information

MDPI

Review

AI in the Financial Sector: The Line between Innovation, Regulation and Ethical Responsibility

Nurhadhinah Nadiah Ridzuan [1], Masairol Masri [1], Muhammad Anshari [1], Norma Latif Fitriyani [2] and Muhammad Syafrudin [2,*]

[1] School of Business & Economics, Universiti Brunei Darussalam, Bandar Seri Begawan BE1410, Brunei; 23h1922@ubd.edu.bn (N.N.R.); masairol.masri@ubd.edu.bn (M.M.); anshari.ali@ubd.edu.bn (M.A.)
[2] Department of Artificial Intelligence and Data Science, Sejong University, Seoul 05006, Republic of Korea; norma@sejong.ac.kr
* Correspondence: udin@sejong.ac.kr

Abstract: This study examines the applications, benefits, challenges, and ethical considerations of artificial intelligence (AI) in the banking and finance sectors. It reviews current AI regulation and governance frameworks to provide insights for stakeholders navigating AI integration. A descriptive analysis based on a literature review of recent research is conducted, exploring AI applications, benefits, challenges, regulations, and relevant theories. This study identifies key trends and suggests future research directions. The major findings include an overview of AI applications, benefits, challenges, and ethical issues in the banking and finance industries. Recommendations are provided to address these challenges and ethical issues, along with examples of existing regulations and strategies for implementing AI governance frameworks within organizations. This paper highlights innovation, regulation, and ethical issues in relation to AI within the banking and finance sectors. Analyzes the previous literature, and suggests strategies for AI governance framework implementation and future research directions. Innovation in the applications of AI integrates with fintech, such as preventing financial crimes, credit risk assessment, customer service, and investment management. These applications improve decision making and enhance the customer experience, particularly in banks. Existing AI regulations and guidelines include those from Hong Kong SAR, the United States, China, the United Kingdom, the European Union, and Singapore. Challenges include data privacy and security, bias and fairness, accountability and transparency, and the skill gap. Therefore, implementing an AI governance framework requires rules and guidelines to address these issues. This paper makes recommendations for policymakers and suggests practical implications in reference to the ASEAN guidelines for AI development at the national and regional levels. Future research directions, a combination of extended UTAUT, change theory, and institutional theory, as well as the critical success factor, can fill the theoretical gap through mixed-method research. In terms of the population gap can be addressed by research undertaken in a nation where fintech services are projected to be less accepted, such as a developing or Islamic country. In summary, this study presents a novel approach using descriptive analysis, offering four main contributions that make this research novel: (1) the applications of AI in the banking and finance industries, (2) the benefits and challenges of AI adoption in these industries, (3) the current AI regulations and governance, and (4) the types of theories relevant for further research. The research findings are expected to contribute to policy and offer practical implications for fintech development in a country.

Keywords: artificial intelligence; banking; finance; ethical considerations of AI; AI governance

check for updates

Citation: Ridzuan, N.N.; Masri, M.; Anshari, M.; Fitriyani, N.L.; Syafrudin, M. AI in the Financial Sector: The Line between Innovation, Regulation and Ethical Responsibility. *Information* **2024**, *15*, 432. https://doi.org/10.3390/info15080432

Academic Editor: Rúben Pereira

Received: 29 June 2024
Revised: 21 July 2024
Accepted: 23 July 2024
Published: 25 July 2024

1. Introduction

Through the introduction of new approaches that are faster, more effective, and frequently more accurate than conventional techniques, artificial intelligence (AI) disrupts established models. Below are examples accompanied by an illustration:

The traditional model of personalization and customer experience generally targets large client segments with identical messaging. On the other hand, by examining unique client information and preferences, AI disruption can tailor customer experiences. This enables companies to better serve each unique customer and increase customer happiness as well as loyalty by customizing marketing campaigns and customer interactions.

Illustration: In finance and banking, for example, a customer wants to know the status of their loan application, transfer money, and check the balance of their account. With the conventional approach, the customer calls the bank's customer care line during regular business hours and is put on hold until a representative answers. On the other hand, the user opens the bank's mobile app and communicates with the AI-powered chatbot. The customer's identity is promptly confirmed by the chatbot through safe authentication methods, after which it displays the account balance. After verifying the facts with the consumer, the chatbot proceeds with processing the transfer request. Real-time application status checks and updates are provided by the chatbot. The advantages of having an AI-powered chatbot are that users may use their computers or cellphones to access services at any time and location. Quick reaction times and instantaneous processing minimize the time spent customers. By having fewer employees for customer support, the bank can cut its operating expenses. Examples of banking chatbots include Ally Assist from Ally Bank, Erica from Bank of America, and Eno from Capital One [1].

Artificial intelligence (AI) has found widespread use in fields such as anomaly detection and forecasting [2–4], recommender systems [5], medical diagnostics [6,7], natural sciences [8–10], and search engines [8,9]. However, these industrial applications of AI are still relatively new. Several issues have emerged since its implementation, linked to various factors [11,12]. Despite the significant attention paid to AI's potential for success, there is still inadequate understanding and handling of its risks, resulting in insufficient focus on its possible drawbacks and hazards [13].

AI adoption is accelerating too quickly. A 2021 KPMG study [14] found that many respondents felt AI technology was advancing too rapidly for comfort across several sectors: technology (49%), financial services (37%), government (37%), industrial manufacturing (55%), and healthcare (35%). The survey also indicated that government intervention is necessary for AI adoption, with a significant number of respondents agreeing that governments should regulate AI technology in sectors like industrial manufacturing (94%), retail (87%), financial services (86%), life sciences (86%), technology (86%), healthcare (84%), and government (82%).

Many businesses are still in the early stages of implementing AI and are unprepared for the changes in business circumstances that occur when a machine-learning model is deployed [13]. Appropriate governance systems can mitigate many of these issues. AI, due to its inherent unpredictability, is risky without such procedures, leading to potentially negative outcomes [15,16]. Incorporating governance into AI systems is essential to ensure production safety [13].

Artificial intelligence, which makes analytical machines intelligent, enables organizations to operate wisely and effectively. The potential of AI and automation to disrupt traditional models and create new opportunities has garnered significant attention. However, because AI systems are unique and have inherent risks, they should be addressed differently from traditional software systems. AI capabilities, driven by technological advancements, are rapidly surpassing those of monitoring and validation tools. The development of AI is decentralized, facilitated by widely available open-source technologies and minimal entry barriers. AI decisions must align with business and national principles, as well as with broader ethical and societal norms [17].

Government support for AI is essential to guaranteeing that these technologies are morally sound, safe, and advantageous to society. Government regulations offer the essential guidelines required to stop misconduct, safeguard the interests of the public, and increase trust in AI systems. AI-powered chatbots, for instance, can perform banking-related duties like transferring money and checking account balances, providing roundthe-clock client support with prompt responses. Without governmental control, these AI systems may operate in violation of the law, cause ethical issues, and trigger public mistrust, which could cause harm and missed opportunities for beneficial effects. Customer satisfaction is one of the main drivers of the AI revolution, or the Fifth Industrial Revolution. AI is a potent instrument that enhances customer experiences and allows for greater personalization of services and products. The financial services sector, one of the first adopters of AI, anticipates significant advantages from its application. Machine learning (ML) in AI is expected to detect market anomalies and predict and prevent financial crises, such as the 2008 crisis. AI is also expected to transform client interactions with banks, leading to new products and services, more employment opportunities, improved transaction security, data protection, and the prevention of financial fraud or abuse. AI can help the financial industry provide more affordable services and products, enhance customer experiences, reduce losses, save money, trade more intelligently, and replace human workers in certain roles with cobots, chatbots, and robo-traders, which can solve problems more quickly and effectively while avoiding human error [18].

AI improves transaction security through real-time monitoring and analysis of transaction patterns to identify unusual activity. In order to detect irregularities that can point to fraud or unauthorized access, it employs machine-learning algorithms to learn typical transaction behaviors. An AI system is used by a bank, for instance, to track credit card transactions. A transaction is flagged as suspicious by the AI if it notices a purchase made in a foreign nation soon after a transaction in the customer's home nation. After that, the bank might notify the customer via an alert to confirm the transaction before completing it.

Through data protection using cutting-edge techniques for encryption and keeping an eye on data access, AI helps safeguard sensitive information. AI systems can examine user behavior and access logs to identify attempts at unauthorized access or data breaches. For instance, a financial institution employs AI to encrypt customer information using sophisticated algorithms, thereby providing data security. The AI system keeps an eye on data access all the time. If it notices an odd pattern of access, like an employee attempting to access a lot of customer data for hours, it sets off an alert and stops access until the behavior is confirmed.

AI helps to avoid financial fraud by identifying fraudulent trends and behaviors by analyzing massive datasets. It has the ability to identify irregularities that point to fraud, such as odd spending patterns or several transactions made quickly from various places. A bank's AI-driven fraud detection system, for instance, examines millions of transactions every day. A pattern of possible ATM-skimming fraud is identified by the AI when it observes a quick transaction from various ATMs using the same debit card. The technology notifies the customer and the bank's fraud investigation team and then automatically freezes the account. The financial industry is currently undergoing a revolution in its AI-driven operations, which are most successfully applied to customer interaction, analytics, decision support, and the observation and identification of patterns to prevent money laundering and identify fraud [19]. Major banks such as JPMorgan Chase, Wells Fargo, Morgan Stanley, HSBC, Bank of America, UBS, and Citibank have embraced AI to provide a rich client experience [20–22]. According to Schroer (2024) [22], AI is applied in the financial sector in several areas, including the following:

- AI assistants and chatbots use natural language processing to deliver immediate customer support and provide customized financial advice.
- AI technologies help banks and credit lenders make wiser underwriting decisions by using a range of factors to analyze historically underserved borrowers.
- AI-powered computers evaluate large, complex datasets faster and more effectively than humans, automating trades through algorithmic processes.
- Financial specialists use AI to spot trends, identify risks, save labor, and ensure better information for future planning. AI and ML are increasingly used to construct more precise, nimble models.

- AI enhances the security of online banking by improving efforts to detect and prevent fraud.

The ultimate goal of this research is to examine the comprehensive landscape of artificial intelligence (AI) in the finance and banking sectors. It will focus on answering the four questions below, which will help identify the gap and understand the current knowledge that contributes to policy and practical implications. This study conducts a descriptive analysis using a literature review of recent research on AI in banking and finance. The paper reviews selected recent papers to answer the following questions:

- What are the applications of AI in the banking and finance industries?
- What are the benefits and challenges of AI adoption in these industries?
- What are the current AI regulations and governance?
- What are the types of theories relevant for further research?

This paper is structured as follows. Initially, it provides an overview of AI in the banking and financial industry. Subsequent sections cover AI applications' benefits, challenges, and ethical considerations in these industries. The literature review addresses the current regulatory landscape and relevant theories, and the paper concludes with a discussion.

2. Overview of AI in Banking/Fintech

2.1. AI Definition

Artificial intelligence (AI) is the capacity of a computer system or machine to simulate and carry out operations like learning, problem solving, and logical reasoning that would typically require human intelligence. Using machine-learning algorithms and technologies to enable computers to apply specific cognitive abilities and carry out activities either fully or partially autonomously is the foundation of artificial intelligence. Tasks that appear difficult today will be completed more swiftly and correctly as artificial intelligence advances, making many procedures more efficient [23]. Artificial intelligence (AI) is a branch of computer research that aims to provide robots with human-like intelligence, enabling them to learn, assess, and respond to many types of information. AI is now a valuable tool that researchers can use to quickly and affordably gather, handle, and analyze massive amounts of data. Statistical data collected and analyzed from a huge number of published research articles will be highly accurate, according to Al-Ameri and Hameed (2023) [24].

Through data analysis, trend recognition, and intelligent decision making, artificial intelligence (AI) is revolutionizing banking and finance. AI systems in banking analyze massive datasets to identify fraud, evaluate credit risk, and engage in personalize interactions with customers. AI can anticipate market movements and improve investing strategies by identifying patterns in transaction data. With the help of this technology, financial services can potentially be provided more quickly and accurately while also increasing efficiency and lowering operating expenses. The goal of AI research is to construct intelligent machines that can perform tasks independently, adapt to changing conditions, and improve over time. AI encompasses a wide range of technologies, including robots, computer vision, natural language processing, and machine learning. AI will enable machines to perform tasks such as problem solving, judgment, natural language understanding, and object identification that would normally require human intelligence [25].

