Danadyaksa: Post Modern Economy Journal, 1(2), 148-163.
16. Bekhet, H. A., & Al-Smadi, R. W. (2016). The dynamic causality between FDI inflow and its determinants in Jordan. International Journal of Economics and Business Research, 11(1), 26-47.

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ألاداء المالي والقيمة السوقية للشركة: الدور المعدل لنظام الإفصاح الإلكتروني بلغة XBRL

Financial Performance and Firm Market Value: The Moderating Role of the Extensible Business Reporting Language (XBRL)

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Abstract
The study aimed to identify the relationship between financial performance—measured by company profitability—and the market value of the company. It also sought to examine the moderating role of electronic disclosure using XBRL (as a moderating variable) on the relationship between financial performance and market value. The study employed the descriptive–analytical approach.
The study sample consisted of Jordanian industrial public shareholding companies listed on the Amman Stock Exchange, totaling 46 companies at the time of data collection. The final sample included 30 industrial companies, representing 65.2% of the study population. The study relied on published annual financial reports of the sampled industrial companies during the period 2017–2022, as well as Amman Stock Exchange bulletins available on the official website, to collect the data needed to measure the study variables.
For data analysis, descriptive statistical methods were used, in addition to multiple linear regression and hierarchical interaction regression to test the study hypotheses, using E-Views software. The study found a statistically significant relationship between financial performance and its indicators and the company's market value. It also revealed a statistically significant relationship regarding the moderating role of XBRL on the relationship between financial performance and market value.
The study recommended that Jordanian industrial companies adopt disclosure policies that contribute to enhancing their financial performance, improving operational efficiency, increasing revenues, expanding profit margins, and generating returns. It also recommended obligating companies to apply electronic disclosure using the XBRL system and integrate it with their accounting systems to facilitate clearer and more accurate presentation of information.

Keywords: Financial Performance, Market Value, Electronic Disclosure Language (XBRL), Amman Stock Exchange.

ملخص
هدفت الدراسة إلى معرفة العلاقة بين الأداء المالي مقاساً (بربحية الشركة) والقيمة السوقية للشركة، بالاضافة الى معرفة الدور المعدل للإفصاح الإلكتروني بلغة XBRL (كمتغير معدل) على العلاقة بين الأداء المالي والقيمة السوقية للشركة، وذلك باتباع المنهج الوصفي التحليلي. وقد تكونت عينة الدراسة من الشركات الصناعية الأردنية المساهمة العامة المدرجة في بورصة عمان، والبالغ عددها (46) شركة صناعية بتاريخ جمع البيانات، حيث تمثلت العينة النهائية (30) شركة صناعية، وبنسبة (65.2%) من الشركات الممثلة لمجتمع الدراسة. وقد تم الاعتماد على التقارير المالية السنوية المنشورة الخاصة بالشركات الصناعية عينة الدراسة خلال الفترة (2017-2022) ونشرات بورصة عمان المنشورة على الموقع الالكتروني الرسمي، وذلك لجمع البيانات اللازمة لقياس متغيرات الدراسة. ولغرض تحليل البيانات تم استخدام أساليب الاحصاء الوصفي، كما تم استخدام تحليل الانحدار الخطي المتعدد وتحليل الانحدار الهرمي التفاعلي لاختبار فرضيات الدراسة، وذلك باتخدام برنامج (E-Views). وتوصلت الدراسة إلى وجود علاقة ذات دلالة إحصائية بين الأداء المالي ومؤشراته وبين القيمة السوقية للشركة، ووجود علاقة ذات دلالة إحصائية بين دور الـ XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة. وأوصت الدراسة بتبني الشركات الصناعية الأردنية سياسة الافصاح والتي تسهم في تحسين أدائها المالي وتحقيق الكفاءة في عملياتها الداخلية ونمو إيراداتها وزيادة هامش الربح وتوليد العوائد من أعمالها، بالاضافة الى الزام الشركات بتطبيق الافصاح الالكتروني باستخدام نظام XBRL ودمجه مع أنظمة المحاسبة لديها لتسهيل مهمة عرض المعلومة بشكل واصح ودقيق.

الكلمات المفتاحية: الاداء المالي، القيمة السوقية، لغة الافصاح الالكتروني XBRL، سوق عمان المالي

1 المقدمة

تعتبر الربحية و تعظيم حقوق المالكين الهدف الرئيسي لأي شركة والذي يتحقق بتعزيز القيمة السوقية للشركة من خلال رفع اسعار الأسهم المتداولة للشركة في الأسواق المالية واللتي تعبر بدورها عن القيمة السوقية لتلك الشركة، حيث ان القيمة السوقية للشركة اصبحت ذات اهمية كبيرة لجميع الاطراف التي تستخدم التقارير المالية الخاصة بالشركة و بالخصوص المستثمرين الحاليين او المستقبليين لانها تساعد على اتخاذ القرار الاستثماري المتعلق بالقيمة السوقية للشركة (السويركي، 2021).

