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Towards Islamic Finance 2.0

(Fusion of Principles with Technology)

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Preface

All praise is due to Allah, the lord of the universes; peace and blessings be upon our prophet Muhammad, his family, and his companions. To proceed!

After the experiment of Islamic finance for almost half a century, during which it underwent significant developments and transformations in terms of its structures, products, and systems, as well as interacted with an environment that largely shaped many of its features. Initially from the generation of theoretical thinking and the conceptualization and across the stages of local savings banks, Islamic banking, Takaful, Islamic finance and investment companies, Islamic financial markets, global products, and Sukuk, in addition to the evolution of standards and legislation specific to the Islamic financial industry; the Islamic finance sought to keep pace with changes and confront challenges while adhering to the legal frameworks and ethical principles it is based on.

Islamic finance has proven, throughout its evolutionary stages, its ability to adapt to developments and flexibility in dealing with challenges. However, the most significant development is seen in the turbulent and accelerating journey of digital transformation, which may reshape the face of Islamic finance and present it differently. Observers believe that the recent period, marked by the widespread applications of financial technology and the emergence and increased use of generative artificial intelligence, heralds the reach of Islamic finance to a new era. The era can be identified as "Islamic Finance 2.0," which is broadly characterized by a shift towards digitalization and technological integration, offering innovative digital finance products that adhere to sustainability standards and integrate with the Islamic system of principles, values, and ethics.

In this conference, we try to define the new face that Islamic finance will have in the digital future and in the world of smart gadgets. We explore how it can navigate these challenges and turn them into opportunities for competition and impact in an innovative way that blends principles with technology.

This conference is held under the generous auspice of His Highness Mohammed Bin Abdulrahman Al-Thani, the Prime Minister and the Minister of Foreign Affairs, and the official sponsorship of the Ministry of Commerce and Industry. The event is organized by Bait Al-Mashura Finance Consultations with the strategic partnership of Dukhan Bank. The General Directorate of Endowments at the Ministry of Endowments and Islamic Affairs is the diamond sponsor, while Qatar Financial Center is the bronze sponsor. The academic partners are College of Shari'ah and Islamic Studies, Qatar University, and the College of Islamic Studies, Hamad Bin Khalifa University.

We ask Allah for His accordance.

The Scientific Committee

Conference Objectives

- To know the advancements in Generative AI and its impact on Fatwa and Shari'ah supervision in Islamic financial institutions.
- To describe the influence of AI applications on the performance of Islamic financial institutions.
- To explore the opportunities and challenges of endowment institutions in the era of AI.
- To comprehend the ethical and legal considerations of Islamic finance within smart systems.

Artificial Intelligence in Finance:
Islamic Ethical Framework and Perspectives

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Abstract

Artificial intelligence (AI) is a key contemporary technological development that will be a driving force in the future and impact individuals, organisations, and society. However, given the potential benefits and significant risks of AI, there is a need for governance and ethical frameworks to guide its use and applications. The aim of the paper is to present an Islamic ethical framework for AI that is based on the relevant Islamic values and principles and can be used in Islamic finance. The qualitative paper reviews the relevant literature and undertakes content analysis of AI principles/guidelines introduced by some countries to examine ethical issues arising in businesses and financial sectors. The analysis reveals that Islamic perspectives and framework focus on the principles of maqasid al Shariah and qawaid al fiqh to derive an ethical decision-making framework of using AI in businesses and Islamic finance. While artificial intelligence (AI) has a lot of potential to create value, it also introduces significant risks. The paper is one of the first to provide Islamic ethical perspectives on AI that can be used by Islamic finance. The key ethical issues arising in AI that need to be addressed include issues such as ensuring that AI makes ethical decisions and that the outcomes are ethical. Therefore, given the benefits and risks of AI, there is a need to come up with governance and ethical frameworks that would guide the development and use of AI in different areas including the financial sector. Thus, the conceptual paper addressed the key issues arising in AI from an Islamic perspective by developing a framework as a guide for the application of AI to benefit Islamic finance while minimising the risks.

Keywords: Artificial intelligence, maqasid al Shariah, Qawaid al fiqh, Islamic finance

1. Introduction

Artificial intelligence (AI) is a key contemporary technological development that is going to be a driving force in the future and impact individuals, organisations and society. Termed as 'new electricity', AI is expected to transform the nature of businesses in different sectors.[(1)] The use of AI in businesses has the potential to generate consumer benefits and increase productivity which can add trillions of dollars to the global economy. Chui et al. (2023) identify various business functions where AI can add value and estimate that an additional $200 billion to $340 billion annually can be added in the banking sector alone. While artificial intelligence (AI) has a lot of potential, it also introduces of risks to individuals, organizations and society that need to be addressed. The risks include issues related to faulty technology or algorithms, privacy, discrimination, disinformation, security issues, etc. which can impact economy, society and politics adversely (Cheatham et al. 2019).

Given the potential benefits and significant risks of AI, there is a need for governance

(1) https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

and ethical frameworks to guide its applications. Though there are various principles developed on the ethics of AI at organisational and country levels, there are scant discussions on this new technology from an Islamic perspective. Few studies have discussed AI from Islamic perspectives. For example, Raquib et al. (2022) provides a framework of using maqasid based virtue ethics for AI. Similarly, Mohadi and Tarshany (2023) discusses discuss ethics of AI from a maqasid perspective and identify privacy, employment and social justice as key concerns.

The paper contributes to the scant literate on Islamic perspectives on AI that is relevant in the economic and financial spheres. The aim of the paper is to present an Islamic ethical framework for AI based on the relevant Islamic values and principles. The analysis focus on behavioural ethics and the principles of maqasid al Shariah and qawaid al fiqh to derive an ethical decision-making framework of using AI.

This paper differs from previous studies on Islamic perspectives on AI in some significant ways. First, this paper examines the key elements of AI systems and identifies ethical issues arising in them. Specifically, it discusses ethical issues related to inputs, algorithms and outputs of AI systems. Second, the framework covers the ethical notions from different perspectives such as behavioural ethics, maqasid al Shairiah and legal maxims. Finally, while studies on AI from Islamic perspectives discuss the topic in general terms, the focus of this paper is on AI used in economics and finance.

The paper is organised as follows. The next section provides an overview of the literature on AI, the benefits, risks and ethics. Section 3 cover the Islamic values and principles that guide economics and finance. After providing an overview of the legal principles, the ethical framework is presented (maqasid al Shariah and qawaid al fiqh). Section 4 develops an Islamic ethical framework for AI that can be applied to economics and finance. The last section concludes the paper.

2. Artificial Intelligence (AI) and Implications: Literature Review

Digital technology has taken a centre stage with the dawn of the 4th Industrial Revolution (4IR) in the latter half of the last century. The revolution represents a dramatic shift from the past and is characterized by the blending of the digital with the physical and biological domains (Schwab 2016). A key development in the digital technologies is artificial intelligence (AI) which enables machines to carry out cognitive tasks intelligently.

Intelligence is defined variously and can viewed as both an activity or process and product or output of an activity (Ronn and Hoffding 2013: 697). Gottfredson 1997: 13) defines it as ‘a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience’. Xiaolan Fu (quoted in Zhao 2022: 2) relates intelligence to knowledge and ‘the ability to obtain knowledge and use it to solve problems. Intelligence is also linked to epistemology that is defined and as the theory of knowledge and deals with 'when and how knowledge can be ascribed to an agent in terms of warrant, methodology, truth, justification' (Ronn and Hoffding 2013: 697).

AI is also defined variously. FSB (2017) defines AI as "The theory and development of computer systems able to perform tasks that have traditionally required human intelligence." AI can be considered as 'machine-based systems with varying levels of autonomy that can, for a given set of human-defined objectives, make predictions, recommendations or decisions using massive amounts of alternative data sources and data analytics referred to as 'big data' (OECD (2021: 15). AI represents cognitive architecture that act as artificial mind exhibiting intelligent behaviour (Laird et al. 2017).

While AI refers to a range of techniques that can create intelligent systems, machine learning (ML) is 'a method of designing a sequence of actions to solve a problem, known as algorithms, which optimise automatically through experience and with limited or no human intervention' (FSB 2017: 1). ML uses algorithms that allows computers to learn from data and find patterns in large amounts of data to make decisions or predictions. Chakraborty and Joseph (2017) identify five components of ML system: a problem, data source, a model, an optimization algorithm and validation and testing.