2.2. AI in Finance

The finance and banking industry has seen significant changes as a result of the incorporation of artificial intelligence (AI) technologies. Artificial intelligence (AI) has transformed traditional banking practices and financial services by utilizing its capacity to analyze vast amounts of data, recognize trends, and make insightful decisions. AI has a wide range of applications in banking and finance, with advantages including increased productivity, better decision making, lower costs, and better client experiences. Furthermore, it results in more precise risk assessments, anti-fraud measures, and investment plans. AI has boosted operational efficiency by automating manual operations, resulting in quicker transaction processing, more efficient account management, and better data analysis [26].

According to Jain (2023) [26], one of the most common applications of AI is fraud detection in banking and finance. Conventional rule-based systems struggle to keep up with the increasingly complex and sophisticated nature of fraudulent behavior. Therefore, the application of AI algorithms is faster, with more accuracy in detecting strange patterns and potential fraud attempts in vast volumes of transactional data. This safeguards the interests of both clients and the financial institution by allowing it to quickly detect and stop fraudulent activity. A further essential aspect of banking, credit rating, has also significantly benefited from AI. Traditional credit-scoring models offer less accurate risk estimates since they often rely on a small number of parameters. AI-based credit-scoring models use machine-learning algorithms to account for a broader range of factors and historical data, resulting in more accurate credit decisions. AI models help lenders make more accurate credit decisions, improve loan portfolio management, and reduce default risk.

Artificial intelligence-driven chatbots have completely changed the way that banks provide customer support. Inquiries, problems, and recommendations are all handled by these virtual assistants, which provide clients with quick and individualized help. They are available around-the-clock and can manage several customer contacts at once. As a result, there has been an increase in customer loyalty and satisfaction [27].

2.3. AI Challenges and Ethical Issues

Although there are many benefits to integrating AI into banking and finance, there are drawbacks as well as ethical issues to resolve. The application of AI requires the processing of enormous amounts of sensitive customer data. Hence, data privacy and security are crucial. Securing customer confidentiality and preventing data breaches require financial firms to have strong security protocols. To maintain fairness and prevent discriminatory results, biases in previous data must be addressed. To ensure that AI is used responsibly and to advance accountability, justice, and transparency, ethical frameworks and guidelines should be put in place [28].

AI integration in banking and finance has resulted in a new era of customer-focused services, accuracy, and efficiency. Advantages include improved decision-making processes, cost savings, and improved client experiences. Artificial intelligence (AI) technologies have revolutionized fraud detection, credit scoring, customer service, and investment management. Financial institutions must carefully address issues with regard to data privacy, bias, and ethical consequences to ensure the responsible and ethical usage of AI. By doing this, they will be able to fully utilize AI to promote innovation and long-term growth in the banking and financial sectors [26].

2.3.1. Data Privacy and Security

Challenges: The danger of confidential financial information being accessed illegally. Potential mishandling of client data for unauthorized uses.

Solutions: To secure data, use robust methods of encryption. To guarantee that only authorized workers have access to data, implement stringent access controls and conduct frequent audits. Adhere to laws regarding data privacy implemented in a nation.

2.3.2. Bias and Fairness

Challenges: Unintentionally discriminating against particular groups is a possibility with AI systems. Unfair lending and credit score decisions might result from biassed data.

Solutions: To train AI models, use a variety of sample datasets. Identify and address biases in AI systems through routine audits. Create and apply algorithms that promote fairness.

2.3.3. Accountability and Transparency

Challenges: Decisions made by AI might be complicated and challenging to comprehend. It is unclear who is in charge of AI-driven outcomes.

Solutions: Use AI models to clarify their decision-making procedures. Provide explicit guidelines outlining who is responsible for AI results. Ensure that AI systems and their selection criteria are well documented.

2.3.4. Skill Gap

Challenges: Lack of experts in data science and artificial intelligence. The current workforce might not have the essential AI expertise.

Solutions: Provide upskilling training courses to current staff members. Collaborate with academic institutions to create courses that emphasize AI. Take steps to draw in and retain AI talent.

2.4. Integration of AI and Fintech

The integration of AI and fintech is illustrated as follows. Digital payments, peer-to-peer transactions, and international payments will all continue to be offered by fintech. It will keep using technology to deliver financial services more quickly and effectively. Data science is assisting fintech in improving fraud detection, future prediction, customer service, and feedback. The fintech sector will keep working toward its objective of providing customers with experiences that are more enhanced and personalized. Although financial technology has greatly simplified the lives of some clients, it is not without its own set of difficulties. Fintech raises concerns about data security and privacy, financial inclusion, and regulatory compliance [29].

3. Methodology

This study used Google Scholar to identify ten years' worth of current works, in accordance with the literature review approach. Few papers address the four research questions, and only a few important papers that help answer the questions have been chosen based on the selection process. Therefore, this indicates the absence of a theoretical framework. Furthermore, this study identified five main paper references. For the case study in Section 7.2, namely Cases of AI Governance Frameworks, the case study information was obtained from secondary data gathered from the selected current publications. In order to examine the comprehensive landscape of artificial intelligence (AI) in the finance and banking sectors, this paper used a descriptive analysis review, answering the four questions by methodically choosing and analyzing pertinent information from reliable sources. In order to present a thorough picture of the current status of the AI landscape in the finance and banking sectors, the descriptive analysis summarized and interpreted the findings from various studies based on the research questions. This method enabled us to draw attention to significant trends and revelations, providing a strong basis for comprehending the applications of AI in the finance and banking sectors, challenges, ethical issues, regulations or guidelines and relevant theories.

4. Applications of AI in Banking and Finance

4.1. Preventing Financial Crimes

The usage of AI algorithms in banking and finance to detect fraud is increasing. These algorithms can immediately scan large volumes of transactional data, allowing them to identify unexpected trends and potentially fraudulent activities. AI systems may continuously learn from fresh data using machine-learning techniques, increasing their ability to successfully detect and prevent fraud [26].

There have been several fraudulently listed corporations throughout Wall Street's history. Investors of the future should avoid "mines" in the deep market, be transparent about their investment strategies, and keep a close check on the Pearl. Wall Street is not beyond the deception committed by Chinese-listed corporations. Currently, there are about 4000 listed companies that trade stocks. They have studied the reliability of the data and the massive financial records, which cannot be handled by human resources, but according to experts, using AI, especially algorithms, can help combat some of the concerns [30,31]. The "mine" in the path of investors' investments is financial data falsehood. The ITL anti-fraud Intelligent Technology Committee was formally formed, with member units like Connected Data promoting the use of emerging technologies like AI and big data to identify and assess fraudulent financial reporting [32].

Big data and AI, according to Shizhong Huang, head of Xiamen National Accounting College, are effective instruments for combating financial fraud. Even though the data and algorithms used to combat financial fraud are still in their early stages, they have demonstrated significant power [32]. Convolutional neural networks [33], feature-engineering strategies [34], a cost-sensitive decision tree approach [35], Bayes minimum risk [36], and a cost-sensitive and hidden Markov model [37] are some of the methods being tried by researchers in the field of Internet financial anti-fraud to detect fraudulent transactions [32].

The fight against financial fraud will likely continue in the future against improved algorithms, data processing, data warehouses, and other areas. Li Feng, vice president of the Shanghai Institute of Finance, noted that it is becoming harder to differentiate between financial fraud and legitimate financial business due to the complexity of financial information brought about by the innovation of business models and the different financial understandings of various emerging businesses. The old methods of preventing fraud are ineffective, difficult to understand, incomplete, and less intuitive in such a complicated context. Using the technological tools of cloud computing, big data, and natural language processing, an anti-fraud system must be designed and developed systematically [32].

By employing an artificial neural network to identify faked financial accounts, Küükkocaolu et al. (1997) [38] achieved a significant advancement. They employed the Beneish model to feed the ANN with data from 126 non-financially listed companies that were sampled from the Istanbul Stock Exchange. The likelihood of a successful forecast is 86.17%, whereas the likelihood of an inaccurate prediction is 13.82%. Küükkocaolu et al. (1997) demonstrated that artificial neural networks (ANNs) are capable of forecasting manipulated financial statements.

The "2018 intelligent anti-fraud insight report", which was made public in Beijing on 9 May 2019, states that Chinese Internet companies and financial institutions were implementing developing technologies like artificial intelligence (AI) as an anti-fraud measure in response to the variety of financial and telecommunications scams. According to the report, the most recent advancements in Internet technologies, like blockchain and artificial intelligence, will lead to more accurate information sources. It is tailored and utilizes targeted risk pricing models that require rigorous and scientific investment decision-making processes, with a more transparent and equitable role for credit intermediaries [32].

Lin et al. (2015) [39] sorted several fraud factors and then graded their importance using expert questionnaires and data-mining techniques. Among these, artificial neural networks, logistic regression, and decision trees are some of the data-mining techniques employed. Albashrawi (2021) [40] made every effort to examine 65 publications to provide information about the frequency and percentage of data-mining technology used in the sphere of financial fraud as well as other general business applications. The significance of AI technology in the realm of financial fraud is demonstrated by these data. Although they are not necessarily linked to the best classification outcomes, logistic regression, decision trees, SVM, NN, and Bayesian networks have been extensively utilized to identify financial fraud.

Regulators and financial institutions all over the world are already using AI to fight fraud and money laundering. HSBC and AI firm Ayasdi from Silicon Valley collaborated to simplify the process of investigating allegations of money laundering. Artificial intelligence (AI) and machine learning are being considered by the UK Financial Regulatory Authority (FCA) for use in KYC and AML procedures related to regulatory compliance enforcement. To strengthen their anti-money laundering initiatives, the Securities and Exchange Commission of the United States (SEC) and the Monetary Authority of Singapore are also utilizing AI to spot suspicious transactions. AI is now being utilized to monitor the financial performance and operational activities of listed companies as well as financial institutions. The SEC employs artificial intelligence (AI) to process and evaluate unstructured data submitted by registration applicants, to evaluate and forecast the applicants' actions across a range of dimensions and to incorporate the data into the risk assessment [32].

4.2. Credit Risk Assessment

When determining a person's or a business's creditworthiness, a credit rating is essential. More accurate risk assessments are made possible by AI-based credit-scoring models, which use machine-learning algorithms to evaluate a variety of factors from previous data. AI models provide lenders with better tools for credit evaluation since they take into account a wider range of parameters and patterns [26].

Lending constitutes a significant commercial activity for banks and other financial institutions. These organizations deal with the assessment and management of consumer credit risk. PWC and the China Banking Association collaborated to release the 2018 Chinese bankers survey report. Based on the survey results, over 60% of bankers' opinions were that the concentrated wave of non-performing loans is the biggest danger facing the global banking sector today, and over 30% agreed that this is the biggest source of pressure on bank operations. People with incomplete records are frequently evaluated using different credit risk assessment models throughout the actual loan-giving and administration process, which results in a rather flexible assessment procedure. As a result, AI uses its advantages in terms of big data analysis to analyze a variety of external, unstructured data connected to credit risk because there are a vast amount of data from different types of users. Unified risk modeling, for instance, uses data from judicial proceedings or court judicial websites, business and industrial data, public opinion data from approved media, and others to avoid prejudgment and non-performing loans [32].

Pacelli (2011) [41] developed a model for credit risk and used AI techniques to conduct credit risk management research. The ANN was trained to forecast the credit risk of the Italian manufacturing industry using the financial data of 24 companies. The findings indicate that these organizations' credit risk can be predicted by artificial neural networks. A strong tool for estimating and forecasting a company's default is the credit risk model.

Furthermore, Pacelli's study presents a novel artificial neural network that is intended to forecast the financial risk for manufacturing companies in Italy. It notes differences in construction and operation between this current model and an older one from 2004. The new network consists of an output layer that provides a risk score, two hidden layers with 10 and 3 neurons each, and an input layer with 24 neurons. In an effort to decrease the errors in its predictions, it employs a technique known as backpropagation to modify its calculations based on samples. The information used is taken from a database including the financial data of Italian companies. Typically, financial analysis and decision-making tasks are performed using this AI-based model [42–46].

Using AI, Alibaba and Jingdong provide credit to merchants as well as individuals ahead of time. Since the entire operation cycle may be watched over in the background, borrowers do not require a collateral guarantee. A client-access white list is created by the platform after it thoroughly and successfully analyzes the qualifications. This includes assets, income level, behavior, and other attributes of customers, before allowing merchants to pursue loans. In addition, it actively determines a pre-credit limit for each customer based on their risk tolerance and creates a pre-credit model that can be dynamically modified at various points in time to accommodate varying demand scenarios and circumstances [32].

The banking sector is calling for more user credit qualification assessments as a result of the growth of Internet finance, which encourages the creation of intelligent risk control. For the majority of businesses, financial risk management can minimize losses and increase revenues. Machine learning is a crucial task since tasks primarily require information-driven decision making [47].