وقد اصبح من المهم اليوم احتساب القيمة السوقية للمشاريع او الشركات سواء كانت للمستثمرين المحتملين الذين يرغبون في الاستثمار او لأصحاب الشركات حيث انها كانت تعتبر في السابق غير مربحة وذات تكلفة عالية ولكن اليوم اصبح من المهم معرفة القيمة الحقيقية الخاصة بالشركة لما توفره لرؤية الشركة بالصورة المناسبة . (Kusainov .et al 2020) وقد بداء المستثمرين بالاهتمام بالقيمة السوقية للشركة لان قيمة الشركة تعد مؤشر مالي حيث اي انه اذا كانت القيمة السوقية للشركة مرتفعة من الممكن ان تشير الى زيادة الوعي للمستثمرين في اختيار الشركات الجيدة لانها تنعكس على اسعار استثماراتهم (Sondakh, R 2019).

ان هناك العديد من العوامل التي تؤثر على القيمة السوقية منها الاداء المالي حيث انه له تأثير كبير على القيمة السوقية كما تم إيجاده من خلال دراسة (عبد العزيز، محمد ،2020)حيث ان الاداء المالي له علاقة إيجابية بدرجة كبيرة مع القيمة السوقية تصل الى نسبة 91%.هناك عدة عوامل تؤثر على الاداء المالي للشركة كما انها تؤثر على مستويات الاداء المالي ومن هذه العوامل البيئية والعواملالمالية والعوامل التنظيمية والعوامل القانونية والعوامل التنافسية واستخدام التكنلوجيا (تواتي حياة ,2019) وقمنا بأضافة نظام الافصاح الإلكتروني بلغة ال XBRL لتعزيز الاداء المالي الذي سنعكس على القيمة السوقية للشركة. حيث تعد لغة ال XBRL لغة برمجة كما تعد اهم اللغات التي تستخدم في مجالات المحاسبية وقد كان هدفها الاساسي بناء نظام معلومات محاسبي وقياسي يقوم على معالجة المعلومات ونقلها عبر الشبكات الى المستخدمين بطريقة سهلة. انا ال XBRL تتيح للمستخدمين التحليل وظبط البيانات المالية بطريقة اكثر فاعلية وكفاءة كما انها تساعد في الارتقاء بالدقة والسرعة في التعامل مع البيانات ايضا تساعد على تحقيق الوفورات في التكلفة اي انها تعزز من دور الاداء المالي (مصطفى و محمد ،2020).

تعتبر القيمة السوقية للشركة من المقاييس الهامة التي يستند اليها المستثمرون في اتخاذ قراراتهم في تخصيص وتوزيع راس المال، بالإضافة الى ان إدارة الشركة تسعى وبشكل كبير الى تعظيم القيمة السوقية للشركة وذلك من خلال عدة وسائل اما من خلال وضع سياسة استثمار مثلى وخطط تنفيذية لتحقيق اعلى قيمة للشركة من خلال تحقيق أداء مالي مميز ،ولكن تسعى بعض الشركات الى تعظيم قيمة الشركة السوقية من خلال اللجوء الى استغلال المرونة في بعض السياسات المحاسبية التي من شأنها تعظيم الربحية مثل إدارة الأرباح وتمهيد الدخل أوعدم الإفصاح عن بعض المعلومات الهامة في الشركة. ومن خلال النتائج التي حصلنا عليها من خلال تحليل نتائج الدراسات السابقة وجدنا ان الاداء المالي الجيد للشركة يساهم بشكل كبير في تعزيز القيمة السوقية للشركة. واذا كان الاداء المالي ضعيف ستكون النتيجة سلبيىة على القيمة السوقية للشركة. ومن خلال تحليلنا ايضا لنتاج الدراسات السابقة في البيئة الاردنية تحديداً، تبين ان اداء الشركات الاردنية والصناعية منها تحديدا يعتبر ضعيف الى حد ما، وهذا يقودنا الى الحكم بأن ضعف الاداء المالي يعتبر السبب الرئيس الذي يؤثر سلبا على القيمة السوقية للشركة، حيث تعتبر هذه القضية هي المشكلة الرئيسية التي تسعى الدراسة الى معالجتها. ولذلك، ومن أجل تعزيز القيمة السوقية للشركة كان لابد لنا من تعزيز الاداء المالي للشركات أولاً. فقامت هذه الدراسة بتسليط الضوء على الافصاح بلغة XBRL (كمتغير معدل) واضافته الى نموذج الدراسة كمساهمة بحثية ولدوره الهام ايضاً (بناء على الدراسات السابقة) في تعزيز الاداء المالي للشركات والذي يقودنا في نهاية الامر الى تحقيق هدف الدراسة والمتمثل بتعزيز قيمة الشركة سوقياً. تواجه الشركات الصناعية الأردنية تحديات في تعزيز الأداء المالي وزيادة القيمة السوقية بسبب محدودية الشفافية في الإفصاح المالي وعدم اعتماد نظم الإفصاح الإلكتروني الحديثة مثل .XBRL على الرغم من أهمية الإفصاح المالي في تحسين كفاءة القرارات الاستثمارية وزيادة ثقة المستثمرين، إلا أن الدراسات السابقة لم تبحث بشكل كافٍ العلاقة بين الأداء المالي والقيمة السوقية، والدور المحتمل لنظام XBRL كمتغير معدل في هذه العلاقة، مما يخلق فجوة معرفية تحتاج إلى استكشافها لمعرفة كيفية تعزيز القيمة السوقية للشركات من خلال تحسين الأداء المالي وفعالية الإفصاح المالي.