Wang (2019: 8) views AI process to be similar to human intelligence which is structured as input signals, internal states and output actions. AI attempts to replicate this framework in terms of inputs, algorithms and outputs and this can be viewed in five domains. Structure of AI attempts to replicate the structure of a human brain by creating artificial neural networks. Behaviour of AI attempts to behave like intelligent humans and relates to modelling human psychology. Capability of AI relates to it problem solving capabilities and potential areas of applications. Function can be viewed in terms of mapping inputs into outputs and identifies the cognitive functions that AI can perform such as searching, learning, planning, perceiving, acting, etc. Finally, principle relates to the use of 'intelligence as a form of rationality' by mimicking the principle used by human mind in terms of get best possible solutions from the options available (Wang 2019: 12).

AI can entail different types of learning process. Whereas in supervised learning relies of labelled input and output data to make predictions by learning patterns form labelled datasets, unsupervised learning models do not contain labels and the algorithm detects patterns by examining the underlying structure and distribution of raw data (Buchanan 2019, FSB 2017, Delua 2021). Reinforced learning falls between supervised and unsupervised learning and deep learning algorithms are structured similar to brain and work in layers (FSB 2017).

Generative AI (GenAI) is a subset of AI/ML that have the ability to create new content by using large language models (LLMs). GenAI are modelled as neural networks that can review and evaluate huge amounts of data, texts and documents and produce original realistic, meaningful and understandable content, human languages or texts (Shabsigh and Boukherouaa 2023: 3-4). Some AI/ML models are capable to learn from data sets to 'self-improve' without being explicitly programmed by humans (OECD (2021: 15).

AI can be used in different spheres and industries, can transform various markets, affect jobs and education and have impact at political, societal and economic levels (EIU 2023). The use of digital technology and AI can improve decision making processes, contribute to economic growth by enhancing productivity and efficiency and help create new products and services (Shabsigh and Boukherouaa 2023)., Being a 'pure information-processing business' (Shaw 1996),(2) AI has the potential of changing the landscape in the financial sector as information and data constitute one of the key elements of financial transactions and products. The financial sector has been in the forefronts of using AI for different services such as algorithmic trading, model validation, portfolio composition and optimisation, robo-advising, market impact analysis, virtual customer assistants, stress testing and regulatory compliance (Buchanan 2019).

While AI can be used for beneficial purposes, it also presents challenges and risks. Ethics and regulations are required to balance between the benefits and risks of AI to create positive impact and increase the overall of welfare of individuals, society and the environment. The benefits, risks, ethics and regulations related to AI and discussed below with particular reference to the financial sector.

2.1. Benefits of AI

Digital world provides access to huge amount of data and information. Given the limitations of human constraints of information processing, AI has the potential of delivering greater efficiency, higher quality and better outcomes (Haefnera et al. 2017). An AI system with higher intelligence with produce an action output for input that is done by human intelligence faster and more efficiently. Furthermore, AI can mitigate the human errors arising from emotional and psychological conditions (Buchanan 2019). FSB (2017) identifies four broad areas of uses in the financial sector: customer-focused (or 'front-office') uses, operations-focused (or 'back-office') uses, trading and portfolio management in financial markets; and regulatory compliance (RegTech) uses by financial institutions or by public authorities for supervision (SupTech). Some of the specific uses and benefits of using AI are discussed below.

(2) A quote form David Shaw, founder of D.E. Shaw & Co. See https://money.cnn.com/magazines/fortune/fortune_archive/1996/02/05/207353/index.htm

2.1.1 Forecasting

AI can be used to forecast different variables that are key to businesses such as financial and macro-economic variables, business conditions, consumer demand, etc. (Boukherouaa et al. 2021). Since AI can use huge amounts of data and process them, it can better predict variables than using simple linear regression models. AI has the capacity of detecting pattens from big data that is difficult to do by humans using traditional forecasting models and tools.

2.1.2 Investment and Banking Services

AI can be used in the financial sector to make investment and banking decisions. AI is being used by the investment management industry that employs large amounts of trading information and data to implement high-frequency trading (Boukherouaa et al. 2021). AI is used in robo-advisory services, chatbots and systems that can extract data from huge amounts of documents quickly and efficiently (Buchanan 2019). Robo-advisors have the potential to reduce costs and improve transparency and quality of financial advice to clients. Furthermore, AI can be used for algorithmic trading that can reduce human error and mistakes, check conditions in multiple markets and execute trades at best possible prices (Buchanan 2019). AI can also be used in the banking sector to assist in financing decisions by reducing the costs of credit-underwriting and help in promoting financial inclusion by providing credit to more clients (OECD 2021). By using big data, AI can provide credit ratings for clients having limited credit history.

2.1.3 Benefits to Consumers

Use of AI in products and services can lead to reducing costs of financing, enhancing efficiency, providing access to various financial services and increasing financial inclusion, and help to provide better personalized products and services and improve client relationships (FSB 2017).

2.1.4 Risk and Compliance Management

AI can be used to improve risk management and regulatory compliance. For example, other non-traditional information and data can be used from big-data sources to come up with better measures of credit risks of clients. AI can also be used for AML/CTF and fraud detection and identify new security threats (Buchanan 2019, FSB 2017). AI can also be used for credit monitoring and risk mitigation (FSB 2017). Since the regulatory burdens and costs have increased significant in the financial sector in the aftermath of global financial crisis of 2008, AI is being used to develop regulatory technology (RegTech) to facilitate regulatory compliance and reporting (Boukherouaa et al. 2021).

2.1.5 Innovation Management

Laird et al. (2017) discusses AI in the framework of innovation management particularly in digitalised firms. Since information processing is a key component in innovation, AI can be used to facilitate this. Specifically, AI can be used in the idea generation and idea development phases.

2.1.6 Prudential Supervision

AI can be used to improve the quality of both micro-prudential and macroprudential supervision. Since supervisors have to deal with huge amounts of data and make decisions on the soundness of financial institutions, AI can be used by supervisors to make informed supervisory decisions (Boukherouaa et al. 2021). Given the complexity of regulations, SupTech can use AI to identify patterns, anomalies and weaknesses that is difficult to detect by humans.

2.1.7 Central Banking

AI can be used by central banks to improve their operations and supporting monetary policies and monitoring economic and financial developments (Boukherouaa et al. 2021). AI can be used to better forecast the macro-economic trends to make informed decisions. The development of the fintech sector with varied business models and formats adds another layer of complexity and risks. AI can be used to develop the appropriate legal and regulatory frameworks to understand and mitigate the risks arising in the financial and monetary systems from FinTechs and innovations.

2.2. Risks of AI

2.2.1 Data Privacy

Since AI uses data and information, there are risks of data leakages and theft (Boukherouaa et al. 2021, Shabsigh and Boukherouaa 2023). In many cases users automatically opt in to share the information which are used by the AI systems and some AI systems state in their disclosures that they cannot ensure the confidentiality and security of the information and data provided.

2.2.2 Embedded Bias

Embedded bias arises when 'computer systems that systematically and unfairly discriminate against certain individuals or groups of individuals in favor of others' (Shabsigh and Boukherouaa 2023: 6). Embedded bias can arise when either the algorithms used in AI system have human bias or data used is unrepresentative, incomplete or has societal prejudices. These biases can lead to AI systems discriminating among some groups of financial consumers (Boukherouaa et al. 2021, OECD 2021).

2.2.3 Robustness

Robustness relates the accuracy of the AI system's output and also concerns governance issues such as biased and harmful outcome and unethical use others' (Boukherouaa et al. 2021, Shabsigh and Boukherouaa 2023). Robustness becomes critical in changing and dynamic environments which AI systems cannot capture and thereby produce wrong results or predictions. The lack of robustness can have adverse impact on financial stability and protecting customers' interests.

2.2.4 Synthetic Data

Synthetic data are created by algorithm that mimics the statistical distribution of real data and used primarily to train AI/ML and for testing model robustness (Boukherouaa et al. 2021, Shabsigh and Boukherouaa 2023). While using synthetic data alleviates the concerns of confidentiality and data privacy, they can hide some of the risks that underlie in real data. The result can lead to making decisions that ignores some of the risks that financial institutions can potentially face.