4.3. Customer Service

Chatbots and other AI-powered virtual assistants have revolutionized customer service in the banking and financial industries. These virtual assistants respond to customers' questions, fix problems, and make recommendations to provide them with efficient individualized help. Chatbots improve the customer experience and expedite service delivery since they are always available and can handle several client conversations at once [26].

Big data and artificial intelligence (AI) are used in marketing to analyze and categorize user-generated data. By combining relevant information, including consumption preferences, financial status, and behavioral patterns, the platform can precisely position customers' demands, create customer profiles, anticipate their wants, match and push customized items, as well as create marketing copywriting. Advertisers and marketers are gradually realizing the benefits of smart marketing, and they have invested in a variety of disciplines to create a well-developed system. For example, the marketing push system's intelligent application architecture [32].

Kumar et al. (2019) [48] presented a comprehensive framework to comprehend the application of AI in customized marketing, stating that firms can use this technology to evaluate consumer data and create individualized products and services. Throughout the process, AI may continue to learn and assist managers in improving the value proposition for customers. By creating and planning products in this manner, they may boost their value to consumers and establish a long-lasting competitive advantage. Marketers utilize AI to segment the market, forecast consumers' specific preferences, deliver targeted digital ads in real time, and provide suppliers with the best promotion and pricing approaches. Timoshenko and Hauser (2019) [49] employed a convolutional neural network to filter out non-informative UGC content and cluster sentences to avoid repetitive content sampling. It has been demonstrated that the machine-learning method effectively eliminates inefficient and repetitive material from UGC while also improving the effectiveness of discovering customer demands.

4.4. Investment Management

The usage of AI algorithms in banking and finance to detect fraud is increasing. These algorithms can immediately scan large volumes of transactional data, allowing them to identify unexpected trends.

AI algorithms are rapidly being used in investment management processes. These algorithms can make smart investment judgments by analyzing large volumes of market data, news, and historical trends. AI-based investment management systems help with portfolio management, risk assessment, and trading strategy formulation, hence boosting overall investment performance [26].

The term "AI investment advisor" primarily refers to the application of theoretical models for portfolio optimization and intelligent algorithm technology to provide users with information, making investment decisions based on risk tolerance, income requirements, investment style, and other information. It also includes recommendations for enhancing asset allocation and portfolio management in response to the financial market's unpredictable shifts [50]. According to Yu and Peng (2017) [51], sophisticated financial advisors are not only more adept at investing and executing transactions than humans but may also assist investors in overcoming emotional vulnerabilities.

Currently, financial institutions are using AI technology more extensively in this industry. In the US, AI investment banking first appeared in 2008. The asset management industry has benefited from the use of AI, such as Wall Street's interest in big data and artificial intelligence, due to the growing demand for wealth management. There are many established smart investment platforms available in the US market, including Wealthfront, Betterment, Charles Schwab, Vanguard Fund, and others [32].

The Chinese market for intelligent investment banking was first dominated by Internet-based companies in 2014. Major Chinese commercial banks and financial institutions then progressively embraced the technology, which has been growing significantly in recent years. The primary players in China's intelligent investment sector at the moment are Internet firms, financial IT companies, and traditional financial institutions such as fund management, securities, etc. The first intelligent domestic investment platform, "Capricorn Investment", was introduced by China Merchants Bank in 2016. Shanghai Pudong Development Bank subsequently introduced its "financial intelligence robot" in a similar manner. The following banks launched their AI investments in 2017: Industrial Bank, Ping An Bank, Everbright Bank, Guangyun Intelligent Investment, and Industrial and Commercial Bank of China [52].

5. Benefits of AI in Banking and Finance

5.1. Enhanced Efficiency and Cost Reduction

AI technology integration automates manual tasks, cutting down on processing times and human errors. AI solutions simplify banking procedures and improve operational efficiency by automating repetitive tasks. Account management, data analysis, and transaction processing all benefit from this, which is becoming quicker and more precise. The Contract Intelligence Network (COIN) system of JPMorgan Chase, a top worldwide bank, was put in place with the use of artificial intelligence. The COIN system analyzes legal documents, including loan agreements, using machine-learning algorithms and natural language processing. By eliminating manual labor and processing time, this AI solution has greatly increased the bank's efficiency in examining and retrieving important information from complicated contracts.

AI use in banking and finance has the potential to significantly lower costs. Financial institutions can save on operating costs and use resources more efficiently by automating manual operations. AI-based solutions also improve risk management, which lowers the possibility of monetary losses. The Robo-Advisory Services from Vanguard are powered by artificial intelligence and utilized by investment management firm Vanguard to offer automated investment advice. These robo-advisors use artificial intelligence (AI) algorithms to assess investor goals, risk tolerance, and preferences. These analyses are used by the robo-advisors to build customized investment portfolios and to provide continuous monitoring as well as rebalancing. Vanguard can provide affordable investment management with a minimum of human intervention because of this AI-powered solution [26].

5.2. Improved Decision Making

Vast amounts of data are easily processed by AI algorithms, which also produce insightful results. AI-based solutions offer more precise risk assessments, fraud prevention measures, and investment strategies in the banking and financial industries. Financial organizations can improve their overall decision-making processes by using these insights to create data-driven judgments. Artificial intelligence (AI) algorithms are employed by Citibank to detect and prevent fraudulent activities. AI systems can detect suspicious patterns and possible fraudulent activity more precisely than conventional rule-based systems. This assists Citibank in proactively preventing financial losses resulting from fraud and safeguarding the accounts of its clients.

The digital payment platform PayPal uses artificial intelligence (AI) in its risk management system to identify and prevent fraudulent activity. Artificial intelligence systems evaluate various factors, including past transactions, user behavior, and geographical location, to determine the probability of fraudulent transactions. This improves user security by allowing PayPal to instantly recognize and stop potentially fraudulent transactions [26].

AI makes future predictions by processing and analyzing historical and current data with data science techniques. These forecasts may address future revenue, the best-selling price for products, or the optimal moment for a corporation to acquire or sell stock. Converting historical and current data into helpful future forecasts takes only a few seconds. AI uses data analysis techniques such as classification and clustering. Clustering allows for the grouping of comparable data points, and each smaller group must be labeled for categorization. Clustering is commonly performed using neutral networks and k-means.

Additionally, AI can detect patterns in data that humans would overlook. These trends lead to insightful comparisons of historical and contemporary data, generating intriguing possibilities for the future.

It is significant to remember that AI-generated projections of the future have flaws. Even when the facts are correct and actual, AI systems are unable to handle abrupt and unusual events beyond the norm, which can result in forecasts that are not accurate. Furthermore, company executives may find it difficult to believe the future forecasts produced by AI systems. Even if it uses data from its organizations, it is nearly impossible to figure out how it can make these forecasts. Though it is impossible to identify the specific neuron in the AI "brain" that produced the prediction, the theories can be discussed. If at all, it will take many years before people fully trust AI.

As previously noted, AI can recognize patterns quickly and with greater accuracy than humans. These machines can detect anomalies that might constitute fraud within these patterns. The fact that AI can distinguish between false and legitimate content is helpful. Numerous transactions are mistakenly reported as fraudulent, even when they are not. Machines with artificial intelligence also assist in transaction monitoring around the clock [29].

Based on ASEAN (2024), AI systems that are highly dangerous and likely to harm should, in general, use a human-in-the-loop approach, in which humans take complete control of the system and determine whether it is safe to carry out decisions. All user types should have these evaluations completed, and deployers are urged to pay particular attention to the impact on marginalized and/or vulnerable communities. Three major forms of human engagement in AI-augmented decision making may be identified based on the risk assessment of AI systems: human-in-the-loop, human-over-the-loop, and human-out-of-the-loop.

Human-in-the-loop: AI systems merely offer suggestions, which humans consider when making decisions. AI can simply offer information, and humans hold complete power over decision making. For example, when AI is used to forecast medical issues in patients, doctors or medical professionals are ultimately the ones who execute the diagnosis and provide the proper remedies. With human-in-the-loop, people need to have an adequate understanding of the factors impacting the AI system's decision and how it reaches its conclusion. This is necessary to assess if the recommendation, prediction, or decision is correct and fair or safe. Instead of blindly accepting the AI system's response in the interest of efficiency, humans should invest the time and energy necessary to conduct such an evaluation. The potential of automation bias, often known as the "rubber stamping risk", should also worry deployers. This occurs when a human becomes accustomed to accepting the AI system's outputs due to its high accuracy and fails to notice the occasional AI error because of "muscle memory" or the habit of clicking "approve". The importance of the AI system's outputs to the human making the decision, whether they are the only input of high significance or one of a dozen inputs of less significance, should also be taken into account.

Human-over-the-loop: When an AI system behaves inappropriately, faces unforeseen circumstances, or poses a risk to human safety, humans can step in to supervise and monitor the system and influence its actions. For instance, even in certain autonomous vehicles "full self-driving" mode, people must keep their hands on the wheel and eyes on the road to take quick control if necessary. As AI supervisors, humans can change the parameters while AI is in operation.

Human-out-of-the-loop: AI systems are fully capable of carrying out choices without the need for human intervention. Without the capability for a human override, the AI system is in complete charge. Recommendation algorithms, for instance, can automatically suggest goods and/or services to customers based on their usage habits and behavioral profiles. This is all without the need for human oversight or approval. Furthermore, concerning risks and human supervision, they are as follows:

- AI systems with low potential for harm are allowed to operate alone with little assistance from humans. Still, the AI system needs to be utilized responsibly and be subject to disclosure as well as transparency obligations.
- AI systems must have a suitable degree of human control (full control or supervisory control), depending on the type of system and the industry in which it is employed, to guarantee that judgments enhanced by AI are supervised.
- AI systems that pose a high risk of harm should be closely inspected and closely supervised by humans to prevent them from making decisions on their own that could have unanticipated or harmful consequences.

5.3. Enhanced Customer Experience

Chatbots and other AI-powered customer service technologies provide customers with quick, individualized assistance. Chatbots are always available to answer questions from customers, fix problems, and provide suggestions in real time. This promotes customer retention and improves the overall customer experience. The well-known financial institution Wells Fargo uses an artificial intelligence (AI) chatbot called "Erika" to improve customer service. Erika answers question, provides account information, and helps with simple transactions when interacting with clients via the bank's website and mobile app. Because of the chatbot's AI capabilities, customers may receive prompt, individualized service that is available around the clock and enhances their overall experience.

Voice recognition technology for authentication at HSBC: AI-driven voice recognition technology is employed by the international banking and financial services giant to verify the identity of its clients. AI systems confirm customers' identities during phone banking transactions by examining distinctive voice patterns and traits. By offering a convenient and safe means of authentication, this solution lessens the need for traditional security measures like PINs and passwords [26].

AI can boost customer engagement, for example, by having the capability to track the content that a customer clicks on and engages with, allowing for more personalized experiences. Customers are happier as a result, and a business makes more sales. In this sense, artificial intelligence has problems since it lacks empathy for and understanding of customers. The AI chatbot will proceed in the same way as usual, even if a customer calls their bank in a distressed, panicked manner and reports that they have misplaced their credit card. Humans occasionally experience stress and overwhelm, which require another person to react with the right amount of empathy [29].

6. Challenges

6.1. Data Privacy and Security

AI is being used in banking and finance to handle private customer information in huge volumes. Strong security measures are necessary for financial institutions to safeguard client privacy and stop data breaches. Encrypting data, storing it securely, and adhering to data protection laws are essential factors [26].

As an information-intensive industry, the financial sector frequently needs to analyze, gather, and manage a lot of customer behavior data to ensure the smooth operation of financial transactions. This also means that the range of data collection must be expanded. It will be challenging to define social problems like accountability and behavior supervision caused by failure or behavior under the current legal or regulatory framework. For instance, it is impossible to identify who is responsible for malevolent conduct caused by developers and designers. The behavior produced by AI's learning and decision-making mechanisms cannot be tracked back, as the processing costs associated with the chain consequences will rise significantly. In certain practices, there is difficulty with data-gathering validity because there is a lack of appropriate collection standards or regulations [32].

From the standpoint of data usage, once financial infrastructure and artificially intelligent communication are hacked, personal data is easily hacked by hackers or controlled by criminals, resulting in property losses for customers and even threats to personal safety.

For example, in a data leakage cost survey in 2015, which was conducted by IBM and the Ponemon Institute, according to Ponemon Institute et al. (2016) [53], there was an increase in the average total cost of data leakage for 350 participating companies from USD 3.52 million to USD 3.79 million. There was also an increase in the average cost of each missing or stolen record, which includes sensitive and confidential information, from USD 145 in 2014 to USD 154 in the 2015 survey.