2 اسئلة الدراسة واهدافها

تسعى الدراسة لقياس الدور المعدل لنظام الافصاح الالكتروني بلغة XBRLعلى العلاقة بين الاداء المالي والقيمة السوقية للشركة من خلال الاجابة على الاسئلة البحثية التالية:

1. ما هي العلاقة بين الاداء المالي والقيمة السوقية للشركات الصناعية الاردنية المدرجة؟
2. ما هو دور الأفصاح الألكتروني بلغة ال XBRL على العلاقة بين الاداء المالي والقيمة السوقية للشركات الصناعية الاردنية المدرجة؟

من خلال الاسئلة البحثية السابقة يمكن تلخيص اهم الأهداف التي تسعى هذه الدراسة الى تحقيقها ومنها :

1- معرفة العلاقة بين الاداء المالي والقيمة السوقية في الشركات الصناعية الأردنية.

2- ما هو دور الأفصاح الألكتروني بلغة ال XBRL على العلاقة بين الاداء المالي والقيمة السوقية في الشركات الصناعية الأردنية.

3 الدراسات السابقة وتطوير الفرضيات

3.1 دراسة العلاقة بين الاداء المالي والقيمة السوقية

هدفت دراسة حابي وبرودى (2023) إلى تحليل تأثير المؤشرات التقليدية والحديثة للأداء المالي على قيمة مجموعة من المؤسسات المدرجة في بورصة عمان على مدى الفترة من عام 2009 إلى عام 2020. تم استخدام نموذج التأثيرات العشوائية لتحليل البيانات الطولية في هذه الدراسة. أظهرت نتائج الدراسة أن للعائد على الموجودات تأثيرًا سلبيًا ذو دلالة إحصائية على قيمة هذه المؤسسات. وهذا يعني أن زيادة في عائد الموجودات تؤدي إلى انخفاض في قيمتها. من ناحية أخرى، كانت لنسبة التداول تأثيراً سلبياً أيضًا على القيمة، ولكنها لم تظهر دلالة إحصائية بالمعنى التام. على الجانب الآخر، أظهرت الدراسة أن للقيمة السوقية المضافة تأثيرًا إيجابيًا ومعنويًا على قيمة هذه المؤسسات.

وفي سياق مماثل اجرى (عبدالله واخرون ، 2022) دراسة هدفت إلى تسليط الضوء على تأثير العائد على الأصول على القيمة السوقية باستخدام مقياس (Tobin's Q)، بالإضافة إلى استكشاف تأثير عوائد حقوق الملكية باستخدام نفس المقياس على البنوك المُدرَجة في البورصة المصرية وكانت عينة الدراسة للبنوك المسجلة في البورصة في الجمهورية المصرية في الفترة الزمنية من 2011 الى 2020. حيث أظهرت نتائج هذه الدراسة أنه لا يمكن الاعتماد على وجود تأثير معنوي للعائد على الأصول على القيمة السوقية للبنوك المدروسة. على الجانب الآخر، أشارت النتائج إلى وجود تأثير معنوي للعائد على حقوق الملكية على القيمة السوقية لهذه البنوك. تجلى أيضًا من خلال نتائج الدراسة أن الفائدة المتحققة لا تترتب عليها تأثير يذكر على القيمة السوقية للبنك

وأجرى جود الحلبي وكنجو (2021) دراسة هدفت الى فهم العوامل التي تؤثر على القيمة السوقية للأسهم، وتحليل هذه العوامل باستخدام المصارف الإسلامية المدرجة في سوق دمشق للأوراق المالية. تمت دراسة ثلاث مصارف محددة (مصرف سورية الدولي الإسلامي، مصرف البركة، ومصرف الشام) خلال الفترة من عام 2015 إلى عام 2019. تبين من نتائج الدراسة أنه لا يوجد تأثير ذو دلالة إحصائية على القيمة السوقية للأسهم للمتغيرات المذكورة (ربحية السهم، القيمة الدفترية للسهم، معدل المديونية، معدل دوران السهم) بالنسبة لمصرفي سورية الدولي الإسلامي والبركة. بالنسبة لمصرف الشام، كانت العوامل غير المؤثرة في القيمة السوقية للأسهم هي معدل العائد على حقوق المساهمين والقيمة الدفترية للسهم ومعدل دوران السهم.