2.2.5 Explainability

Since AI uses algorithms to come up with decisions and predictions it is difficult to explain how these conclusions are arrived at. The black box of decision making in AI systems have embedded explainability problems which may not be compatible with laws and regulations and also with internal governance and risk management frameworks (OECD 2021). Financial institutions are expected to explain their actions and decisions to different stakeholders including the regulators and supervisors as ability to explain decisions is essential for a sound financial system (Boukherouaa et al. 2021, OECD 2021, Shabsigh and Boukherouaa 2023).

2.2.6 Cybersecurity

Other than being a target of cyberattacks that can lead to data poisoning, AI introduces an additional layer of cybersecurity problem related to fake-ness and increased ability of identity theft and fraud due to its ability to generate sophisticated phishing messages (Boukherouaa et al. 2021, OECD 2021, Shabsigh and Boukherouaa 2023). Some of the 'jailbreaking' attacks can insert malicious instructions or data that can tap into sensitive data or distort AI operations (Shabsigh and Boukherouaa 2023).

2.2.7 Financial stability

Use of AI in financial institutions has the potential of introducing newer transmission channels and sources of systemic risks (Boukherouaa et al. 2021, Shabsigh and Boukherouaa 2023). Since AI systems are likely to use similar macro-level data for risk assessments it is likely that they will react similarly to macroeconomic shocks that can increase the interrelations and contagion (OECD 2021). The inter-linkages of reactions to data and information can exacerbate the herd mentality and cause systemic risks. For example the high-frequency trading is blamed for the 2010 Flash Crash and 2015 market turmoil of S&P 500 and the crash of pound sterling during 2016 Brexit referendum (Buchanan 2019).

2.3. Ethics of AI

AI has raised various ethical issues that are novel and discussed under technology ethics or machine ethics which relate to 'ethical norms of artificial agent' (FSB 2017: 39). There are strong arguments of providing ethical guidelines for AI since it has the potential of surpassing human intelligence which raises concerns of the challenges that AI can pose due to unknow and unintended consequences. Floridi et al. (2018) identify two advantages of adopting ethics in AI. Ethics can enhance its positive impact by enabling organisations to take advantage of the social value that AI can create by leveraging new socially acceptable opportunities. Ethics also enables organisations to minimise the negative impacts by anticipating and avoiding costly mistakes and socially unacceptable outcomes.

Ethical issues in AI can be viewed in terms of ethical theories which can be broadly classified into three types: deontological, teleological and virtue. The Kantian deontological approach defines a set rules and duties as ethical (Ananny 2016). This theory considers ethics to be inherent in specific actions or behaviours which are done as a sense of duty and from good will to act ethically (Bowie 1999). The deontological approach focuses on principles and values such as justice, duties, obligations, fidelity, gratitude, proper conduct, etc. (Akaah 1997, Hunt and Vitell 1986). The deontological norms are predetermined value and rules of behaviour which individual undertake without consideration to consequences (Rallapalli et. al 1998).

The teleological or utilitarian ethical framework proposed by John Stewart Mill and Jeremy Bentham view ethics in terms of good consequences and assesses the consequences of actions and behaviours to ascertain their ethicality (Koehn 1995). The teleological philosophy examines costs and benefit on a decision to make ethical judgments (DeConinck and Lewis 1997). The consequences can be evaluated narrowly for individuals from an egoistic perspective or for the society collectively in the utilitarianism approach (Akaah 1997: 72; Rallapalli et. al 1998). In the former, a decision would be considered proper if it benefits the management of a firm and in the latter an act would be right if it produces good for the majority of the people.

Finally, rooted in Aristotle's discussions in ethics, virtue ethics focuses on character building of agents or individuals by increasing the virtuous actions and behaviour. Whereas the focus of deontological and teleological theories is on acts done as duty and their outcomes respectively, virtue ethics is concerned with the character dispositions of persons (Hagendorf 2020, Whetstone 2001, 101-114). Virtues are enduring character traits that individual have and is about making sound moral judgments (Dobson 1997, Moore 2005). Examples of virtues include empathy, piety, respect, reliability, and incorruptibility (integrity) (Shanahan and Hyman 2003).

The deontological approach to AI ethics would entail technology developers adhering to certain ethical principles (Ananny 2016). Virtue ethics identifies the moral behaviour traits that individual developers or software engineers should have (Leonelli 2016). These traits include honesty, empathy care, justice, etc. (Hagendorf 2020). The teleological ethics would judge AI by its impact and assessing the benefits and risks. However, Raquib et al. (2022) argue that the consequentialist approach of AI ethics assesses the costs and benefits of their applications may be difficult given that their impact on abstract issues such as human ideas, thoughts, worldviews and values are difficult to measure. Since assessment of risks of technological innovations and AI and their impact socio-economic systems and are hard to measure or predict, they suggest using virtue ethics as a viable alternative to frame ethics for AI.

AI ethics can be viewed in different dimensions. Ashok et al. (2022) identify four domains under which digital ethics of AI can be examined: physical, social, life and governance. The first three domains are linked to Popper's ontological notions of three worlds of physical, cognitive and information. The physical world relates to states and processes of objects, the cognitive world concerns mental states and processes relating to interpretations and involves thoughts and sensations, and information world are symbols and signs representing products of thought. In terms of digital technology, the physical relates to the device layer that entails physical machines and logical capabilities, the cognitive domain is the service layer in terms of applications and algorithms and the information domain is the content layer dealing with data (Ashok et al. 2022). The governance domain covers governance issues of all of these three domains.

While the ethical issues arising in the physical domain would include notions of 'dignity and well-being, safety, and sustainability', ethics for the cognitive domain relates to implications of machine learning and algorithms and coves issues such as intelligibility, accountability, fairness, promoting prosperity, solidarity, autonomy (Ashok et al. 2022). A key issue in the latter is to ensure that humans do not become subservient to machines or algorithms by preserving of human agency and freedom of choice. The ethics of information domain concerns privacy and security of data and the governance domain relates to establishing and implementing policies, standards and procedures to ensure ethical use of technologies.

Implementing AI within organizations would also require introducing governance frameworks that guides the lifecycle of AI systems (OECD 2021). An important issue in the governance domain is to assess the positive and negative impacts of technologies at different levels such as individual, societal, economic and financial (Ashok et al. 2022). Furthermore, accountability mechanisms must be introduced to ensure that AI operates within the ethical guidelines. This becomes important as AI is being increasingly used for making important decisions that affect customers. Thus, a new role of AI and data governance and risk management will be needed in firms that use AI in their operations.

After examining six high-profile standards of AI, Floridi and Cowls (2019) identify five ethical principles that should govern AI. First, beneficence relating to promoting well-being, preserving dignity and sustaining the planet. Second, non-maleficence in terms of protecting privacy and security and 'capability caution' that limits the misuse of AI. Third, autonomy of human beings that balances the decision-making power between humans and machines so that artificial autonomy does not undermine human autonomy. Fourth, justice that promotes prosperity, preserves solidarity and avoids unfairness. Finally, explicability that is understandable and enables other principles through intelligibility, transparency and accountability. Similarly, Floridi et al. (2018: 696) study six guidelines on AI ethics identify five key ethical principles for AI as beneficence, non-maleficence, autonomy, justice and explicability.

Hagendorf (2020) systematically evaluates 22 guidelines on AI and identifies the following issues covered in them:(3) privacy protection (18); fairness, non-discrimination, justice (18); accountability (17); transparency, openness (16); safety, cyber security (16); common good, sustainability, well-being (16); human oversight, control, auditing (12); solidarity, inclusion, social cohesion (11); explainability, interpretability (10); science policy link (10); legislative framework, legal status of AI systems (10); future of employment/workers' rights (9); responsible/intensified research funding (8); public awareness, education about AI and its risks (8); dual-use problem, miliary, AI arms race (8); field-specific deliberations (health, military, mobility etc.) (8); human autonomy (7); diversity in the field of AI (7); certification of AI products (4); protection of whistle blowers (3); cultural differences in the ethically aligned design of AI systems (2); and hidden costs (labeling, clickwork, content moderation, energy, resources) (2).

Jobin et al. (2019) 84 guidelines on AI from different jurisdictions and identified 11 overarching ethical values from them: transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, dignity, sustainability, and solidarity.