Furthermore, because AI is still in its early stages of development, security flaws take longer to fix. As a result, criminals may employ related technologies to precisely identify possible targets and launch real-time attacks on the system, putting the entire social credit system at risk. The primary goals of the attackers are to steal, modify, and destroy information, as well as to impersonate people. These actions can result in fraud and financial losses. The use of personal identification for illegal purposes includes the theft of devices to gain access to and control over networks and data [54]. It will be challenging to identify social issues like accountability and behavior supervision that are brought on by failure or behavior under the current legal and regulatory framework [55].

From the standpoint of information storage, these days, with the Internet, a lot of data are typically stored on hard drives or floppy disks. There is a chance of data leaking if users mistakenly or purposely lose their data. Furthermore, in terms of data transfer, for example, the standards for algorithm application, information control, and disclosure that China's financial industry has currently embraced are not consistent. On the one hand, this poses challenges in ensuring the privacy of the AI system's data and the user's right to know. However, it also restricts the ability to integrate and transmit data, which leads to inconsistent historical data quality that is prone to errors and data loss [32].

There are potential threats to technological security as AI is still in its exploratory stages, which means there will always be a lot of technical issues and risks. For instance, face recognition is a common method used by banks to withdraw cash from ATMs. The state of face recognition technology is not quite developed enough at this point. There are some concerns associated with large-scale online face-brushing transaction services if facial recognition is the only feature. Furthermore, several technological difficulties confront intelligent investment advisory bodies due to the dependence on only AI technology [56].

There is insufficient technical depth. The black swan phenomenon has become more common in the financial market in recent years, but machine learning cannot keep up with the market's rhythms, particularly the rhythm of financial risks. However, there are also some flaws and weaknesses in the algorithm that cause a significant detachment between the scheme, investment assistance, and the reality of the market. As a result, investors suffer significant losses on their investments.

Many small and medium-sized financial organizations or institutions worldwide have a relatively low willingness or ability to apply artificial intelligence (AI). The application process is sluggish, and the benefit is not immediately apparent. This is due to the impact of technology reserves, capital scale, and talent. For instance, financial technology has not been integrated into the strategic planning of commercial banks in many locations. Financial stability will be threatened if many investors in the financial market utilize the same algorithm and manner of operation.

If an AI transaction procedure fails or an algorithm transaction error occurs, it will not just result in inaccurate data analysis and decision making but also have an impact on related business activities. This will make it difficult for financial transactions to be completed smoothly and cause financial consumers to suffer significant losses. In addition, it will have an impact on the stability of the entire financial market if it is severe. Basic research and data constraints mean that AI will not be able to handle the full, complex financial sector on its own [32].

6.2. Bias and Fairness

AI systems may unintentionally reinforce prejudices found in previous data, producing biased results. Financial organizations need to make sure that their AI systems are fair and deal with these biases. To prevent biased decision making, AI models must be routinely monitored, assessed, and adjusted [26]. Regulatory risks occur as there are now insufficiently precise regulations governing the use of AI technology in the financial sector. A dispute involving a business or service will result in several regulatory issues [56], while financial risks become increasingly hidden and complicated.

Modern technology like artificial intelligence (AI) encourages quick changes in the financial sector, new businesses, new products, and new models. It also connects businesses in other industries and makes financial risks more complex. Real-time clearing of financial transactions will be facilitated by artificial intelligence and other financial technologies. As a result, risks will spread more quickly and broadly, making it harder for financial authorities to protect the market and identify risks. It will also make market participants more fearful.

There are more hidden financial risks. Participants in financial activities now have several identities at once due to the application of AI in the industry. Financial risks are more difficult to detect and more concealed when there is a lack of supervision. Furthermore, the use of AI lowers the bar for entry into the financial industry, increases the incentive for financial institutions to take on high-risk ventures, and emphasizes the overall financial system's inclination for risk.

However, as AI is continuously promoted, financial regulators will have to address new issues in the financial sector brought about by technological advancements. In addition to the ongoing problems with the behavior and mode of traditional financial businesses. However, the present financial regulatory framework makes it more expensive to receive follow-up care and makes it rather difficult to determine who bears the risk. The stability of the financial market's order is at risk since there is a deficiency in AI simulation of certain scenarios. This can easily result in deviations in task execution and judgment, as well as irregular fluctuations in the financial market [32].

Due to the failure of a third party, financial services companies frequently collaborate with tech companies and other outside service providers rather than creating their own AI systems. A major risk to any vital system is the failure of any third-party provider. From the perspective of the regulators, this threat is increased if the market is concentrated around a small number of providers, particularly if those suppliers are unregulated and hence not directly under their control. Certain regulatory bodies, such as those in the UK and EU, are intensifying their oversight of third parties who supply "critical" services to the financial services industry [57].

6.3. Accountability and Transparency

There are ethical concerns regarding the use of AI in banking and finance. The ethical use of customer information, accountability for automated decisions, and transparency in algorithmic decision making are all requirements that financial institutions must meet. AI system development and implementation should be governed by established ethical frameworks and guidelines [26].

The importance of pertinent rules and regulations must be considered. Since the 2008 financial crisis, the global regulatory landscape has expanded and become more complex. Due to the complexity of hard and soft laws, which are not well understood or appreciated, this is posing serious issues for financial industry organizations [58]. The extensive use of AI in finance requires a legal foundation; however, at the moment, there are no systematic and standardized laws or regulations. Instead, it remains at the level of Internet finance, regardless of the standardization of regulatory laws or the specifics of regulatory policies. The regulatory boundary is unclear due to the lack of rules and regulations.

Numerous AI-related business models can only be handled by consulting the rules and legislation of both traditional and Internet-based finance. After disagreements arise, there is frequently no legal foundation for determining culpability. The financial regulatory system is facing new difficulties as a result of the creative application and advancement of AI. Even though China has released several pertinent guidelines, the industry's "legal gap" and "regulatory vacuum" still need to be filled with relevant supporting policies from different industries to be further improved. Furthermore, the growing use of AI in the financial sector is changing the regulatory and financial operations models. Adapting to these changes and continuously enhancing the legal system is a critical issue that requires the attention of the relevant authorities [32].

6.4. Skills Gap

Teams without these skills may find it difficult to support and implement AI/ML technologies within their institutions. Due to a shortage of individuals possessing these skills, employees with an AI/ML skill set are currently in great demand [59]. New technologies, such as the most potent open-source AI and ML libraries, are still in their early stages of development. TensorFlow, Google Brain's second-generation technology, for instance, was made available in 2017. In 2015, GUI libraries like Shiny R (Version 0.11 and 0.12) and Pandas (Python Version 0.16 and 0.17) were made available. In 2017, Microsoft proposed Open Neural Network Exchange Version 1 (ONIX), an open-source platform for interchangeable AI models [60].

A combination of technical, analytical, managerial, and strategic abilities is required for organizations to effectively employ AI. Programming, data science, and machine learning are examples of technical abilities. Analytical abilities include the ability to analyze critically and solve problems. Management of projects and changes is a component of managerial abilities. Finally, the development of AI requires strategic skills. Overcoming skills gaps can be accomplished through collaborating with educational institutions, providing online courses and certificates, developing internal training programs, and employing experts in the field.

The black box phenomenon means that certain machine-learning algorithms fall under this category. This implies that it is challenging to understand and confirm how algorithms carry out a certain activity. It is challenging to link predictions made by deep-learning neural networks, for instance, to the model's significant features. Research on explainable AI has been conducted to solve this problem and increase the transparency of AI [61]. AI systems nowadays often function as black boxes, making system replacement difficult. This has the potential to make it unclear at times regarding the dependencies and how the system functions. If it is unclear how the AI system functions during a system breakdown, such as a "black swan" occurrence, it could be exceedingly challenging to maintain business continuity by switching systems [57].

Generally, AI systems known as "black box" models are those in which humans cannot readily understand or see the internal decision-making processes. Though it is difficult to describe how these models arrive at their conclusions due to their complexity, they are capable of producing reliable results. Deep neural networks, which are employed for image and speech recognition applications, are one example.

In other words, when "black box" models are used, it becomes difficult, if not impossible, to describe how AI systems operate. In these situations, outcome-based explanations that concentrate on explaining the effects of decision making or the outcomes produced by the AI systems may be relied upon. AI model cards are a different approach that can be taken into consideration. These are brief documents that come with trained machine-learning models and explain the context in which the models are meant to be used, specifications of the performance evaluation process, and other pertinent information [62]. AI model cards are one type of data that deployers can obtain from third-party developers. These cards include information on the limitations of the model, the process of developing and testing the model, and how the AI model works. Examples of AI model cards include Salesforce's Einstein Optical Character Recognition (OCR) Model Card and Google's Face Detection Model Card [16].

Salesforce developed the Einstein OCR model, which is intended to identify and extract text from PDFs and pictures. When it comes to duties like recognizing serial numbers, VINs, or contact details from business cards, this model is especially helpful. It functions by first identifying the text inside the image, then identifying specific characters, and then associating the text with relevant information, such as names or addresses. To ensure its accuracy, the model is trained on a combination of synthetic and actual data. Nevertheless, for the moment, it is limited to English and works best with high-quality photos. It is mostly intended for enterprise users and is accessible via the Salesforce API [63].

7. Regulatory Landscape

7.1. Existing AI Regulations and Guidelines

In the financial sector, discussions are currently taking place on the creation of regulatory and supervisory frameworks for AI [64]. The application of artificial intelligence (AI) and machine learning (ML) was listed as one of the objectives by the Basel Committee on Banking Supervision (BCBS) in their work program for 2021–2022, which was released in April 2021 [65]. The BCBS then announced in their March 2022 newsletter that they planned to carry on with the following topics: (i) how much the results of models can be comprehended and explained; (ii) governance structures related to AI/ML models; and (iii) possible consequences of broader application of AI/ML models for the stability of individual banks and financial stability [66].

In October 2022, the Bank of England, Financial Conduct Authority (FCA), and Prudential Regulation Authority (PRA) in the UK released a discussion paper titled "Artificial Intelligence and Machine Learning". The paper discusses several important topics, such as (i) the possible advantages, risks, and disadvantages of using AI in financial services; (ii) the suitability of the existing legal requirements and guidelines for the risks connected with AI; and (iii) the need to investigate further policy actions and others [67]. By the end of 2023, stakeholder feedback on this discussion paper should be published.

"Artificial intelligence governance principles: Towards ethical and trustworthy artificial intelligence in the European Insurance Sector" was the title of the AI governance guidelines that the European Insurance and Occupational Pensions Authority (EIOPA) released in June 2021. The six principles that are highlighted are as follows: (i) proportionality; (ii) fairness and nondiscrimination; (iii) transparency; (iv) human oversight; (v) data governance of record keeping; and (vi) robustness and performance [68].

The exposure draft of the National Association of Insurance Commissioners' (NAIC) July 2023 publication titled "Model Bulletin: Use of algorithms, predictive models, and artificial intelligence systems by insurers" includes some of the most recent achievements in the insurance sector. This suggested model bulletin focuses on governance, risk management, internal controls, and third-party risk management. It offers regulatory standards and expectations for insurers' usage of AI systems [69].

In September 2021 [70], a report titled "The use of artificial intelligence and machine learning by market intermediaries and asset managers: Final Report" was released by the International Organization of Securities Commissions (IOSCO) in the securities industry. In terms of (i) governance, (ii) testing and monitoring of algorithms, (iii) compliance and risk management, (iv) management of third-party service providers, (v) disclosures, and (vi) data governance, the IOSCO lays out guidelines for supervisory bodies.

Based on Linklaters (2023) [57], the following are general descriptive examples of six jurisdiction-specific AI-specific methods. These include Hong Kong SAR, the United States, China, the United Kingdom, the European Union, and Singapore.

Hong Kong SAR has specific policies and directives for the banking regulator's guidelines on financial consumer protection and high-level principles for AI usage in financial services. However, there are no explicit rules governing the use of AI in financial services. The data regulator has sought more formal legislation and released guidelines for developing or using AI.

In the United States, there are an increasing number of AI rules and standards. Although it is still early, there is a growing call for federal control of AI. Currently, the regulatory approach is more industry-specific, with standards for AI applications in the banking, healthcare, and transportation sectors. Various individual states have passed legislation to regulate AI to oversee specific applications of the technology. For example, California and Washington have regulations on facial recognition. The National Institute of Standards and Technology has developed the most complete AI risk management framework.