وهدفت دراسة (زملط، إياد، عابد، ومحمد ،2019) إلى فهم كيفية تأثير مؤشرات السيولة النقدية المصرفية ومؤشرات الربحية على مؤشرات القيمة السوقية للمصارف المُدرجة في بورصة فلسطين خلال الفترة من 2010 إلى 2017 وعددها 6 مصارف. أظهرت نتائج الدراسة أن هناك تأثيرًا إيجابيًا لمؤشرات الربحية على مؤشرات الأداء السوقية باستثناء معدل دوران السهم. بالمقابل، لم تظهر أثرًا معنويًا لمؤشرات السيولة النقدية على مؤشرات الأداء السوقية باستثناء نسبة الاحتياطي النقدي في بعض الحالات، وذلك عند استخدام مقياس (Tobin's Q) و(القيمة السوقية القيمة الدفترية). علاوة على ذلك، تبين أن هناك علاقة إيجابية قوية تربط بين مؤشرات الربحية ومؤشرات الأداء السوقية بشكل عام. حيث توصي الدراسة بضرورة توجيه المستثمرين للانتباه والاهتمام الكبير بمؤشرات الربحية عندما يقومون بتقييم المؤسسات الاقتصادية. أسواق مالية أكثر صحة واستقرارًا. كما هدفت دراسة(Jihadi et. al., (2021 إلى استكشاف تأثير عدة عوامل على قيمة الشركة، بما في ذلك السيولة، والنشاط، والرافعة المالية، والربحيةباستخدام عينة تتألف من 22 شركة مُدرجة ضمن مؤشر LQ45 في بورصة إندونيسيا خلال فترة 2014-2019 .أظهرت نتائج الدراسة أن السيولة، والنشاط، والرافعة المالية، والربحية لها دور مهم في تحديد قيمة الشركة، مما يؤكد على أهمية هذه العوامل وفقًا لفرضيات البحث الأولية.

وعليه، ومن خلال ما سبق من تحليل للدراسات السابقة وبيان نتائجها، يمكن تطوير الفرضية البحثة الاولى بما يلي:

"يوجد علاقة ذات دلالة احصائية بين الاداء المالي والقيمة السوقية في الشركات الصناعية الأردنية "

3.2 العلاقة بين الافصاح الالكتروني بلغة XBRL على العلاقة بين الاداء المالي والقيمة السوقية

فيما يتعلق بالدراسات التي تناولت الافصاح الالكتروني بلغة XBRL على العلاقة بين الاداء المالي والقيمة السوقية في الشركات الصناعية الأردنية، فقد استعان الباحث بالدراسات السابقة وربط العلاقات بين هذه المتغيرات لتقديم فرضية بحثية تتناسب وطبيعة العلاقة التي توصلت اليها الدراسات السابقة حيث انه لا يوجد دراسات (على حد علم الباحث) تناولت العلاقة بين لافصاح الالكتروني بلغة XBRL على العلاقة بين الاداء المالي والقيمة السوقية.

هدفت دراسة Cormier, D., Teller, P., & Dufour, D. (2022) إلى استكشاف ما إذا كان الكشف عن امتدادات XBRL من قبل الشركة يوفر معلومات ذات صلة للمشاركين في السوق. تتناولت هذه الورقة أيضًا تحقيق مستوى مناسب من توازن المعلومات بين أصحاب المعرفة داخل الشركة وبين المستثمرين. نتائج الدراسة أظهرت أن بعد مستوى معين من الكشف عن امتدادات XBRL، يكون لهذا التأثير تأثير سلبي على تسعير الأسهم (مما يؤدي إلى زيادة التشوش في أسواق الأسهم). بالتحكم في هذه الظاهرة، تكون كل من امتدادات IFRS و US-GAAP XBRL ذات قيمة عملية. بالإضافة إلى ذلك، تشير النتائج إلى أن امتدادات XBRL ترتبط إيجابيًا (أو سلبيًا) بقيمة السوق للأسهم فيما يتعلق بالشركات التي تحقق أرباح إيجابية (أو سلبية). وهذا يشير إلى وجود تأثير تكميلي بين الأرباح وامتدادات XBRL فيما يتعلق بعلاقتهما بسعر السهم أو Tobin's Q. وأخيرًا، تشير النتائج أيضًا إلى أن كل من امتدادات IFRS وامتدادات US-GAAP تترافق مع تقليل عدم تناظر المعلومات (أي زيادة تناسق المعلومات بين المشاركين في السوق).

كما هدفت دراسة Selfiani, S., & Yunita, I. (2022) الى فهم تأثير الثقافة الخضراء والمسؤولية الاجتماعية للشركات على الأداء المالي، مع استخدام XBRL كمتغير معتدل. تم جمع البيانات الكمية والثانوية لشركات التصنيع المُدرجة في بورصة إندونيسيا (IDX) لعام 2020. تم قياس الأداء المالي باستخدام مؤشر ROA (عائد على الأصول)، الثقافة الخضراء باستخدام مؤشر مخصص لها، المسؤولية الاجتماعية للشركات باستخدام مؤشر مخصص لها، وتنفيذ XBRL باستخدام مؤشر مخصص له. تم تحليل البيانات باستخدام الإحصاءات الوصفية لحساب المتوسط والحد الأدنى والحد الأقصى والانحراف المعياري. توضح النتائج أن تطبيق XBRL يعزز العلاقة بين الثقافة الخضراء والأداء المالي، وكذلك يعزز العلاقة بين المسؤولية الاجتماعية للشركات والأداء المالي.