3. Islamic Legal Principles and Ethical Values: An Overview

The overall aim of Shariah is to promote welfare or benefit (maslahah, pl. masalih) of mankind and prevent harm (mafsadah). To achieve these aim, Islamic teachings provide the legal rules and ethical values that govern human behaviour and economic activities. The legal framework of commercial and economic activities is governed by the 'principle of permissibility' (ibahah) which asserts that all acts are permissible unless they are prohibited by Shariah texts (Kamali 2000: 66).(4) Other than forbidding

(3) The number in the parentheses indicates number of guidelines covering the issue.

(4) The principle of permissibility is derived from maxims such as 'permissibility is the original rule of things' or 'the norm in transactions is that of permissibility' (Laldin et.al. 2013:10).

some goods and activities such as wine, pork and gambling, two broad categories of prohibitions in economic transactions are riba and gharar.

Ethics in Islamic economics and finance is discussed from different perspectives and come from different sources. The key sources of Islamic ethics are the Quran and Sunnah. There are many Quranic verses and ahadith that provide ethical and moral teachings related to various issues. Beyond the Shariah texts, ethical values and principles also exist in maqasid al Shariah (hereafter maqasid) and legal maxims. As indicated, broad ethical principle guiding Shariah is to maximize welfare (maslahah) and minimize harm (mafsadah). Maslahah and maqasid provide teleological ethical perspectives as they related to the consequences of acts in terms of Shariah's goals of achieving good. Many maxims provide ethical guidance including some maxims that support maslahah. Given the above, Islamic ethics related to economics can be presented in following four perspectives.

1. *Human Behavioural Ethics (Deontological & Virtue Ethics):* The ethical axioms provide the ontological foundations and derive the moral values that guide human behaviour and actions in an Islamic economy (Iqbal and Mirakhor 2020). The righteous behaviour conceptualised in adab (or more recently in akhlaq) relates to moral integrity that guide humans in economic transactions (Al-Daghistani 2022). The Islamic worldview and ethics change the nature of human behaviour from homo economicus to homo islamicus (Asutay 2007, Haneef and Furqani 2009). Instead of maximizing utility, the objective of Muslims is to achieve falah which is success in this world and the hereafter. Thus, homo islamicus will be imbibed with behavioural ethics such as respect for property rights, trust, honesty, transparency, cooperation, compassion, benevolence, etc., prescribed by Shariah (Ahmad 1992, Asutay 2007, Aydin 202). A Muslim with means will engage in charitable acts beyond zakat such as sadaqah and create waqf.

2. *Maslahah and Maqasid (Teleological Ethics):* Some scholars identify the underlying guiding principle governing Shariah to be 'enhance welfare (maslahah) and minimize harm (mafsadah) (Dien 2004:3, Heinrichs 2002: 372, Kamali 2008: 32, 35). Maqasid al Shariah signifies the aims, objectives or ends of Shariah representing the essentials elements that can achieve the best interests of humans and promote good life (Ibn Ashur 2006, Laldin 2020). Maqasid provides the 'ethical aspects of legal norms' (Al-Daghistani 2022: 63) and reflects the underlying normative wisdom of Islamic law and represent the permanent and universal goals of Shariah (Kamali 2006, 2011). Maqasid is related to the consequences of acts and neglecting them can lead to rules that deviate from Shariah's intent of enjoining good. Maqasid perspective asserts that Shariah ordains doing certain acts as they secure the welfare of the community and forbids evil because it is against the public welfare (Abdel-Wahab 1962-63). Scholars identify maqasid as the protection and enhancement of faith, self, intellect,

posterity, wealth and human dignity[5] (Chapra 2008, Hallaq 2004, Kamali 2003, Laldin 2020). Maqasid implies guaranteeing a good quality of life by securing the religion, intellect and dignity of individuals and ensuring a minimum level of income or wealth for all in the society and protecting the interests of the future generations.

While these general maqasid relate to human welfare, there are specific maqasid identified by scholars that relate to economic transactions. Ibn Ashur (2006: 285) identifies the maqasid specific to economic transactions and activities as circulation/marketability, transparency, preservation, durability and equity or justice. Circulation or marketability is defined as "the fair circulation of wealth in the hands of as many people as possible" (Ibn Ashur 2006: 286). Preservation of property and wealth is among the primary maqasid al Shariah and 'is one of the fundamental and universal principles of the Shariah' (Ibn Ashur 2006: 286). Persistence or durability implies that an owner of a property has the exclusive right to property that is earned lawfully and this right is not subject to any kind of delay. Transparency in wealth and property is aimed to 'avoid harm and disputes as much as possible, for which reason pledges and documentation have been prescribed' (Ibn Ashur 2006: 295). Justice means that 'wealth and property should not be acquired wrongfully or unjustly' (Ibn Ashur 2006: 298-99). Justice also implies equality of countervalues in exchange transactions and has distributive dimension in terms of providing equal access and opportunities to various economic activities and markets to all segments of the population.

3. *Legal Maxims and Ethics:* Legal maxims (qawaid al-fiqh) form another important genre of Islamic methodological tool. The maxims are based on and derived from Shariah texts reflecting the spirit or essence of Islamic law (Dien 2004:3, Kamali 2011).[6] The maxims of qawaid al fiqh (hereafter qawaid) can be used as guide in law making as they embody universal rules that can be applied to particular cases (Rabb 2010, Musa 2014). While some legal maxims have legal connotations, others as having ethical overtures. For example, the maxims of 'if permissibility and prohibition coincide, prohibition prevails' and 'what is prohibited to take is also prohibited to give' (Laldin et al. 2013: 188, 194)' fall under the legal category. Maxims with ethical undertones include 'the fundamental requirement in every contact is justice' (Laldin et al. 2013: 22) It should be noted that many principles governing maslahah/maqasid are reflected in the legal maxims. Maxims related to maslahah include 'averting harm takes precedence over achieving benefit' and 'harm is to be eliminated' (Laldin et al. 2013: 110, 117).

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(5) While honour/dignity (al-'ird) is mentioned as a maqsad by some classical scholars such as al Ghazali and al-Shatibi and more recently by Yusuf al Qaradawi (Auda 2008:22, Kamali 1999).

(6) Given the importance of legal maxims in Islamic law, Majjalah the first codified document of Islamic commercial law produced in the Muslim world in the 19th century lists 99 maxims before presenting specific rules related to different transactions. See (Majjalah 2001).

4. Islamic Ethical Framework for AI in Economics/Finance

AI from an Islamic perspective will take an epistemological approach in terms of viewing role of intelligence as knowledge creation. Thus, the from knowledge sources, the processes and applications of AI would be guided by Islamic principles and values. As indicated, Islamic principles and ethical values are reflected in behavioural ethics, maqasid and maxims and these will influence the process and product of AI.

AI is directly related to key maqsad of 'intellect' which plays a very important role in Islam as it is one of the distinguishing features of being human. Ghazali identifies intellect as the 'fountain head of knowledge and its foundation' and it should be 'honoured as it the cause of the fortune in this world and the hereafter' (Ghazali 1993:92). Inclusion of the hereafter provides an important feature of Islamic worldview on knowledge and intellect. Intellect is not only a key maqsad in itself, but guides and supports the other maqasid. Specifically, intellect is needed to achieve the objectives of protecting and enhancing faith, self, progeny and wealth. In particular, faith and intellect are closely related. Faith provides the right direction to intellect and intellect is needed to understand faith. From an Islamic point of view, intellect has to be guided by faith to produce knowledge that can enhance human well-being (Chapra 2008). This is apparent in guidance from Shariah which encourages acquiring and creating beneficial knowledge. For example, the Messenger of Allah (PBUH) said: "Ask Allah for beneficial knowledge and seek refuge with Allah from knowledge that is of no benefit."(7)

Since the focus of the paper is on ethics of AI in economics/finance, the relevant behavioural ethics and the specific maqasid related to economic transactions identified by Ibn Ashur which include circulation, transparency, preservation, durability and justice would be relevant. It is important to note a couple of underlying principles that apply to ethics of AI in economics/finance. The principle of permissibility guides issues in muamalat which includes economics/finance which implies that new notions and activities are permitted as long as they do not have the prohibitions. The principle of permissibility also applied to AI implies that AI would not be used for illegitimate transactions such as those entailing riba and gharar. However, the epistemological approach implies that AI will be guided by Islamic ethical guidelines and values.