The Chinese Cybersecurity Administration has imposed guidelines and limitations on businesses creating products similar to ChatGPT (In 2023 Version GPT-4 and GPT-3.5) and other generative AI technologies. Both the "models and rules" as well as the AI algorithms are covered by these measures while creating content. By the end of 2023 or the beginning of 2024, a more comprehensive draft of the AI law is anticipated for public consultation.

The government of the United Kingdom has declared its intention to follow an industry-led and light-touch approach, which means that no legislation similar to the EU AI Act will be implemented. Rather, it will enable current regulators to devise customized strategies that align with the real-world applications of AI in their industries, underpinned by five fundamental principles. Based on [62], the five fundamental principles are (1) safety, security, and robustness; (2) appropriate transparency and explainability; (3) fairness; (4) accountability and governance; and (5) contestability and redress.

The EU's AI Act is the world's first AI-specific regulation. The EU is developing a comprehensive regulatory and liability framework. The EU's AI Act, which is planned to be approved by the end of 2023 and put into force in 2025, is projected to have extraterritorial implications. It emphasizes openness, accountability, and human control while categorizing AI systems into three risk levels: low, limited, and high, each with specific requirements.

Singapore is a nation of self-regulation. Encouraging AI innovation through responsible AI use is the typical regulatory strategy. For regulated businesses, the financial regulator has released AI-friendly guidelines and best practices. Failure to follow these rules will not result in penalties or liabilities. Additionally, the data regulators of the nation are consulting on cross-sectoral guidance on the usage of AI in relation to personal data.

7.2. Cases of AI Governance Framework

The ASEAN (2024) [17] guide provides steps supporting safe AI use for organizational implementation, which consist of four key areas: establishing internal governance measures and structures; determining the level of human involvement in augmented decision-making; operations management through documenting data lineage, ensuring data quality and mitigating bias; and stakeholder interaction and communication. Further explanation was provided as follows:

Establish internal governance measures and structures (see Table 1) by modifying or creating internal governance policies and procedures. This includes obligations, risks, and values related to algorithmic decision making. Examples of cases were Aboitiz Group and Smart Nation Group (SNG), Singapore.

Determining the level of human involvement in Al-augmented decision making (Table 1). A system that helps businesses determine acceptable risks and the right amount of human engagement in AI-augmented decision making, so that they may better establish their readiness for using AI. Examples of cases were EY and Smart Nation Group (SNG), Singapore.

Operations management involves documenting data lineage, ensuring data quality, and mitigating bias (see Table 1). These concerns about data management should be taken into account while creating, choosing, and managing AI models. For example, one case was UCARE. AI.

Stakeholder interaction and communication are strategies for maintaining connections and interacting with an organization's stakeholders (Table 1), for example, Gojek.

Table 1. Overview of cases for the AI governance framework.

<table>
<tr><th colspan="2">Establish Internal Governance Measures and Structures</th></tr>
<tr><td>Aboitiz Group</td><td>-Acknowledges that Al and ML algorithms are essential group assets. It is critical to establish a strategic Al governance framework to guarantee that the programs and algorithms are appropriately managed as well as support the group strategic business daily operations.
-Al's use-related ethical issues were consistent with company values.
-Roles and duties for the moral application of Al technology should be clearly stated.
-The management committee must review and approve all Al-related procedures and decisions.
-Model governance management committee consists of:
Chief Information Security Officer (CISO),
Data Protection Officer (DPO),
Chief Operations Officer,
Chief Data Officer,
Chief Risk Officer,
Chief Technology
Operations Officer, audit, Risk, and Compliance Al,
Al and Innovation Center of Excellence,
Chief Marketing Officer,
Senior Managers.</td></tr>
<tr><td>Smart Nation Group (SNG), Singapore</td><td>-Gates of approval for various LLM (large language models) for product development phases. Singapore's National AI Office (NAIO) has set up standards for government product teams creating custom LLM products. It has also formed an Al workgroup of government stakeholders to supervise the product's safety.
-From beta testing onward, product teams just need to request approval from the central Al workgroup to promote experimentation and guarantee sufficient review of LLM products.</td></tr>
<tr><th colspan="2">Determining the Level of Human Involvement in Al-Augmented Decision Making</th></tr>
<tr><td>EY</td><td>-EY is dedicated to creating and implementing reliable Al solutions for clients as well as for internal use.
-EY evaluates and categorizes the models as high, medium, or low risk using the Al model risk-tiering approach.
-Risk tier based on an evaluation of the main risk areas related to Al, including use case design, ethical, data, privacy, algorithmic, performance, compliance, technology, and business risks.
-Appropriate monitoring and human oversight are implemented for the Al models according to the risk tier.</td></tr>
<tr><td>Smart Nation Group (SNG), Singapore</td><td>-Advising product teams on necessary mitigating actions, NAIO adopts a risk-based approach. The degree of risk varies according to the Al products.
-For instance, AI products that are intended for public use should be strengthened against hostile attacks. The product teams' efforts to strengthen the robustness of their products, such as through robustness tests to enhance performance to prevent users from using brute-force attacks, are among the corresponding mitigating measures.</td></tr>
</table>

Table 1. *Cont.*

Operations Management through Documenting Data Lineage, Ensuring Data Quality, and Mitigating Bias	
UCARE.AI	-UCARE.AI is a deep-tech start-up established in Singapore that offers real-time predictive insights that can be used in the healthcare industry and other fields. Its unique, multi-award-winning online ML and Al platform is built on a cloud-based microservices architecture. -Collected data in a safe, centralized log storage system and recorded data consistently. -The organization took care to ensure that the data were of high quality and that it were presented correctly to build Al models. -Placed a high priority on developing Al models that were unique for their clients rather than relying on third-party data for model construction. -Patient bill estimates were more accurate as a result of this approach, which distinguished between patient profiles and the features chosen for each Al model differently for every hospital. -Reducing the possibility of bias. Patients received personalized, data-driven estimates of their medical bills from objective and reliable machine projections rather than those that were influenced by human biases in the creation of the algorithms.
Stakeholder Interaction and Communication	
Gojek	-Gojek is a digital payment group and on-demand multi-service platform based in Jakarta, Indonesia. Al is used, within financial restrictions, to build the user base and keep customers engaged by allocating promotions automatically. -With incentives, automated promotion allocation finds users with high incremental engagement and prioritizes promotion distribution while projecting campaign costs. -Campaign managers deploy promotional campaigns that customers can interact with and they offer implicit commentary about the applicability of campaigns, which is reflected in online metrics models. -The Data Science team and Campaign Managers can make decisions regarding model version management because of this mechanism.

8. Summary of Findings

The major findings, which the research compiles in Tables 2 and 3, were based on the preceding literature. Table 2 provides an overview of the AI applications, benefits, challenges, and ethical considerations in the banking and finance industry. Table 3 provides recommendations to counter the challenges and ethical issues by providing examples of existing regulations and strategies for AI governance to guide the safe implementation of AI in organizations.

Table 2. Overview of AI applications, benefits, challenges, and ethical considerations in the banking and finance industry adapted from existing studies.

AI Applications	Benefits	Challenges and Ethical Issues
• To prevent financial crimes—fraud and money laundering. • To manage credit risk assessment—includes assets, income level, behavior, and other customer attributes. • To provide customer service—chatbot, big data combined with AI used in marketing to analyze customers' preferences. • To manage investment management—smart investment platforms and "financial intelligence robot" or robot advisor.	• Enhanced efficiency and cost reduction—cutting down on processing times and human error. Save operating costs and use resources more efficiently by automating manual operations. • Improved decision making—more precise risk assessments, fraud prevention measures, and investment strategies in the banking and financial industries. • Enhanced customer experience—chatbots and AI-driven voice recognition technology.	• Data privacy and security—safeguard client privacy and stop data breaches or hacked. • Bias and fairness—to prevent biased decision making, AI models or regulations must be routinely monitored, assessed, and adjusted. • Accountability and transparency—the ethical use of customer information, accountability for automated decisions, and transparency in algorithmic decision-making • Skill gap—teams without these skills may find it difficult to support and implement AI/ML technologies within their institutions.

Table 3. Recommendations to counter the challenges and ethical issues adapted from existing studies.

Existing Regulations	Strategies for an AI Governance Framework in an Organization
• Creation of regulatory and supervisory frameworks for AI by the Basel Committee on Banking Supervision (BCBS). • Paper titled "Artificial Intelligence and Machine Learning" by FCA and PRA. • Paper titled "Artificial intelligence governance principles: Towards ethical and trustworthy artificial intelligence in the European Insurance Sector" (EIOPA). • Paper titled "Model Bulletin: Use of algorithms, predictive models, and artificial intelligence systems by insurers", by NAIC. • Paper titled "The use of artificial intelligence and machine learning by market intermediaries and asset managers: Final report" (IOSCO) • Hong Kong SAR banking regulator's guidelines on financial consumer protection and high-level principles for AI usage in financial services. • US regulations on face recognition and hiring restrictions on AI. AI Risk Management Framework created by the National Institute of Standards and Technology. • China, the Chinese Cybersecurity Administration has imposed guidelines and limitations on businesses creating products similar to ChatGPT and other generative AI technologies • UK, intention to follow an industry-led and light-touch approach, enable current regulators to devise customized strategies that align with the real-world applications of AI in their industries. • EU, comprehensive AI policy, namely the EU AI Act, is the world's first AI-specific regulation, and the EU is building a comprehensive regulatory and liability framework. • Singapore, the financial regulator has released AI-friendly guidelines and best practices. Failure to follow these rules will not result in penalties or liabilities.	Establish internal governance measures and structures. • Ethical issues are consistent with company values. • Roles and duties should be clearly stated. • The management committee must review and approve all Al-related procedures and decisions. • Create a model governance management committee Determining the level of human involvement in Al-augmented decision making. • Evaluate and categorize models as high, medium, or low risk using the Al model risk-tiering approach. • Evaluate use case design, ethical, data, privacy, algorithmic, performance, compliance, technology, and business risks. • Appropriate monitoring and human oversight for the Al models. Operations management through documenting data lineage, ensuring data quality, and mitigating bias. • Offers real-time predictive insights that can be used in many industries. • Online ML and Al platform is built on a cloud-based microservices architecture. • Collected data in a safe, centralized log storage system and recorded data. Stakeholder interaction and communication Al is used, within financial restrictions, to build the user base and keep customers engaged by allocating promotions automatically. • With incentives, automated promotion allocation finds users with high incremental engagement potential, while projecting campaign costs. • Consumers interact which offers implicit commentary about the applicability of campaigns and is reflected in online metrics models. • Therefore, the Data Science team and Campaign Managers are able to make informed decisions regarding model version management.

9. Relevant Theories

Here are some pertinent theories that should be investigated in the future. This combines Lewin's three-step change theory, united theory of acceptance and use of technology (UTUAT), and crucial success criteria.

The study first sets out the theories and provides conclusions for further investigation. Use the UTAUT model, for instance, to survey customer acceptance and usage of AI technologies. It incorporates components from the technology acceptance model (TAM). The performance expectancy, effort expectancy, social influence, and facilitating conditions that affect AI adoption are all better understood with the aid of the UTAUT framework. Furthermore, use expert insights and real-world implementation experiences to focus the interviews to determine the critical success factors for AI best practices. Adoption of AI is seen from both a theoretical and practical perspective, which is attributable to this combination of survey and interview approaches.

Inspired by the ASEAN's AI governance framework and change theory, use institutional theory to investigate how regulatory, social, and cultural changes impact AI adoption. The way that organizations adjust to new technology, such as the shift from traditional to artificial intelligence, is better understood through the use of institutional theory. This shift is supported by the ASEAN principles, which place a strong emphasis on ethical conduct and collaboration. Similar to adjustments to laws, customs, and cultural norms, they may also be necessary for the adoption of AI.

9.1. TAM

Fintech adoption has been associated in the past with several theories, such as the individual innovativeness theory (IIT), institutional theory (IT), technology acceptance model (TAM), technology readiness (TR), theory of interpersonal behavior (TIB), and united theory of acceptance and use of technology (UTUAT). Additionally, Faraj and Pachidi (2021) [71] discovered that institutional theory helps analyze fintech adoption. The TAM is the most effective theory for measuring technology adoption [72], and it is also effective at predicting and explaining the acceptance of new technologies [73]. IT serves as the cornerstone of an institutional environment that facilitates technological engagement and the promotion of fintech services [71]. According to Davis and Sinha (2021) [74], institutional factors are crucial in supporting breakthroughs in information and communication technology (ICT) capable of reorganizing companies, particularly fintech companies. Lastly, IIT is defined by Rogers et al. (2014) [75] as a person's relative ability to adjust to a technology. Individual innovativeness began with variations in how each person accepted a new development. Acceptance of new technologies is largely dependent on individual innovation [76,77].