وعليه، ومن خلال ما سبق من تحليل للدراسات السابقة وبيان نتائجها، يمكن تطوير الفرضية البحثة الثانية بما يلي:

"يوجد علاقة ذات دلالة احصائية بين الافصاح الالكتروني بلغة XBRL على العلاقة بين الاداء المالي والقيمة السوقية في الشركات الصناعية الأردنية".

4 منهجية الدراسة

اعتمدنت الدراسة الحالية على الشركات الصناعية الاردنية المدرجة في سوق عمان المالي، حيث تم التركيز على القطاع الصناعي لما له من اسهامات واضحة في الناتج القومي الاجمالي ويشغل نسبة اكبر من 30% من الايدي العاملة. بلغ عدد الشركات الصناعية بتاريخ جمع البيانات (53) شركة صناعية بمعدل (28%) من العدد الإجمالي للشركات . حيث تبين أن هنالك (30) شركة صناعية تنطبق عليها

الشروط المذكورة خلال الفترة، وبذلك تكون عينة الدراسة قد شكلت ما نسبته (56.6%) من حجم العينة الاولية للدراسة، والبالغ (53) شركة مدرجة. وتم التركيز على القطاع الصناعية

تتضمن فترة الدراسة (6) سنوات، تمتد منعام 2017 الى عام 2022، تم تقسيم الفترة الزمنية إلى مرحلتين، مرحلة ما قبل تطبيق نظام الإفصاح الإلكتروني بلغة XBRL (2017–2019) ومرحلة ما بعد التطبيق (2020–2022)، مما يتيح تقييم تأثير XBRL كمتغير معدل على العلاقة بين الأداء المالي والقيمة السوقية بشكل واضح. ثانياً، توفر البيانات المالية السنوية الموثقة والمتوافقة مع معايير الإفصاح الدولي IFRS خلال هذه الفترة بشكل كامل ودقيق لجميع الشركات الصناعية الأردنية المدرجة في سوق عمان المالي. ثالثاً، اختيار هذه الفترة يسمح بإجراء المقارنة مع الدراسات السابقة التي تناولت أداء الشركات قبل وبعد إدخال نظم الإفصاح الإلكترونية، كما أن البيانات الأحدث (2023–2024) لم تتوافر بعد بشكل كامل أو معتمد رسميًا عند بداية إعداد الدراسة، مما قد يؤثر على موثوقية التحليل.

4.1 طرق قياس متغيرات الدراسة

4.1.1 المتغير التابع (القيمة السوقية للشركة)، وقد تم قياسه بالمتغيرات الآتية:

نسبة Tobin's Q: والذي قد تم استخدامه من قبل العديد من الدراسات السابقة ومنها (علي، 2019؛ عيد ومحمد، 2023)، من خلال المعادلة التالية:

$$\text{نسبة Tobin's Q} = \frac{\text{القيمة السوقية لحقوق الملكية + القيمة الدفترية لاجمالي الديون}}{\text{القيمة الدفترية لاجمالي الاصول}}$$

4.1.2 المتغير المستقل (الأداء المالي)، وقد تم قياسه من خلال الربحية مقاسة بنسبة معدل العائد على الاستثمار. تم اختيار معدل العائد على الاستثمار (ROA) كمؤشر لقياس الأداء المالي للشركات الصناعية الأردنية لعدة أسباب: أولاً، يُعد ROA من المقاييس الشائعة والدقيقة في تقييم مدى كفاءة إدارة الشركة في استخدام أصولها لتحقيق الأرباح، وهو ما يربط الأداء المالي بالقيمة السوقية للشركة بشكل مباشر. ثانياً، يشير الأدبيات السابقة إلى أن ROA متوافق مع قياس الربحية في الدراسات المقارنة للشركات الصناعية، مثل دراسة Eshov (2020)وAbd El Aziz & Mohammad (2020)، مما يعزز إمكانية المقارنة مع نتائج سابقة. ثالثاً، يوفر ROA مؤشراً شاملاً يأخذ في الاعتبار كل من حقوق الملكية والديون طويلة الأجل، وبالتالي يعكس الصورة المالية الكاملة للشركة مقارنة بمقاييس الربحية الأخرى مثل صافي الربح أو العائد على حقوق الملكية فقط. حيث تم استخدام هذا المقياس من قبل العديد من الدراسات السابقة ومنها (Eshov, 2020). من خلال المعادلة التالية:

معدل العائد على الاستثمار = صافي الربح / (الالتزامات طويلة الأجل + حقوق الملكية)

4.1.3 المتغير المعدل (الإفصاح الإلكتروني بلغة XBRL)، وقد تم قياسه بمتغير وهمي يعطى قيمة (1) للشركة التي تستخدم نظام XBRLفي افصاحاتها، وقيمة (0) للشركة التي لا تستخدم هذا النظام، وقد تم استخدام هذا المقياس من قبل العديد من الدراسات السابقة ومنها (Cong et al., 2019; Li et al., 2021; Tawiah & Borgi, 2022).