4.1. Islamic Ethics and AI in Economics/Finance: An Evaluative Framework

The Islamic framework for AI can be developed by examining the ethical issues arising in its key components. As indicated, AI attempts to replicate human intelligence which is structured as input signals, internal states and output actions. The AI equivalent of these elements would be information inputs, algorithms and outputs. The ethical issues arising in each of these elements are discussed below.

(7)Hadith narrated by Jabir. Sunan Ibn Majah 3843, https://sunnah.com/ibnmajah:3843

4.1.1. Inputs

Informational ethics would be relevant for inputs of AI systems since the key inputs of AI are information and data. There are several ethical issues that arise in terms of inputs. There is a need to ensure that the information are that are used in the AI systems are sourced legally and not contradict Islamic principles and values. There are not only ethical issues that arise in gathering personal data and information, but also legal requirements on how to access personal data in some jurisdictions. Thus, data protection and privacy issues need to be taken care of in developing AI systems. Another key issue is the type of data that is sources from open sources such as big data. For Islamic finance some information and data from these sources may not be suitable. For example, these sources will have abundance of information on the banking system that is dominated by interest-based financing which may not be relevant for Islamic finance. Furthermore, ethical issues arise related to the biases and discriminatory aspects of the data and information. Finally, care has to be taken about the authenticity of the data fed in the AI systems.

While the above informational ethics identified above are important aspect of AI ethics, it should be noted that some of these issues do not appear explicitly in classical fiqh literature. For example, the focus of information related issues in economics/finance is on gharar in contracts which may not be directly relevant to some of the information related issues such as privacy and data protection. The way to approach this is to use the principle of permissibility and apply the maxims of enhancing benefits and minimising harms. Furthermore, from a Shariah point of view, the status of information as property needs to be clarified. While OIC Fiqh Academy has recognises intellectual property such as copyrights and patent rights to be valid form of property, this has to be extended to information and data.[8]

4.1.2. AI Algorithms

Algorithms provide the computational framework that maps the inputs to the desired outputs. Some ethical issues arise in AI algorithm as it attempts to technologically replicate human brain and develop neural networks digitally. These ethical issues can be understood by examining how human agent acts intelligently and can be discussed in terms of behaviour, functions, capacity and principles (Wang 2019: 12).

Behaviour of AI relates to performance of AI in its expectations of behaving like intelligent human agent. The behavioural aspects of the AI framework will be embedded in the algorithm that would attempt to reproduce human psychology of converting inputs into desired outputs. Since behavioural aspect relates to making AI behave as humans psychologically, the relevant ethics that will apply for this domain will be similar to those applied in case of human intellect.

(8) See OIC (2021: 78), Resolution No. 43 (5/5), OIC International Fiqh Academy 5th session in Kuwait City, State of Kuwait, on 1–6 Jumādā al-Ūlā 1409h (10–15 December 1988).

The behavioural features of economic agents in an Islamic economy/financial system will be represented by homo islamicus and this should also apply to AI. The ethical features of homo islamicus would include respect for property rights, trust, honesty, transparency, compassion, benevolence, etc., which are prescribed by Shariah.

AI capability relates to its problem-solving capacities of AI which relates to technology and is ethically neutral. Ethicality of function depends on the type of cognitive functions that AI is performing. While certain functions such as searching, learning, forecasting are Shariah neutral, some other functions may have legal and ethical implications. For example, if AI is used to exploit or discriminate against a group of people, these functions will be considered either illegitimate or unethical. Principle of AI underscores the rationality used by AI to use the best possible decision to produce outputs from inputs (Wang 2019: 12). The rationality from an Islamic perspective will be guided by Islamic values and principles.

While the rationality of homo economicus would be focussed of the outcomes that are most efficient and profitable, the rationality of homo islamicus will be governed by Islamic values and principles. This will require using acceptable inputs to arrive at the best possible outputs that satisfy Islamic principles and values.

4.1.3 Outputs

The potential applications would reflect the outputs of AI and relates to the problem being solved. The outputs of AI systems need to be screened for their impact of maqasid al Shariah which can be done by applying guidelines from the maxims. At a general level, maqasid entails the protection and enhancement of faith, self, intellect, posterity, and wealth (Chapra 2008, Hallaq 2004, Kamali 2003, Laldin 2020). While these general maqasid related to human welfare must be protected or enhanced by AI protocols, there are additional maqasid related to economic transactions that also should be satisfied in the economic/financial spheres.

The legal maxims provide some guidance on the criteria used to achieve the maqasid when applying AI. Some maxims that may apply to AI include 'Harm is to be eliminated' which requires that harm caused to humans need to be removed (Majallah 2001: 6, Laldin et al. 2013: 110). The maxim is derived from a hadith that says 'harm should neither be inflicted nor reciprocated' (Majallah 2001: 6, Laldin et al. 2013: 114). A related maxim 'Averting harms takes precedence over-achieving benefit' means that when harm and benefits of an act are of similar magnitude, preventing harm should be given precedence and the act should be undertaken (Laldin et al. 2013: 117). An implication of the maxim is that an act should be undertaken only when the benefits exceed the harms. Similarly, maxim 'Severe damage is made to disappear by a lighter damage' (Majallah 2001: 6) implies that a problem causing major harm can be resolved by one that causes lesser harm. Another maxim 'A private harm is tolerated in order to ward off a public harm' (Majallah 2001: 6) suggests that if there is a trade-off between a private harm and a public harm, then eliminating the latter will be given preference. However, a key issue in applying the maxims is the difficulty in measuring benefits and harms of AI on different maqasid.

When use of AI produces both benefits and risks (harms), then the maxims can be used to define the principles that govern AI from an Islamic perspective. The implications of the maxims is the any activity that has harmful impact on the protecting the maqasid need to be avoided. AI can be introduced as long as the benefits to maqasid outweigh the risks of impacting them adversely and all attempts should be made to mitigate the risks. The implementation of ethical values in AI would require supervised AI rather than unsupervised AI.

The dimensions of outputs in applying AI would be to assess the benefits and harms caused to the general maqasid and the maqasid specific to economics. As indicated, Ibn Ashur (2006: 285) identifies the maqasid specific to economic transactions as circulation/marketability, transparency, preservation, durability and equity or justice. For example, AI that promotes the growth of wealth will be accepted, but if AI leads to unjust outcomes it will be ethically repugnant. Similarly, if AI is used to exploit or discriminate against a group of people, these functions will be considered either illegitimate or unethical.

5. Islamic Ethical AI for Economics/Finance: Concluding Remarks

While AI has potential to produce various benefits it also introduces various risk. The risks and harms of AI can be mitigated by guiding its development and use by ethics. Shariah provides legal principles and ethical values that guide various spheres. The Islamic ethics that are relevant to AI include behavioural ethics, maqasid al Shariah and legal maxims. This paper uses these dimensions of ethics to develop a framework of assessing ethics that can be applied to AI used in economics and finance.

When comparing the AI ethics discussed in contemporary literature and Islamic ethical values for AI, three types of cases can be identified. First, some of ethical principles of AI identified in conventional literature are aligned to the behavioural ethics, maqasid and maxims, there are some other that are not specifically mentioned in the Shariah sources. The AI ethical values identified in contemporary literature that are aligned to the Islamic ethical principles include beneficence (beneficial to, and respectful of, people and environment)[9] which relates to the general Shariah maxim of enhancing welfare and mitigating harm; autonomy (or respect for human values) relating to the maqsad of protecting and enhancing life, human dignity and intellect; fairness and justice which is a maqsad for economic transactions and explicability (understandable, accountable and understandable) relating to the maqsad of transparency. Similarly, some behavioural aspects such as trust, dignity and solidarity appear in both contemporary AI ethics and Islamic ethics.

(9) Morley et al. (2020: 2145).

Second, there are certain unique Islamic AI ethical values that do not appear in contemporary AI ethics. They relate to circulation, protection and durability of wealth. Finally, some contemporary AI ethical values that do not appear explicitly in Shariah texts. Shariah perspectives on these issues can be derived by using the Islamic legal and ethical values. For example, although there is no explicit mention of non-maleficence that requires AI to not infringe on data privacy and undermine security (Morley et al. 2020), this can be considered compatible with Shariah principles based on maqasid that protects wealth and upholds human dignity. As discussed, intellectual property such as copyrights and patent rights are recognised and protected by Shariah and can be extended to information and data.