There has long been a relationship between technology and finance. The development of fintech is divided into three stages by Arner, Barberis, and Buckle (2016) [78]. The first stage, known as fintech 1.0, dates back to the construction of the transatlantic telegraph wire, which supported the telecommunications infrastructure between 1866 and 1967. Fintech 2.0 emerged as a result of the development of digital technologies and communication between 1967 and 2008. The fintech industry is currently in its third phase, supported by the emergence of new start-ups that can bridge the gap between financial products and technological advances to directly meet the demands of people and businesses in the financial services space.

According to the EY Report (2019) [79], 87 out of 100 consumers in China and India have accepted fintech, compared to 35 and 34 in France and Japan, respectively. This indicates that the adoption of fintech services is still not uniform across nations. According to the study by Ryu (2018) [80], financial risk, legal ambiguity, security and privacy concerns, and the insufficient operational frameworks of fintech firms are among the barriers to the adoption of fintech. People can reduce the risk that comes with implementing new technologies by embracing innovation [81]. Additionally, the public's understanding of fintech adoption is hampered by low levels of financial literacy [82,83]. Davis (1985) [84] initiated an investigation into the impact of technology adoption by putting forward the TAM as a means of testing consumers' internal perceptions regarding the acceptability of information technology. The TAM seeks to pinpoint the changes that need to be made to new technology before it can be embraced by users and reach a final stage of adoption. The TAM has been used in several recent studies to quantify technology adoption in a variety of industries, including credit cards [82], mobile banking [85], and insurance customer intents [86].

The TAM was expanded by Hu et al. (2019) [87] by including new factors as predictors of fintech acceptance in China, such as user innovation and government support. Brand image, government support, and user innovation are significantly correlated with fintech acceptance, according to the structural equation modeling (SEM) analysis. On the other hand, fintech adoption in China is not greatly impacted by the perceived ease of use. Morgan and Trinh (2020) [83] explored the adoption of fintech in Vietnam by examining the influence of behavioral intention, trust, perceived utility, and enjoyment of mobile wallet services. The findings suggest that the behavioral intention to use M-wallets is significantly positively impacted by the perceived ease of use, perceived usefulness, and enjoyment, but there is no direct relationship between trust and M-wallet usage in Vietnam.

Furthermore, the impact of organizational patterns on society more broadly is explained by institutional theory (IT), which also explains the process of organizational and rational conduct. Teigland et al. (2018) [88], for instance, showed how institutional theory incorporates changes that take place at the institutional level, such as the rise of fintech. Braido and Klein's (2020) [89] study combined institutional theory with fintech acceptance in Brazil. Their research suggests that the organizational modifications of the normative, regulatory, and cultural components of the mobile payment system are supported by institutional theory.

9.2. UTAUT

Almunawar and Anshari (2024) [90] explained the connection between the TAM and UTAUT model. The TAM framework was criticized by Bagozzi (2007) [91] as being too simple. The unified theory of acceptance and use of technology (UTAUT) was developed by Venkatesh et al. (2003) [92] as a predictive framework for user intention and behavioral application of ISs. It is composed of eight user acceptance factors combined into one framework. The components of the TAM are included in the framework. The TAM's perceived usefulness and ease of use variables were used to build the UTAUT model, which are defined as performance expectancy and effort expectancy. Performance expectation, effort expectancy, social influence, and facilitating conditions are the four main variables of the framework that were initially developed in an organizational context.

A unique variation of age, gender, experience, and voluntariness of usage operates as a moderator of diverse UTAUT connections. These variables influence the BI while utilizing technology. The UTAUT model helps managers identify factors that affect users' acceptance of new technology by serving as a framework for assessing the likelihood of a successful technology introduction. The model's application is crucial for understanding people who are less adept at using modern technologies.

Many academic disciplines have examined different technologies from the viewpoint of employees by using the UTAUT model. The UTAUT was enhanced into the UTAUT2, which was more suited for consumer usage due to including crucial constructs and relationships in the model [88]. The framework, according to Venkatesh et al. (2012) [93], is the most recent model in terms of technology adoption and has the strongest prediction strength among other models, with an interpreting strength of roughly 50% of the discrepancy in technology usage and nearly 70% of the discrepancy in BI.

9.3. Lewin's Three-Step Change Theory

In 1951, Kurt Lewin presented the three-step change model. According to this social scientist, behavior is a dynamic balance of forces acting in opposition to one another.

Because they push workers in the right direction, driving factors make change easier. Employees are pushed in the opposite direction by restraining forces, which hinder change. Lewin's three-step model can assist in shifting the balance in favor of the intended change, but analysis of these factors remains necessary [94].

Lewin states that unfreezing the status quo or current circumstances is the first step in altering behavior. The equilibrium state is regarded as the current situation. To break through the bonds of both collective conformity and individual resistance, there are three ways to unfreeze. First, strengthen the driving forces that steer behavior away from the current circumstances or status quo. Second, lessen the restraints that prevent the movement from the current balance. Third, combine the two approaches mentioned previously. Developing trust and acknowledging the need for change, motivating participants via readiness for change, and actively engaging them in problem identification as well as solution brainstorming in a group are some activities that might help with the unfreezing process.

Movement is the second phase in Lewin's model of changing behavior. The target system must be pushed to a new equilibrium level. Three actions can help with the movement step: convincing employees that the current situation is unfavorable to them, motivating them to see the issue from a different angle, and collaborating in the search for new and pertinent data. Then, link the group's opinions to influential and well-respected leaders who are also in favor of the change.

Lewin's three-step change model has refreezing as its third stage. For the change to be maintained or to "stick" over time, this step must be performed after the modification has been put into effect. If this step is not taken, there is a strong likelihood that the shift will be temporary and the employees will return to their previous equilibrium or behavior. It is the real process of incorporating new values into the customs and values of the community. The goal of refreezing is to balance the driving and restraining forces to stabilize the new equilibrium that has resulted from the shift. Reinforcing new patterns and institutionalizing them through official and informal processes, such as rules and procedures, is one way to put Lewin's third step into practice. Lewin's approach therefore demonstrates the impact of factors that either encourage or hinder change. To be more precise, restraining forces resist change, while pushing forces support it. Therefore, when one force's total strength exceeds the combined strength of the opposing set of forces, change will occur [95].

Lewin's methodology is very goal-oriented, plan-oriented, and logical. It ignores individual factors that may have an impact on change. On the other hand, social cognitive theory suggests that the characteristics of the behavior itself are effects of the environment and have an impact on changing behavior. Therefore, the social cognitive theory considers both internal and exterior environmental circumstances, while Lewin's model makes rational sense. Although the shift seems reasonable on paper, it may backfire in practice if human emotions and experiences are not taken into account. Sometimes workers become so enthused about a new development that they ignore the attitudes, sentiments, previous advice, or experiences of other workers. As a result, they encounter opposition or an uninspired response.

Regarding change management, there is no right or wrong theory. This science is not precise. But a clearer picture of what it takes to successfully lead a change initiative will continue to emerge according to the industry's top experts' continued research and study. We must keep analyzing and taking into account how our evolving culture and society will necessitate new perspectives on the best ways to implement change [94].

9.4. Critical Success Factors

The concept that a few factors determine a company's success was first put forth by Daniel (1961) [96] and subsequently primarily developed in the context of developing management information systems by Rockart (1979) [97] and Bullen and Rockart (1981) [98]. It is evident that the problem of finding the best possible fit between external influences and business attributes represents the fundamentals of business strategy inspired by Rockart's idea of crucial success factors. It is thought that the external environment has some basic needs, constraints, opportunities, and threats. To succeed, organizations must match their resources, capabilities, and strategies. Five different sources of critical success factors are distinguished by Rockart [97]:

- The industry includes factors like product attributes, the technology employed, demand characteristics, etc. These have the potential to impact all competitors in a given industry, but their impact will differ based on the traits and vulnerability of certain industry sectors.
- The competitive positioning and industry history of the business under consideration is based on its competitive strategy.
- Environmental factors are the macroeconomic variables, such as government legislation, economic conditions, and demographics. This has an impact on all competitors in an industry, but they have little or no control over it.
- Temporal factors are aspects of a company that interfere with the execution of a planned strategy for a limited amount of time, such as a lack of managerial experience or skilled personnel.
- Every functional managerial role within a company has a general set of associated important success factors. These are known as managerial positions.

It is important to consider the purpose of the research while assessing the contribution of Rockart and his colleagues. The goal was to create management information systems that upper management could utilize and find beneficial. Managers found it easier to identify and express their information needs when they learned the importance of critical success factors and how to determine them through direct inquiry. However, Rockart was not interested in creating a competitive advantage or offering an explanation for success [99].

Only three schools of thinking will be differentiated in the following for simplicity [100]. The shared experiences school, the planning school, and the design school. Key success factors are a feature of a business. According to the design school, as each firm is unique in every way, it must also find a special fit with the environment. As a result, generalizations concerning the reasons behind success are impossible to provide. The CSF can only be meaningful about a certain company. As such, the case study is the only type of research methodology that can be used to identify critical success factors [101]. Essential success criteria serve as a tool for planning. With the guidance of the planning school, firms will be able to identify the most appropriate plan of action. The primary premise is that decision making can be made of higher quality if feedback is provided to decision makers to assist them in organizing their ideas. One such example is the use of key success characteristics as a planning tool to encourage decision makers to think about their presumptions about what makes a successful venture.

Key success factors serve as a description of the market. This school is known as the "shared experience school" because it is predicated on the idea that by exchanging business strategy experiences it will be possible to accumulate general, theoretical knowledge that is supported by empirical evidence and that will ultimately be able to inform business strategy selection. According to this school, causal relationships that are based on an objective fact that can be gradually revealed via research are what determine the success of businesses. An extended perspective on critical success factors integrates the previously mentioned views of the market with planning tools. A planning tool that seeks to improve understanding of market conditions will always be dependent on its utility based on the reliability of the insights it generates.

Assumptions made by meta-theoretical analyses are essential for the advancement of theory and method. They cannot be objectively proven, like all assumptions. Rather, the validity of their claims is based on how well they convince other scholars. Once the potential causes and effects are known, a straightforward technique for estimating the strength of subjective causal linkages is to rate the prespecified causal networks. The basic idea is to provide participants with a matrix with rows and columns representing potential causes and effects. Then, fill in the cells with estimates of the strength of causal linkages. It is possible to use subjective ratings of the relevant variable, such as those on a five-point rating scale. The corporate executive would place his company on a pole-based scale, for example, ranging from "very high-cost advantage" to "very high-cost disadvantage" [99].

10. Discussion of Limitations and Recommendations

Given the popularity of the current nature of the topic of artificial intelligence (AI) and its application in the financial sector, as well as the well-known fact that academic publications on these subjects are often delayed due to publication procedures [102], what could appear to be a research limitation is that a lack of scientific papers in this field has been replaced by online literature and expert opinions from the Financial Times, Forbes, Microsoft, conference presentations, reports from organizations and institutions, insiders in the AI sector, owners and founders of AI companies, etc. This suggests that technology is not behind the times and that, like in finance and artificial intelligence, it is helping to fix other flaws and improve things and user experiences. We may find that the long-term effects of AI on the financial sector in general can be much more profound and revolutionary than they seem at the time [18].

The ASEAN (2024) [17] provides the following suggestions for AI development at the national and regional levels:

- Developing AI talent and workforce upskilling. Make sure a nation's workforce is equipped with the digital skills necessary to communicate with AI systems and can adjust to new work practices by collaborating closely with both the private and public sectors.
- Encouraging investment in AI start-ups and supporting the ecosystem for AI innovation. Collaborate closely with both the private and public sectors to establish an environment that is conducive to the development of AI. Allowing businesses to access and utilize digital technologies, infrastructure, and data.
- Investment in the research and advancement of AI. To make sure that the safety and resilience of AI systems or tools progress with new use cases. Stay up to date on the most recent advancements in AI and support research on AI ethics, governance, and cybersecurity.
- Encouraging companies to follow the ASEAN Guide on AI Governance and Ethics by adopting useful tools. Install technologies to make it possible for operations by applying AI governance to guarantee more effective documentation and validation procedures.
- Increase public knowledge of the implications of AI. Educate the public on the possible advantages and risks of artificial intelligence (AI) so that they can utilize it wisely. Also, so they can take the necessary precautions to keep themselves safe from harmful AI applications.
- Establishing an ASEAN Working Group on AI Governance to direct and supervise regional efforts related to AI governance.
- Representatives from each of the ASEAN member states may form the Working Group, which can collaborate to implement the recommendations outlined in this Guide. It will also offer guidance to ASEAN nations that want to adopt specific sections of the Guide, and when necessary, it will consult with other industry partners to obtain their opinions.
- AI risks should include anthropomorphism and mistakes. Replies that are untrue and misleading. Impersonation, deepfakes, fraud, and malevolent actions. Intellectual property rights are being violated. Confidentiality, privacy, and the spread of bias propagation.
- AI governance should include the adaptation of current frameworks and tools. Guidance on creating a framework for shared accountability. Guidance on enhancing the ability to control generative AI risks. Guidance on how to tell the difference between information produced by AI and that produced by·humans.
- Assembling a list of use cases showing how ASEAN-based organizations have applied the Guide in real-world situations. A collection of use cases demonstrating these

organizations' dedication to AI governance and aiding in their self-promotion as ethical AI practitioners.