نتائج الدراسة

يبين الجدول ادناه الاحصاء الوصفي لمتغيرات الدراسة (المستقل والتابع) خلال سنوات الدراسة. يظهر الجدول رقم (1) القيم الإحصائية الوصفية للمتغيرات المستقلة (معدل العائد على الاستثمار) والمتغير التابع (القيمة السوقية للشركة) خلال فترة الدراسة. يوضح الجدول أن متوسط معدل العائد على الاستثمار بلغ 1.459، مع انحراف معياري مرتفع نسبياً (13.186)، مما يشير إلى تباين كبير في الأداء المالي بين الشركات. أما بالنسبة للقيمة السوقية، فيظهر المتوسط 1.032 مع انحراف معياري 0.760، مما يعكس تفاوتاً في القيمة السوقية للشركات ضمن العينة. تُظهر هذه البيانات الأساسية التوزيع الأولي للمتغيرات وتدعم استخدام الانحدار الخطي لتحليل العلاقة بين الأداء المالي والقيمة السوقية.

جدول (1) الاحصاء الوصفي للمتغير التابع والمتغير المستقل

المقياس	القيمة السوقية للشركة	معدل العائد على الاستثمار
الوسط الحسابي	1.032	1.459
الانحراف المعياري	0.760	18613.
القيمة العليا	4.592	42.685
القيمة الدنيا	0.117	-93.064

بينما يظهر الجدول (2) ادناه الاحصاء الوصفي للمتغير المعدل في الدراسة (الإفصاح الإلكتروني بلغة XBRL):

الجدول (2): الإحصاء الوصفي للإفصاح الإلكتروني بلغة XBRL في الشركات الصناعية الأردنية

السنة	تطبق نظام XBRL		لا تطبق نظام XBRL	
	التكرار	النسبة المئوية	التكرار	النسبة المئوية
2019-2017	**0**	**0.0**	**90**	**100.0**
2020	**28**	**93.3**	**2**	**6.7**
2021	**29**	**96.7**	**1**	**3.3**
2022	**30**	**100.0**	**0**	**0.0**

يظهر الجدول (2) أنه خلال الفترة (2017-2019) بلغ عدد الشركات الشركات الصناعية الأردنية المساهمة العامة التي لا تطبق نظام الإفصاح الإلكتروني بلغة XBRL (30) شركة والتي شكلت ما نسبته (100%) من إجمالي الشركات، بينما بلغ عدد الشركات التي

استخدمت هذا النظام عام 2020 (28) شركة وبنسبة بلغت (93.3%) وفي عام 2021 بلغت نسبة استخدام النظام (96.7%) وبعدد شركات بلغ (29) شركة، بينما في عام 2022 بلغ عدد الشركاتالتي استخدمت هذا النظام (30) شركة وبنسبة بلغت (100%). وهذا التوزيع في نسب الشركات يتوافق مع توقيت استخدام نظام الإفصاح الإلكتروني بلغة XBRL في الأردن، والذي بدء في عام 2020.

4.2 اختبارات مدى ملاءمة البيانات لنموذج الدراسة

تم اجراء العديد من الاختبارات للتأكد من صلاحية بيانات الدراسة الى التحليل لاحصائي وذلك من خلال فحص **اختبار الارتباط الخطي المتعدد (الامتداد الخطي) Multicollinearity Test**، فقد تم التحقق من عدم وجود هذه المشكلة من خلال إيجاد مصفوفة الارتباط، والتي تشير إلى خلو البيانات من هذه المشكلة إذا لم تتجاوز قيمة الارتباط بين أي متغيرين مستقلين القيمة (±0.80) (Guajarati, 2004).

كما تم اختبار معامل تضخم التباين بين المتغيرات المستقلة وأن قيم معامل تضخم التباين جميعها كانت أكبر من العدد 1 وأقل من العدد 10، مما يشير إلى عدم وجود مشكلة الارتباط الخطي المتعدد بين المتغيرات المستقلة في الدراسة، وهذا يعني أن البيانات صالحة لعملية التحليل. اما فيما يتعلق باختبار **الارتباط الذاتي (Autocorrelation)** من خلال إجراء اختبار داربن - واتسون (Durbin - Watson Test (D - W))، والذي يعد من أكثر الاختبارات الشائعة الاستخام في هذا المجال. حيث تبين عدم وجود ارتباط بين حدود الأخطاء العشوائية في نموذج الانحدار، أي خلو البيانات من مشكلة الارتباط الذاتي، حيث تراوحت قيم معامل (D-W) المحسوبة ما بين (1.817 – 2.090) وهي تقترب من العدد 2. كما تم التأكد من التوزيع الطبيعي لبيانات الدراسة وخلوها من القيم الشاذة وذلك قبل البدء بعملية التحليل.