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Evolution of the Generative AI in the Financial Industry

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Abstract

This paper delves into the evolution of Generative Artificial Intelligence (AI) in the finance sector, tracing its journey from inception to its current integral role in both conventional and Islamic finance. It examines the progressive applications of Generative AI, including automated trading, fraud detection, and personalized financial advice, and explores its compatibility with Islamic financial principles. Highlighting the benefits and addressing the challenges posed by Generative AI, such as ethical, regulatory, and security concerns, the paper provides a comprehensive overview of its transformative impact. Through case studies, it illustrates not only the current applications but also forecasts future trends, emphasizing the need for an ethical approach in integrating Generative AI into financial services.

1. Introduction

This introduction sets the stage for a comprehensive exploration of the evolution of Generative AI in finance. It aims to shed light on how this technology, moving from being a mere auxiliary tool, has become a pivotal force in reshaping financial strategies and operations. Generative AI's applications are diverse and far-reaching, ranging from automating trading systems and personalizing financial advice to enhancing fraud detection mechanisms and revolutionizing aspects of Islamic Finance. This evolution paints a future where finance is not just about numbers and algorithms but about the potential to generate new paradigms and possibilities, with Generative AI playing a central role in this transformation.

At the intersection of innovation and intelligence lies Generative AI, a frontier in the realm of artificial intelligence that is redefining the possible. Unlike its predecessors, which primarily focused on interpreting and reacting to existing data, Generative AI is a trailblazer capable of creating new data, simulating scenarios, and envisioning outcomes that extend beyond the existing knowledge base. This transformation is underscored by the McKinsey report, which highlights the substantial economic impact of generative AI, estimating a global economic boost of $2.6 to $4.4 trillion annually. Specifically for the banking industry, the implementation of generative AI use cases could lead to an additional annual value of $200 to $340 billion.

Generative AI refers to a subset of AI technologies that generate new content, ideas, or data that are coherent and contextually relevant. This is achieved through advanced machine learning models like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), which learn to produce outputs that are indistinguishable from real-world data. The journey of Generative AI began with the exploration of neural networks and deep learning, evolving from image and voice generation to sophisticated applications in finance. Key milestones include the development of GANs in 2014, which marked a significant advancement in the field, and the introduction of transformer models, revolutionizing natural language processing.

2. Overview of Generative AI

Generative AI, representing a groundbreaking frontier in artificial intelligence, has undergone a significant transformation in its role within the financial sector. Originally serving as an auxiliary tool for basic data analysis, Generative AI has evolved to become a cornerstone technology, revolutionizing financial strategies, operations, and decision-making processes.

The journey of Generative AI in finance began with foundational neural networks and machine learning algorithms that primarily focused on data interpretation and reaction. This early stage of AI in finance was characterized by straightforward applications, such as automating routine tasks and analyzing structured data. However, the limitations of these initial models soon became apparent, paving the way for more advanced forms of AI.

The advent of Generative AI marked a turning point. Unlike traditional models, Generative AI technologies like GANs and VAEs were capable of not only processing existing data but also creating new, synthetic data. Introduced around 2014, GANs represented a paradigm shift, enabling AI to simulate realistic scenarios and outcomes, thus broadening the scope of its application in finance.

The evolution of Generative AI in finance has had a profound economic impact. According to McKinsey, the implementation of generative AI could potentially boost the global economy by $2.6 to $4.4 trillion annually. In the banking sector alone, this could translate into an additional value generation of $200 to $340 billion annually. These figures highlight the substantial role of Generative AI in enhancing efficiency and driving revenue growth in financial services.

Generative AI's capabilities extend beyond traditional data analysis. It involves understanding complex data patterns and replicating them to produce coherent and contextually relevant outputs. This has led to innovative applications in finance, such as AI-driven platforms like RBC Capital Markets' Aiden. Utilizing deep reinforcement learning, these platforms have revolutionized trading strategies, enabling real-time adaptation to market conditions - a feat unachievable with traditional methods.

Moreover, the technology has branched out into areas like real-time fraud detection, automated financial advising, and sophisticated risk assessment models. These applications demonstrate how Generative AI complements human expertise, often surpassing it in terms of efficiency and scalability.

In its current state, Generative AI in finance is characterized by a blend of maturity and continuous exploration. Financial institutions are increasingly adopting these technologies, integrating them into their core operations. This integration reflects an ongoing journey - one where financial institutions are continually exploring new ways to leverage AI for enhancing decision-making, personalizing customer experiences, and managing risks more effectively.

As we move forward, Generative AI continues to evolve, adapting to the ever-changing landscape of the financial sector. Its journey represents a continuous progression, marked by technological innovations and expanding its scope of applications, shaping the future of finance in unprecedented ways.

3. Generative AI in Finance: Applications and Case Studies

The integration of Generative AI into conventional finance has been nothing short of transformative, bringing about efficiency, precision, and innovation in various financial operations. This shift represents a significant evolution from traditional financial technologies, marking a new era in the financial industry characterized by data-driven and AI-powered operations. The change is not merely incremental but foundational, redefining the very mechanisms through which financial services operate and engage with the rapidly changing global market.

According to the survey conducted by KPMG, 83% of respondents in a survey use AI for financial planning, including predictive models, scenario creation, and budget insights.(1) The survey data reflects a growing trend in the financial industry's evolution, where advanced AI applications are becoming increasingly integral to diverse financial operations. Generative AI is being used for developing forecasts and budgets, generating financial commentary and presentations, gathering market intelligence, producing strategic insights from data, and managing contracts. It is also utilized in detecting anomalies and fraud protection.

The following key applications and case studies illustrate not just the capabilities of Generative AI but also its evolving role in reshaping financial practices.

3.1. Automated Trading Systems

Generative AI has revolutionized the landscape of trading by introducing automated systems capable of analyzing market data, predicting trends, and executing trades with a level of speed and accuracy unattainable by human traders. These systems use complex algorithms to identify profitable trading opportunities based on historical data and market indicators. A notable example is the use of AI-driven platforms like RBC Capital Markets' Aiden, which employs deep reinforcement learning to adapt its trading strategies in real-time, optimizing performance under varying market conditions.

3.2. Fraud Detection and Risk Management

In fraud detection and risk management, Generative AI has emerged as a crucial tool. By analyzing patterns in transaction data, AI models can identify anomalies that

(1) https://kpmg.com/us/en/articles/2023/generative-ai-finance.html

may indicate fraudulent activity. This proactive approach to fraud detection not only enhances the security of financial transactions but also reduces the incidence of false positives, thereby improving operational efficiency. For instance, banks like Wells Fargo have implemented AI features in their mobile apps to provide personalized account insights, enhancing fraud detection capabilities. This shift represents a significant evolution from traditional manual fraud detection methods. Previously, such processes were heavily reliant on human analysis and simpler statistical methods. The integration of Generative AI in institutions like Wells Fargo demonstrates a major advancement in the financial industry, offering a more sophisticated, data-driven approach to identifying and mitigating financial fraud, showcasing the evolution from traditional practices to modern, AI-enhanced methods.

3.3. Personalized Financial Advice

Generative AI is also reshaping the domain of financial advisory services. By leveraging customer data, AI algorithms can offer personalized investment advice, tailor financial plans to individual needs, and predict future financial trends. This personalization extends beyond mere data analysis; it involves understanding customer behaviors, preferences, and financial goals to provide bespoke advice. Robo-advisors, for instance, use AI to offer investment advice and portfolio management services at a fraction of the cost of traditional financial advisors. This transformation marks a significant shift from conventional, one-size-fits-all financial advice to AI-powered, personalized services, illustrating the evolution in financial advisory models. Traditional financial advisory services typically relied on human judgment and standard models, but the introduction of AI and robo-advisors represents a major advancement, offering a more nuanced, data-driven approach that caters to the unique financial circumstances and objectives of each client, thereby highlighting the progressive journey from traditional methods to modern, AI-enhanced advisory services.

3.4. Credit Scoring and Loan Approval:

Generative AI has significantly improved the accuracy and efficiency of credit scoring and loan approval processes. Companies like Upstart use AI to analyze non-traditional data points, providing a more comprehensive assessment of a borrower's creditworthiness. This approach not only streamlines the loan approval process but also expands access to credit for underserved populations. The evolution from traditional credit scoring methods, which often relied on a narrower set of data points, to AI-driven approaches marks a considerable advancement in the field. Traditional methods were primarily based on limited financial histories and conventional metrics, whereas the introduction of Generative AI has broadened the perspective, incorporating a wider range of data for a more holistic assessment. This shift demonstrates how Generative

AI has expanded the capabilities and inclusivity of financial assessment processes, showcasing a significant progression in the methods used to evaluate creditworthiness and extending credit opportunities to a more diverse range of borrowers.