By understanding the literature review in this paper, further research using a combination of the extended UTAUT, change theory, and institutional theory, as well as the critical success factor, can fill the theoretical gap through mixed-methods research. The population gap can be addressed by research undertaken in a nation where fintech services are projected to be less accepted, such as a developing or Islamic country. The significance and potential of this study involve providing suggestions and a general understanding of AI applications, notably in the banking and finance industries. Carrying out the above suggestions is expected to contribute to the policy and practical implications for fintech development in a country [103,104].

This study promotes the creation of strategic initiatives guided by the ASEAN AI Governance Guidelines. As with ASEAN's focus on transparency and accountability, these measures include the establishment of explicit ethical rules and regulatory standards for AI, encouraging the development of frameworks for the responsible deployment of AI and guaranteeing the safety, fairness, and respect for user privacy of AI systems. The main goal is to establish a strong framework for AI governance that balances innovation, ethical issues, and the impact on society [105].

The recommendations focus on ASEAN countries because the majority of them are developing nations with less-developed AI technology and legal frameworks than the US and Europe. The US and Europe are moving toward AI-specific regulations, per Section 7.1 on current AI regulations and guidelines. It is suggested that the US and Europe create their own AI regulations and guidelines tailored to their respective industries. Even though there may be similarities and differences in AI regulation, regulators should carefully analyze the potential consequences of AI regulation to prevent harming the development of their respective countries.

11. Conclusions

In conclusion, this study aimed to examine the comprehensive landscape of artificial intelligence (AI) in the finance and banking sectors. By answering the four research questions, this paper showcases the applications of AI in the banking and finance industries. AI applications in banking and finance include fraud detection, credit risk analysis, customer service chatbots, trading algorithms, and forecasting models. The key benefits are increased efficiency and better risk management, while the major challenges involve data quality issues, transparency, skills gaps, and regulatory uncertainty. Current AI governance focuses on ethical principles like transparency and accountability, although comprehensive cross-industry regulations are still lacking. Relevant theories for further research include principal–agent problems, behavioral finance, algorithmic bias/fairness, adversarial machine learning, and automation's workforce impacts. The most prominent uses of AI are preventing financial crimes, credit risk assessment, customer service, and investment management. The benefits of these applications contribute to enhanced efficiency and cost reduction. Furthermore, they lead to improved decision making and enhanced customer experience, particularly in banks. However, there are still challenges and ethical considerations to take care of due to the complexity of AI systems. These include data privacy and security, bias and fairness, accountability and transparency, and the skills gap. Implementing an AI governance framework requires rules and guidelines to address these issues. This paper also offers instances of how organizations have integrated AI governance into their systems. The research concluded includes sections on pertinent theories and suggestions for further research.

Author Contributions: Conceptualization, N.N.R., M.M., M.A., N.L.F. and M.S.; methodology, N.N.R., M.M., M.A., N.L.F. and M.S.; formal analysis, N.N.R., M.M. and M.A.; investigation, N.L.F. and M.S.; writing—original draft preparation, N.N.R., M.M. and M.A.; writing—review and editing, N.L.F. and M.S.; supervision, M.M. and M.A.; funding acquisition, M.A. and M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the first/corresponding author/s.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kate, K. Banking Chatbots Examples and Best Practices for Implementation. 2024. Available online: https://tovie.ai/blog/banking-chatbots-examples-and-best-practices-for-implementation (accessed on 19 July 2024).
2. McKendrick, J. AI Adoption Skyrocketed over the Last 18 Months. Harvard Business Review. 2021. Available online: https://hbr.org/2021/09/ai-adoption-skyrocketed-over-the-last-18-months (accessed on 20 May 2024).
3. Sultani, W.; Chen, C.; Shah, M. Real-world anomaly detection in surveillance videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 6479–6488.
4. Gordeev, D.; Singer, P.; Michailidis, M.; Müller, M.; Ambati, S. Backtesting the predictability of COVID-19. *arXiv* **2020**, arXiv:2007.11411.
5. Portugal, I.; Alencar, P.; Cowan, D. The use of machine learning algorithms in recommender systems: A systematic review. *Expert Syst. Appl.* **2018**, *97*, 205–227. [CrossRef]
6. Suzuki, K. Overview of deep learning in medical imaging. *Radiol. Phys. Technol.* **2017**, *10*, 257–273. [CrossRef] [PubMed]
7. Esteva, A.; Chou, K.; Yeung, S.; Naik, N.; Madani, A.; Mottaghi, A.; Liu, Y.; Topol, E.; Dean, J.; Socher, R. Deep learning-enabled medical computer vision. *npj Digit. Med.* **2021**, *4*, 5. [CrossRef]
8. Conde, V.; Choi, J. Few-shot long-tailed bird audio recognition. *arXiv* **2022**, arXiv:2206.11260.
9. Conde, V.; Turgutlu, K. CLIP-Art: Contrastive pre-training for fine-grained art classification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Nashville, TN, USA, 20–25 June 2021; pp. 3956–3960.
10. Henkel, C.; Pfeiffer, P.; Singer, P. Recognizing bird species in diverse soundscapes under weak supervision. *arXiv* **2021**, arXiv:2107.07728.
11. Floridi, L.; Cowls, J.; Beltrametti, M.; Chatila, R.; Chazerand, P.; Dignum, V.; Luetege, C.; Madelin, R.; Pagallo, U.; Rossi, F.; et al. AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds Mach.* **2018**, *28*, 689–707. [CrossRef]
12. Marr, B. Is Artificial Intelligence dangerous? 6 AI risks everyone should know about. *Forbes*. 19 November 2018. Available online: https://www.forbes.com/sites/bernardmarr/2018/11/19/is-artificial-intelligence-dangerous-6-ai-risks-everyone-should-know-about/ (accessed on 20 May 2024).
13. Gill, N.; Mathur, A.; Conde, V. A brief overview of AI governance for Responsible Machine Learning Systems. *arXiv* **2022**, arXiv:2211.13130.
14. KPMG. AI Adoption Accelerated during the Pandemic but Many Say It's Moving too Fast. 2021. Available online: https://info.kpmg.us/news-perspectives/technology-innovation/thriving-in-an-ai-world/ai-adoption-accelerated-during-pandemic.html (accessed on 20 May 2024).
15. Zadeh, A. Is probability theory sufficient for dealing with uncertainty in AI: A negative view. *Mach. Intell. Pattern Recognit.* **1986**, *4*, 103–116.
16. Bresina, J.; Dearden, R.; Meuleau, N.; Ramkrishnan, S.; Smith, D.; Washington, R. Planning under continuous time and resource uncertainty: A challenge for AI. *arXiv* **2012**, arXiv:1301.0559.
17. ASEAN. ASEAN Guide on AI Governance and Ethics. 2024. Available online: https://asean.org/book/asean-guide-on-ai-governance-and-ethics/ (accessed on 20 May 2024).
18. Golić, Z. Finance and artificial intelligence: The fifth industrial revolution and its impact on the financial sector. *Zb. Rad. Ekon. Fak. Istočnom Sarajev.* **2019**, *19*, 67–81. [CrossRef]
19. Georgiev, J. Setting the Scene: Digital Technologies in the Financial Sector. 2018. Available online: https://www.jkg-advisory.com/docs/16072018_Finance_5.0 (accessed on 20 May 2024).
20. Sharma, S. 10 Artificial Intelligence Applications Revolutionizing Financial Services. 2019. Available online: https://www.datadriveninvestor.com/2019/07/08/10-artificial-intelligence-applications-revolutionizing-financial-services/ (accessed on 20 May 2024).
21. Noonan, L. AI in banking: The reality behind the hype. *Financial Times*. 12 April 2018. Available online: https://www.ft.com/content/b497a134-2d21-11e8-a34a-7e7563b0b0f4 (accessed on 20 May 2024).
22. Schroer, A. 36 Examples of AI in Finance. AI Has Revolutionized the Finance Industry. These Examples Show How. 2024. Available online: https://builtin.com/artificial-intelligence/ai-finance-banking-applications-companies (accessed on 20 May 2024).

23. Morandín, F. What is Artificial Intelligence? *Int. J. Res. Publ. Rev.* **2022**, *3*, 1947–1951. [CrossRef]
24. Al-Ameri, T.; Hameed, K. Artificial intelligence: Current challenges and future perspectives. *Al-Kindy Coll. Med. J.* **2023**, *19*, 3–4. [CrossRef]
25. Kenchakkanavar, Y. Exploring the Artificial Intelligence Tools: Realizing the Advantages in Education and Research. *J. Adv. Libr. Inf. Sci.* **2023**, *12*, 218–224.
26. Jain, R. Role of artificial intelligence in banking and finance. *J. Manag. Sci.* **2023**, *13*, 1–4.
27. Luger, F. *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*, 5th ed.; Pearson Education: Noida, India, 1998.
28. Russell, S.; Norvig, P. *Artificial Intelligence: A Modern Approach*, 2nd ed.; Pearson Education, Inc.: Upper Saddle River, NJ, USA, 2003.
29. Zheng, X.; Gildea, E.; Chai, S.; Zhang, T.; Wang, S. Data Science in Finance: Challenges and Opportunities. *AI* **2023**, *5*, 55–71. [CrossRef]
30. Chu, B. Mobile technology and financial inclusion. In *Handbook of Blockchain, Digital Finance, and Inclusion*; Academic Press: Cambridge, MA, USA, 2018; Volume 1, pp. 131–144.
31. Killeen, A.; Chan, R. Global financial institutions 2.0. In *Handbook of Blockchain, Digital Finance, and Inclusion*; Academic Press: Cambridge, MA, USA, 2018; Volume 2, pp. 213–242.
32. Li, Y.; Yi, J.; Chen, H.; Peng, D. Theory and application of artificial intelligence in financial industry. *Data Sci. Financ. Econ.* **2021**, *1*, 96–116. [CrossRef]
33. Fu, K.; Cheng, D.; Tu, Y.; Zhang, L. Credit card fraud detection using convolutional neural networks. In *Neural Information Processing, 23rd International Conference, ICONIP 2016, Kyoto, Japan, 16–21 October 2016*; Proceedings, Part III 23; Springer International Publishing: Cham, Switzerland, 2016; pp. 483–490.
34. Bahnsen, C.; Aouada, D.; Stojanovic, A.; Ottersten, B. Feature engineering strategies for credit card fraud detection. *Expert Syst. Appl.* **2016**, *51*, 134–142. [CrossRef]
35. Sahin, Y.; Bulkan, S.; Duman, E. A cost-sensitive decision tree approach for fraud detection. *Expert Syst. Appl.* **2013**, *40*, 5916–5923. [CrossRef]
36. Bahnsen, C.; Stojanovic, A.; Aouada, D.; Ottersten, B. Cost sensitive credit card fraud detection using Bayes minimum risk. In Proceedings of the 2013 12th International Conference on Machine Learning and Applications, Miami, FL, USA, 4–7 December 2013; Volume 1, pp. 333–338.
37. Bhingarde, A.; Bangar, A.; Gupta, P.; Karambe, S. Credit card fraud detection using hidden markov model. *Int. J. Comput. Sci. Inform. Technol.* **2015**, *76*, 169–170.
38. Küükkocaolu, G.; Benli, Y.; Küçüksözen, C. Detecting the manipulation of financial information by using artificial neural network models. *ISE Rev.* **1997**, *9*, 10–17.
39. Lin, C.; Chiu, A.; Huang, Y.; Yen, C. Detecting the financial statement fraud: The analysis of the differences between data mining techniques and experts' judgments. *Knowl. Based Syst.* **2015**, *89*, 459–470. [CrossRef]
40. Albashrawi, M. Detecting financial fraud using data mining techniques: A decade review from 2004 to 2015. *J. Data Sci.* **2021**, *14*, 553–570.
41. Pacelli, V. An artificial neural network approach for credit risk management. *J. Intell. Learn. Syst. Appl.* **2011**, *3*, 103–112. [CrossRef]
42. Khandani, E.; Kim, J.; Lo, W. Consumer credit-risk models via machine-learning algorithms. *J. Bank. Financ.* **2010**, *34*, 2767–2787. [CrossRef]
43. Yu, L.; Yue, W.; Wang, S.; Lai, K. Support vector machine based multiagent ensemble learning for credit risk evaluation. *Expert Syst. Appl.* **2010**, *37*, 1351–1360. [CrossRef]
44. Khashman, A. Credit risk evaluation using neural networks: Emotional versus conventional models. *Appl. Soft. Comput.* **2011**, *11*, 5477–5484. [CrossRef]
45. Lessmann, S.; Baesens, B.; Seow, V.; Thomas, C. Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. *Eur. J. Oper. Res.* **2015**, *247*, 124–136. [CrossRef]
46. Abellán, J.; Castellano, G. A comparative study on base classifiers in ensemble methods for credit scoring. *Expert Syst. Appl.* **2017**, *73*, 1–10. [CrossRef]
47. Mashrur, A.; Luo, W.; Zaidi, A.; Kelly, A. Machine learning for financial risk management: A survey. *IEEE Access* **2020**, *8*, 203203–203223. [CrossRef]
48. Kumar, V.; Rajan, B.; Venkatesan, R.; Lecinski, J. Understanding the role of artificial intelligence in personalized engagement marketing. *Calif. Manag. Rev.* **2019**, *61*, 135–155. [CrossRef]
49. Timoshenko, A.; Hauser, R. Identifying customer needs from user-generated content. *Mark. Sci.* **2019**, *38*, 1–192. [CrossRef]
50. Jiang, Y.; Wu, F. Development status and regulatory suggestions of intelligent investment consultant. *Secur. Mark. Herald.* **2016**, *293*, 4–10.
51. Yu, J.; Peng, Y. The Application and Challenges of Artificial Intelligence in the Field of Financial Risk Management. *South. Financ.* **2017**, *9*, 70–74.
52. Wang, D. Traditional financial institutions are ready to move. Is it more advantageous to set foot in intelligent investment advisory. *Chinas Strateg. Emerg. Ind.* **2017**, 70–72.