4.2.1 نتائج إختبار الفرضية الرئيسية الأولى

تهدف الفرضية الرئيسة الأولى إلى اختبار العلاقة بين الأداء المالي (المتغير المستقل) وبين القيمة السوقية للشركة (المتغير التابع)، حيث تنص هذه الفرضية على أنه: "**يوجد علاقة ذات دلالة إحصائية بين الأداء المالي والقيمة السوقية للشركة**". وقد تم إخضاع هذه الفرضية لتحليل الإنحدار الخطي المتعدد، وظهرت النتائج كما يأتي:

الجدول (3): نتائج اختبار العلاقة والأثر بين الأداء المالي والقيمة السوقية للشركة

المتغير التابع	ملخص النموذج Model Summary		تحليل التباين ANOVA	
	معامل التحديد R^2	معامل التحديد المعدل Adj. R^2	قيمة F المحسوبة	Sig (F)
القيمة السوقية للشركة	0.407	0.369	10.694	0.000

يظهر الجدول (3) وجود الأثر المعنوي للأداء المالي في القيمة السوقية للشركة، حيث بلغت قيمة F المحسوبة (10.694) وبمستوى دلالة (SigF=0.000) وهي أقل من 0.05، كما وأشارت قيمة معامل التحديد (R^2=0.407)إلى أن ما نسبته (40.7%) من التباين في القيمة السوقية للشركة يمكن تفسيره من خلال مقاييس الأداء المالي مجتمعة، مع بقاء أي عوامل أخرى ثابتة، ولذلك يعتبر نموذج الدراسة ذو دلالة إحصائية.

وبناءً على ما سبق، يتم قبول الفرضية الرئيسة الأولى والتي تنص على أنه: "يوجد علاقة ذات دلالة إحصائية بين الأداء المالي والقيمة السوقية للشركة".

الجدول (4): نتائج اختبار العلاقة والأثر بين الأداء المالي والقيمة السوقية للشركة

معاملات الإنحدار Coefficients				
	المتغير المستقل	المعاملات (B)	قيمةT المحسوبة	Sig(T)
	معدل العائد على الاستثمار	0.027	23.705	0.000

. ومن خلا لانتائج الظاهرة بالجدول رقم (4)، حيث بلغت قيمة B (0.027)، وبلغت قيمة T المحسوبة (23.705)، وبمستوى دلالة (SigT=0.000)، وهي أقل من 0.05، مما يشير إلى وجود أثر معنوي لمعدل العائد على الاستثمار في القيمة السوقية للشركة

4.2.2 نتائج إختبار الفرضية الرئيسية الثانية

تهدف الفرضية الرئيسة الثانية إلى اختبار العلاقة للدور المعدل للإفصاح الإلكتروني بلغة XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة، حيث تنص هذه الفرضية على أنه: "**يوجد علاقة ذات دلالة إحصائية بين دور الـ XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة**". وقد تم إخضاع هذه الفرضية لتحليل الإنحدار الخطي الهرمي التفاعلي، وظهرت النتائج كما يأتي:

الجدول (5): نتائج اختبار العلاقة بين دور الـ XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة

المتغير التابع	ملخص النموذج Model Summary		تحليل التباين ANOVA	
	معامل التحديد R^2	معامل التحديد المعدل Adj. R^2	قيمة F المحسوبة	Sig (F)
القيمة السوقية للشركة	0.556	0.491	8.554	0.000

يظهر الجدول (5) وجود الأثر المعنوي لـ XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة، حيث بلغت قيمة F المحسوبة (8.554) وبمستوى دلالة (SigF=0.000) وهي أقل من 0.05، كما وأشارت قيمة معامل التحديد (R^2=0.556) إلى أن

ما نسبته (55.6%) من التباين في القيمة السوقية للشركة يمكن تفسيره من خلال التباين في المتغيرات مجتمعة، مع بقاء أي عوامل أخرى ثابتة.

وبناءً على ما سبق، يتم قبول الفرضية الرئيسة الثانية والتي تنص على أنه: "يوجد علاقة ذات دلالة إحصائية بين دور الـ XBRL على العلاقة بين الأداء المالي والقيمة السوقية للشركة".

5 الخاتمة

هدفت الدراسة الحالية إلى تحليل العلاقة بين الأداء المالي والقيمة السوقية للشركات الصناعية الأردنية، مع دراسة الدور المعدل لنظام الإفصاح الإلكتروني بلغة .XBRL اعتمدت الدراسة المنهج الوصفي التحليلي، مع تحليل البيانات المالية السنوية للشركات خلال الفترة 2017–2022، وقُيمت المتغيرات باستخدام نماذج الانحدار الخطي والمتعدد والمتغير المعدل.XBRL

أظهرت النتائج وجود علاقة ذات دلالة إحصائية بين الأداء المالي والقيمة السوقية للشركة، كما بينت الدراسة أن الإفصاح الإلكتروني بلغة XBRL يعزز هذه العلاقة، مما يؤكد أهمية تطبيق نظم إفصاح حديثة وموحدة لتعزيز الشفافية المالية. تعكس هذه النتائج أهمية تبني الشركات الأردنية سياسات إفصاح واضحة وفعالة، بما يسهم في تحسين كفاءتها المالية وزيادة ثقة المستثمرين. استنادًا إلى النتائج، توصي الدراسة بضرقرة تبني الشركات الصناعية الأردنية نظام الإفصاح الإلكتروني XBRL ودمجه مع أنظمة المحاسبة الداخلية. تعزيز الشفافية في إعداد التقارير المالية لتسهيل اتخاذ قرارات استثمارية مبنية على معلومات دقيقة. وضرورة تطوير كفاءة الموظفين الماليين من خلال التدريب على المعايير الدولية وإعداد التقارير باستخدام.XBRL .