3.5. Market Simulation and Forecasting:

Financial institutions are leveraging Generative AI for market simulation, creating realistic and complex models to forecast market behavior under various scenarios. This represents a significant advancement from earlier market simulation tools, which were often less dynamic and unable to capture the intricacies of rapidly changing market conditions. Goldman Sachs, for example, has been utilizing AI-driven models to simulate financial markets, marking a considerable evolution in the approach to understanding market dynamics and improving investment strategies. Previously, market simulations relied heavily on static models and historical data, which limited their ability to adapt to real-time market changes. The introduction of Generative AI into this domain has revolutionized these processes, enabling the creation of more sophisticated and adaptive models that can more accurately reflect and predict complex market behaviors, thereby offering financial institutions a more powerful tool for strategic planning and decision-making.

3.6. Automated Regulatory Compliance:

Generative AI is also being used to ensure regulatory compliance more efficiently. AI systems can monitor transactions and flag any that might be non-compliant with regulations like anti-money laundering (AML) laws. Deloitte, for instance, has developed AI-based tools that help financial institutions automate and enhance their compliance processes.

3.7. Portfolio Management:

AI-driven portfolio management systems are capable of analyzing vast amounts of financial data to make investment decisions. BlackRock's Aladdin platform uses AI to provide risk analysis and portfolio management services, helping investors make more informed decisions.

3.8. Insurance Underwriting:

In the insurance sector, companies are using Generative AI to transform underwriting processes. Lemonade, a tech-driven insurance company, utilizes AI to assess risk and determine premiums, making the underwriting process faster and more accurate.

3.9. Customer Service Enhancement:

AI-powered chatbots and virtual assistants are being widely adopted in finance for customer service. Bank of America's virtual assistant, Erica, uses predictive analytics and natural language processing to assist customers with transactions, bill payments, and providing financial guidance.

3.10. Fraud Pattern Detection in Transactions:

Generative AI is instrumental in detecting complex fraud patterns. Mastercard uses AI algorithms to analyze transaction data in real-time, identifying fraudulent activities and preventing unauthorized transactions.
Additional case studies illustrating the practical applications of Generative AI include:

3.11. Contract Intelligence by JPMorgan Chase:

The use of machine learning algorithms in JPMorgan Chase's COiN platform automates the analysis of legal documents, significantly reducing review time and improving accuracy.

3.12. Chatbots and Virtual Assistants in Finance:

The deployment of chatbots and virtual assistants by financial institutions enhances customer service and engagement. These tools utilize natural language processing to interact with customers, providing assistance and information efficiently.
The examples and case studies discussed here, from JPMorgan Chase's COiN platform to AI-powered customer service innovations, clearly demonstrate that Generative AI is far more than a technological advancement; it is a catalyst for a paradigm shift in the financial industry. By harnessing the power of AI for varied applications, from improving operational efficiency to enhancing customer experiences, financial institutions are not only addressing current challenges but also paving the way for future innovations. As these technologies continue to evolve and integrate deeper into the financial ecosystem, we can anticipate further advancements that will shape the future of finance in unprecedented ways.

4. Generative AI in Islamic Finance

Islamic Finance, characterized by its adherence to Sharia law, presents a unique set of challenges and opportunities for the integration of Generative AI.
Islamic Finance operates under strict ethical guidelines, emphasizing risk-sharing, prohibition of interest (usury), and ensuring financial transactions are backed by real assets. Generative AI, with its capabilities for advanced data processing and decision-making, can potentially enhance the efficiency, transparency, and ethical compliance of Islamic financial services. The key is to develop AI systems that not only comply with technical requirements but also adhere to the ethical and moral standards central to Islamic Finance. This involves ensuring transparency, avoiding bias, and maintaining the integrity and privacy of financial transactions.
The potential of Generative AI in Islamic Finance is underscored by its growing

global market. According to a report by AGBI, the economic impact of generative AI in the Middle East could reach nearly $23.5 billion per year by 2030, with substantial growth expected in the financial sector.(2)

However, it's crucial to acknowledge the distinct regulatory challenges in Islamic Finance, such as ensuring compliance with Sharia principles and addressing ethical considerations like bias and transparency. The path forward involves establishing an organizational framework that is aligned with the sector's risk tolerance, cultural intricacies, and technological appetite.

Generative AI can play a significant role in various aspects of Islamic banking and finance:

- *Risk Assessment and Compliance*: AI can assist in the risk assessment of Sharia-compliant financial products and ensure adherence to Islamic financial regulations. By analyzing market data and trends, AI systems can provide insights into the compliance and profitability of Islamic financial instruments.
- *Product Development*: Generative AI can aid in the development of new Sharia-compliant financial products by analyzing market needs and customer preferences, ensuring these products align with Islamic ethical standards.
- *Customer Personalization*: Similar to its role in conventional finance, Generative AI can offer personalized financial advice and product recommendations to customers of Islamic banks, ensuring these suggestions are in line with Sharia principles.
- *Islamic Wealth Management*: Generative AI can revolutionize Islamic wealth management by offering sophisticated portfolio management solutions that adhere to Sharia law. It can analyze a vast array of Sharia-compliant investment options, optimize asset allocation, and provide dynamic risk management, catering to the unique investment strategies of Islamic finance clients.
- *Sharia Compliance Monitoring*: The use of AI in continuous monitoring of transactions and operations for Sharia compliance is another vital area. AI systems can automatically analyze and flag transactions that might not comply with Sharia principles, ensuring ongoing adherence to Islamic ethical standards in real-time. This is particularly important given the complexity and dynamic nature of financial transactions in modern Islamic banking.

Generative AI's potential in Islamic finance extends beyond conventional applications, providing innovative solutions that are not only technologically advanced but also ethically and religiously compliant.

(2)https://www.sharqetrade.com/en/news--events/market-news/generative-ai-could-help-gcc-reap-235bn-in-benefits-by-2030-report#:~:text=16%2C%20July%202023-,Generative%20AI%20could%20help%20GCC%20reap%20%2423.5bn%20in%20benefits,grow%2C%20according%20to%20a%20report.

5. Case Studies: Successes and Challenges

As Islamic financial institutions increasingly embrace technological advancements, Generative AI is emerging as a pivotal tool in enhancing and transforming their services. This technology's integration aligns perfectly with the principles of Islamic Finance, which emphasizes ethical financial practices, risk-sharing, and the prohibition of interest. Generative AI's ability to analyze complex data sets, predict market trends, and offer personalized services makes it an ideal match for the unique demands of Sharia-compliant banking.

Here are some of the Islamic financial institutions that have begun exploring the use of AI to enhance their services:

- *Abu Dhabi Islamic Bank (ADIB):* ADIB has implemented AI solutions for enhancing customer service and operational efficiency. Their use of AI for credit scoring and personalized banking services is a testament to the potential of AI in Islamic Finance.
- *Al Rajhi Bank:* One of the largest Islamic banks globally, Al Rajhi Bank, has utilized AI for fraud detection and risk management, showcasing the potential of AI in enhancing the security and reliability of Islamic financial transactions.
- *Kuwait Finance House (KFH):* KFH has been at the forefront of incorporating AI into Islamic banking services. They have employed AI-driven analytics for customer segmentation and product customization, ensuring that their financial solutions are both Sharia-compliant and tailored to individual customer needs.
- *Qatar Islamic Bank (QIB):* QIB has integrated AI into its banking systems for enhanced customer service and operational efficiency. They use AI algorithms for credit scoring and risk assessment, ensuring that their financial practices remain within the bounds of Islamic finance principles.
- *Bank Islam Malaysia Berhad:* As a pioneer in Islamic banking, Bank Islam has embraced AI for various purposes, including fraud detection and enhancing customer engagement. Their AI initiatives are focused on improving the efficiency and effectiveness of their Sharia-compliant products and services.
- *Dubai Islamic Bank (DIB):* DIB has implemented AI solutions to streamline its banking operations and improve customer experiences. They have utilized AI for personalized financial advice, ensuring that the advice aligns with both customer preferences and Islamic financial regulations.
- *Meezan Bank, Pakistan:* Meezan Bank, known for its adherence to Islamic banking principles, has adopted AI for better customer relationship management and personalized service offerings. Their use of AI in analyzing customer data for Sharia-compliant product recommendations sets an example in the sector.
- *Islamic Bank of Britain (Al Rayan Bank):* Al Rayan Bank has leveraged AI

to enhance its customer service and operational efficiency. Their use of AI in processing customer inquiries and transactions demonstrates the potential of AI in facilitating Sharia-compliant banking practices.