53. Ponemon, L.; Julian, T.; Lalan, C. IBM & Ponemon Institute Study: Data Breach Costs Rising, Now $4 million per Incident. *PR Newswire*. 15 June 2016. Available online: https://www.prnewswire.com/news-releases/ibm--ponemon-institute-study-data-breach-costs-rising-now-4-million-per-incident-300284792.html (accessed on 20 May 2024).
54. Alvarez, Y.; Leguizamón, A.; Londoño, J. Risks and security solutions existing in the Internet of things (IoT) in relation to Big Data. *Ing. Compet.* **2020**, *23*, 9–10. [CrossRef]
55. Cheng, L. Application status and security risk analysis of artificial intelligence in financial field. *Financ. Technol. Era* **2016**, *2016*, 47–49.
56. Ma, L.; Wei, Y. Application of artificial intelligence technology in financial field: Main difficulties and countermeasures. *South. Financ.* **2018**, 78–84.
57. Linklaters. *AI in Financial Services 3.0 Managing Machines in an Evolving Legal Landscape*; Linklaters: London, UK, 2023.
58. Brummer, C. How international financial law works (and how it doesn't). *Geo. LJ* **2010**, *99*, 257.
59. Allen, A. Business Challenges with Machine Learning, Machine Learning in Practice. 2018. Available online: https://medium.com/machine-learning-inpractice/business-challenges-with-machine-learning-3d12a32dfd61 (accessed on 19 May 2024).
60. Opala, M. 7 Challenges for Machine Learning Projects. 2018. Available online: https://www.netguru.com/blog/7-challenges-for-machine-learningprojects (accessed on 20 May 2024).
61. Bathaee, Y. The artificial intelligence black box and the failure of intent and causation. *Harv. J. Law Technol.* **2017**, *31*, 889.
62. OECD. AI Policy Observatory. Catalogue of Tools & Metrics for Trustworthy AI. 2022. Available online: https://oecd.ai/en/catalogue/tools (accessed on 20 May 2024).
63. Salesforce. Einstein OCR Model Card. 2024. Available online: https://developer.salesforce.com/docs/analytics/einstein-vision-language/guide/einstein-ocr-model-card.html (accessed on 19 July 2024).
64. Deloitte. *AI Regulation in the Financial Sector. How to Ensure Financial Institutions' Accountability*; Deloitte Japan: Tokyo, Japan, 2023.
65. Basel Committee on Banking Supervision. Basel Committee Publishes Work Programme and Strategic Priorities for 2021–2022. 2021. Available online: https://www.bis.org/press/p210416.htm (accessed on 20 May 2024).
66. Basel Committee on Banking Supervision. Newsletter on Artificial Intelligence and Machine Learning. 2022. Available online: https://www.bis.org/publ/bcbs_nl27.htm (accessed on 19 May 2024).
67. Bank of England. DP5/22—Artificial Intelligence and Machine Learning. 2022. Available online: https://www.bankofengland.co.uk/prudential-regulation/publication/2022/october/artificial-intelligence (accessed on 19 May 2024).
68. EIOPA. *Artificial Intelligence Governance Principles: Towards Ethical and Trustworthy Artificial Intelligence in the European Insurance Sector: A Report from EIOPA's Consultative Expert Group on Digital Ethics in Insurance*; EIOPA: Frankfurt am Main, Germany, 2021.
69. NAIC. Exposure Draft of the Model Bulletin on the Use of Algorithms, Predictive Models, and Artificial Intelligence Systems by Insurers 7/17/2023. 2023. Available online: https://content.naic.org/sites/default/files/07172023-exposure-draft-ai-model-bulletin.docx (accessed on 20 May 2024).
70. IOSCO. The Use of Artificial Intelligence and Machine Learning by Market Intermediaries and Asset Managers: Final Report. 2021. Available online: https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf (accessed on 20 May 2024).
71. Faraj, S.; Pachidi, S. Beyond Uberization: The co-constitution of technology and organizing. *Organ. Theory* **2021**, *2*, 1–14. [CrossRef]
72. Shaikh, A.; Karjaluoto, H. Mobile banking adoption: A literature review. *Telemat. Inform.* **2015**, *32*, 129–142. [CrossRef]
73. Teo, T.; Faruk, Ö.; Bahçekapili, E. Efficiency of the technology acceptance model to explain pre-service teachers' intention to use technology: A Turkish study. *Campus-Wide Inf. Syst.* **2011**, *28*, 93–101. [CrossRef]
74. Davis, F.; Sinha, A. Varieties of Uberization: How technology and institutions change the organization(s) of late capitalism. *Organ. Theory* **2021**, *2*, 2–17. [CrossRef]
75. Rogers, M.; Singhal, A.; Quinlan, M. Diffusion of innovations. In *An Integrated Approach to Communication Theory and Research*; Routledge: London, UK, 2014; pp. 432–448.
76. Ayub, M.; Zaini, H.; Luan, S.; Jaafar, W. The influence of mobile self-efficacy, personal innovativeness and readiness towards students' attitudes towards the use of mobile apps in learning and teaching. *Int. J. Acad. Res. Bus. Soc. Sci.* **2017**, *7*, 364–374.
77. Yoon, C.; Lim, D. An empirical study on factors affecting customers' acceptance of internet-only banks in Korea. *Cogent Bus. Manag.* **2020**, *7*, 1792259. [CrossRef]
78. Arner, W.; Barberis, J.; Buckley, P. 150 years of Fintech: An evolutionary analysis. *JASSA* **2016**, *3*, 22–29.
79. EY. *Global FinTech Adoption Index 2019*; EY: Singapore, 2019.
80. Ryu, S. What makes users willing or hesitant to use Fintech? The moderating effect of user type. *Ind. Manag. Data Syst.* **2018**, *118*, 541–569. [CrossRef]
81. Dermody, J.; Yun, J.; Della, V. Innovations to advance sustainability behaviours. *Serv. Ind. J.* **2019**, *39*, 1029–1033. [CrossRef]
82. Yoshino, N.; Morgan, J.; Long, Q. *Financial Literacy and Fintech Adoption in Japan*; Asian Development Bank Institute: Tokyo, Japan, 2020.
83. Morgan, J.; Trinh, Q. *FinTech and Financial Literacy in Vietnam*; ADBI Working Paper Series; Asian Development Bank Institute: Tokyo, Japan, 2020; pp. 1–23.
84. Davis, D. A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 1985.
85. Akturan, U.; Tezcan, N. Mobile banking adoption of the youth market: Perceptions and intentions. *Mark. Intell. Plan.* **2012**, *30*, 444–459. [CrossRef]

86. Gidhagen, M.; Gebert, S. Determinants of digitally instigated insurance relationships. *Int. J. Bank Mark.* **2011**, *29*, 517–534. [CrossRef]
87. Hu, Z.; Ding, S.; Li, S.; Chen, L.; Yang, S. Adoption intention of fintech services for bank users: An empirical examination with an extended technology acceptance model. *Symmetry* **2019**, *11*, 340. [CrossRef]
88. Teigland, R.; Siri, S.; Larsson, A.; Puertas, M.; Bogusz, I. Introduction: FinTech and shifting financial system institutions. In *The Rise and Development of FinTech*; Routledge: London, UK, 2018; pp. 1–18.
89. Braido, M.; Klein, Z. Digital Entrepreneurship and Institutional Changes: Fintechs in the Brazilian Mobile Payment System. Available online: https://aisel.aisnet.org/confirm2020/20 (accessed on 20 May 2024).
90. Almunawar, N.; Anshari, M. Customer acceptance of online delivery platform during the COVID-19 pandemic: The case of Brunei Darussalam. *J. Sci. Technol. Policy Manag.* **2024**, *15*, 288–310. [CrossRef]
91. Bagozzi, R.P. (The legacy of the technology acceptance model and a proposal for a paradigm shift. *J. Assoc. Inf. Syst.* **2007**, *8*, 3. [CrossRef]
92. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
93. Venkatesh, V.; Thong, J.Y.; Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* **2012**, *36*, 157. [CrossRef]
94. Kritsonis, A. Comparison of change theories. *Int. J. Sch. Acad. Intellect. Divers.* **2005**, *8*, 1–7.
95. Robbins, P. *Organisational Behaviour*, 10th ed.; Prentice Hall: London, UK, 2003.
96. Daniel, D.R. Management information crisis. *Harv. Bus. Rev.* **1961**, *39*, 111–121.
97. Rockart, J.F. Chief executives define their own data needs. *Harv. Bus. Rev.* **1979**, *57*, 81–93.
98. Bullen, C.V.; Rockart, J.F. *A Primer on Critical Success Factors*; Center for Information Systems Research, MIT: Cambridge, MA, USA, 1981.
99. Grunert, K.G.; Ellegaard, C. *The Concept of Key Success Factors: Theory and Method*; Mapp Working Paper No 4; Aarhus University: Aarhus, Denmark, 1992; pp. 1–24.
100. Mintzberg, H. The design school: Reconsidering the basic premises of strategic management. *Strateg. Manag. J.* **1990**, *11*, 171–195. [CrossRef]
101. Mintzberg, H. Strategy formation: Schools of thought. In *Perspectives on Strategic Management*; Fredrickson, J.W., Ed.; Harper: Grand Rapids, MI, USA, 1990; pp. 105–236.
102. Anshari, M.; Almunawar, M.N.; Masri, M.; Hamdan, M. Digital marketplace and FinTech to support agriculture sustainability. *Energy Procedia* **2019**, *156*, 234–238. [CrossRef]
103. Hamdan, M.; Anshari, M. Paving the Way for the Development of FinTech Initiatives in ASEAN. In *Financial Technology and Disruptive Innovation in ASEAN*; IGI Global: Hershey, PA, USA, 2020; pp. 80–107.
104. Anshari, M.; Almunawar, M.N.; Masri, M. Digital twin: Financial technology's next frontier of robo-advisor. *J. Risk Financ. Manag.* **2022**, *15*, 163. [CrossRef]
105. Firmansyah, E.A.; Masri, M.; Anshari, M.; Besar, M.H. Factors affecting fintech adoption: A systematic literature review. *FinTech.* **2022**, *2*, 21–33. [CrossRef]