6 المراجع

1. تواتي، حياة، خدام، قدام، &جمال، (مشرف). (2019). دراسة العوامل المؤثرة على الأداء المالي للمؤسسة الاقتصادية: دراسة قياسية للمؤسسات المدرجة في مؤشر داو جونز الصناعي (أطروحة دكتوراه، جامعة جيجل).
2. جود الحلبي، &كنجو، أ. د. كنجو. (2021). العوامل المؤثرة في القيمة السوقية لأسهم المصارف الإسلامية المدرجة في سوق دمشق للأوراق المالية .مجلة جامعة حماة، 4.(2)
3. زملط، إياد، عابد، &محمد. (2019). أثر مؤشرات السيولة والربحية على مؤشرات الأداء السوقية للمصارف المدرجة في بورصة فلسطين.
4. السويركي، هاني جودت. (2021). أثر آليات الحوكمة في القيمة السوقية للشركات: دراسة تطبيقية على الشركات الصناعية المدرجة في بورصة فلسطين .مجلة الجامعة الإسلامية للدراسات الاقتصادية والإدارية، 29.(3)
5. القزاز، عبدالله، &السقا، زياد. (2019). دور لغة تقارير الأعمال الموسعة (XBRL) في تحسين جودة الإفصاح المحاسبي الإلكتروني: التطبيق على مصروف الموصل للتنمية والاستثمار .مجلة تنمية الرافدين، 283.38–255 ,
6. مصطفى، سليمان، &أبو مصطفى، محمد. (2020). العوامل المؤثرة على تطبيق اللغة العالمية للتقارير المالية الإلكترونية الموسعة (XBRL) في الشركات المدرجة في بورصة فلسطين للأوراق المالية.
7.
8. Abdullah, A., & Others. (2022). The impact of return on assets on market value using Tobin's Q: Evidence from listed banks in Egypt (2011–2020). *[Journal/Publisher missing – needs completion]*
9. Abu Nassar, M., & Humadat, J. (2019). *International financial reporting*. Dar Wael, Amman, Jordan.
10. Al-Qazzaz, A., & Al-Saqqa, Z. (2019). The role of XBRL in improving the quality of electronic accounting disclosure: Application to development and investment projects. Tanmiyat Al-Rafidain Journal, 38, 255–283.
11. Al-Sweirki, H. J. (2021). The effect of governance mechanisms on firm market value: An applied study on industrial companies listed on the Palestine Stock Exchange. Islamic University Journal of Economic and Administrative Studies, 29(3).
12. Al-Sweirki, H. J. (2021). The effect of governance mechanisms on market value of firms: A case study on industrial companies listed in Palestine Stock Exchange.
13. Cong, F., et al. (2019). [Title missing – needs completion]
14. Cormier, D., Dufour, D., Luu, P., Teller, P., & Teller, R. (2019). The relevance of XBRL voluntary disclosure for stock market valuation: The role of corporate governance. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration, 36*(1), 113–[page range missing].
15. Eshov, [Initials]. (2020). *[Title missing – needs completion]*
16. Eshov, M. P., Abdurakhmanova, G. K., Burkhanov, A. U., Abdusalomova, N. B., & Ergasheva, S. T. (2024). Development of international entrepreneurship based on corporate accounting and reporting according to IFRS: Part B. Emerald Publishing.
17. IFRS Foundation. (2022). IFRIC Interpretation 6: Liabilities arising from participating in a specific market — Waste Electrical and Electronic Equipment. IFRS Foundation.

Jihadi, M., Vilantika, E., Hashemi, S. M., Arifin, Z., Bachtiar, Y., & Sholichah, F. (2021). The effect of liquidity, leverage, and profitability on firm value: Empirical evidence from Indonesia. *Journal of Asian Finance, Economics and Business, 8*(3), 423–431. .18

Joud Al-Halabi, & Kinjou, K. (2021). Factors affecting market value of Islamic banks listed on Damascus Securities Exchange. *Hama University Journal, 4*(2). .19

Kusainov, H., Demeuova, G., Nurmanov, A., Toktarova, M., & Azhaipova, I. (2020). Ways to improve company value assessment. *Social and Human Sciences, 120*. .20

Mustafa, S., & Abu Mustafa, M. (2020). Factors affecting the application of XBRL in listed companies: Evidence from Palestine Stock Exchange. .21

Selfiani, S., & Yunita, I. (2022). The effect of green culture and CSR on financial performance with XBRL application as moderating variables. *International Journal of Educational Research and Social Sciences (IJERSC), 3*(5), 1797–1807. .22

Sondakh, R. (2019). The effect of dividend policy, liquidity, profitability and firm size on firm value in financial service sector industries listed in Indonesia stock exchange 2015–2018 period. *Accountability, 8*(2), 91–101. .23

Tawati, H., Khidam, G., & Jamal, G. (2019). Factors affecting financial performance of economic institutions: A regression study of companies listed in the Dow Jones Industrial Index. (Doctoral dissertation, University of Jijel). .24

Zamlout, I., Abed, M. (2019). The impact of liquidity and profitability indicators on market performance indicators of listed banks in the Palestine Stock Exchange. .25