Potential for Generative AI to Enhance Sharia-Compliant Financial Products and Services can be seen through these case studies which illustrate the growing trend of Islamic financial institutions leveraging Generative AI to enhance their services while adhering to Sharia principles. Its potential is not limited to operational efficiency but extends to creating innovative financial products, risk assessment, and ensuring Sharia compliance through sophisticated AI algorithms.

6. Advantages of Generative AI in Finance

The integration of Generative AI in the realm of finance, encompassing both conventional and Islamic sectors, marks a significant advancement in how financial institutions operate and interact with their customers. This technology's application is transforming the industry by introducing new levels of efficiency, precision, and customer-centric services. There are several key advantages of employing Generative AI in the financial sector.

6.1. Efficiency and Accuracy

One of the most significant benefits of Generative AI is the substantial increase in operational efficiency and accuracy it brings to financial processes. AI algorithms can process and analyze vast amounts of data at speeds unattainable by human capabilities, leading to quicker decision-making and more accurate predictions. For instance, in high-frequency trading, AI algorithms can execute trades at optimal prices in milliseconds, a task that would be impossible for human traders. This marks a significant evolution from earlier financial technologies, where processes were more manual and less precise. Generative AI's ability to process and analyze data rapidly represents a leap forward from traditional methods, offering a new level of operational finesse in finance.

6.2. Predictive Analytics and Decision-Making

Generative AI excels in predictive analytics, a crucial aspect of financial decision-making. By analyzing historical data and current market trends, AI can forecast future market movements, identify investment opportunities, and anticipate potential risks. Generative AI is a key evolutionary step from traditional financial forecasting models. Earlier methods, while effective in their time, lacked the depth and scale of analysis that AI-powered tools provide, revolutionizing how financial institutions anticipate market trends and make strategic decisions. This predictive power enables financial institutions to make more informed decisions, whether in investment management, risk assessment, or customer relationship management.

6.3. Cost Reduction and Accessibility

The automation capabilities of Generative AI also led to significant cost reductions for financial institutions. By automating routine tasks such as data entry, report generation, and customer inquiries, institutions can reduce operational costs and allocate resources more efficiently. This transition to AI-driven processes from more labor-intensive methods illustrates a significant evolution in financial operations, making sophisticated financial advice and services accessible to a broader audience, which was previously unattainable.

6.4. Enhanced Customer Experience

Generative AI has a profound impact on customer experience in finance. Personalized financial advice, tailored product recommendations, and efficient customer service through AI chatbots are just a few examples of how AI is used to enhance customer engagement and satisfaction. This enhancement in customer service represents an evolution from traditional, less personalized customer interactions. The integration of AI in customer engagement strategies reflects a shift towards more tailored and responsive financial services, catering to the evolving needs and expectations of modern customers.

6.5. Streamlined Compliance and Risk Management

In an industry heavily regulated and fraught with risks, Generative AI offers effective tools for compliance and risk management. AI systems can monitor transactions in real-time, ensuring adherence to regulatory standards and identifying potential risks before they materialize. The use of AI for compliance and risk management signifies a major evolutionary step from previous risk assessment and compliance methods. Traditional approaches often relied on manual monitoring and were less efficient, whereas AI provides a more dynamic, comprehensive, and proactive approach to these critical aspects of finance.

In transitioning to the Islamic finance sector, Generative AI's application reflects unique advantages tailored to the sector's specific needs and principles. Islamic Finance, characterized by its adherence to Sharia law, presents distinct challenges, making the integration of AI not just a technological upgrade but a strategic alignment with its ethical principles.

- *Ethical and Sharia Compliance*: Generative AI can be tailored to respect the ethical guidelines of Islamic Finance, such as risk-sharing and the prohibition of usury. AI algorithms can be programmed to automatically identify and avoid transactions and investment opportunities that do not comply with Sharia principles, ensuring ethical adherence in all operations.
- *Customized Financial Products*: AI's data analysis capabilities enable the creation of personalized Sharia-compliant financial products. By understanding

individual customer needs and preferences within the framework of Islamic law, AI can help design financial solutions that are both ethical and tailored to specific customer profiles.

- *Risk Assessment Tailored to Islamic Finance*: In Islamic Finance, where risk-sharing is a fundamental principle, Generative AI's predictive analytics can play a critical role in risk assessment and mitigation. AI can analyze market trends and historical data to accurately assess risk levels in various financial operations, aiding in making Sharia-compliant investment and lending decisions.
- *Market Expansion and Inclusivity*: Generative AI can help Islamic financial institutions expand their market reach and inclusivity. By automating processes and utilizing AI-driven insights, these institutions can attract a wider customer base, including those who prioritize ethical banking, and provide them with accessible, Sharia-compliant financial services.
- *Regulatory Adherence and Reporting*: AI systems can assist in ensuring that all financial operations are in line with not only global financial regulations but also specific Sharia requirements. This includes automated reporting and compliance checks, which are essential for maintaining transparency and trust in Islamic financial institutions.

Overall, the role of Generative AI in finance, both conventional and Islamic, underscores its transformative impact across the industry. In conventional finance, it enhances efficiency and decision-making, while in Islamic finance, it aligns with ethical principles, demonstrating its versatility and adaptability to diverse financial paradigms.

7. Challenges and Risks

While Generative AI presents numerous opportunities for the finance sector, it also brings with it a set of challenges and risks that need careful consideration and management.

7.1. Ethical Considerations

One of the primary concerns surrounding the use of Generative AI in finance is the ethical implications, particularly in terms of bias and privacy. AI systems are only as unbiased as the data they are trained on, and there is a risk of perpetuating existing biases if the training data is not diverse and representative. Additionally, the use of personal data in AI models raises privacy concerns, necessitating stringent data protection measures and transparent data usage policies.

7.2. Regulatory Challenges

The rapidly evolving nature of AI technology poses a challenge for regulatory frameworks, which may struggle to keep pace with the advancements in AI. This is particularly pertinent in finance, a heavily regulated sector. Ensuring that AI systems comply with existing regulations, and adapting those regulations to accommodate new AI capabilities, is a complex but necessary task. In Islamic finance, this also includes ensuring Sharia compliance, which adds an additional layer of complexity.

7.3. Dependability and Security Risks

The reliability of AI systems is another significant concern. While AI can process and analyze data at an unprecedented scale and speed, there is always the risk of errors, which can have substantial consequences in financial contexts. Moreover, the increasing reliance on AI systems makes them a target for cyber threats, necessitating robust cybersecurity measures to protect sensitive financial data.

7.4. Challenges in Implementation and Integration

Implementing AI technology in existing financial systems is not a straightforward task. It requires substantial investment, both in terms of technology and skilled personnel. Additionally, integrating AI into existing workflows and processes can be challenging, requiring a change in both infrastructure and corporate culture.

7.5. Managing Expectations

There is also the risk of overestimating the capabilities of AI or expecting quick returns on investment. Managing expectations, both within the organization and with clients, is crucial to ensure a realistic understanding of what AI can and cannot do.

While Generative AI holds great promise for efficiency, customer experience, and regulatory compliance in the financial industry, its adoption should be approached with caution. Financial service companies need to assess various risks, including those concerning customer data privacy, bias in training datasets, and limited explainability. Regulation of Generative AI will evolve over time, and interim action is needed to guide its use in financial institutions. In the interim, human supervision is necessary to deal with risks, and oversight authorities should improve their capacity to monitor the adoption of GenAI in the sector.

8. Future Prospects and Potential Developments

The future of Generative AI in finance is indeed poised at an exciting juncture, with several emerging trends and innovations shaping its transformative trajectory. As technology continues to evolve, we are likely to see more sophisticated applications of Generative AI in both conventional and Islamic finance.

- *Advanced Predictive Models:* Future developments in Generative AI are expected to produce even more accurate and nuanced predictive models, capable of analyzing complex financial scenarios and providing deeper insights into market trends and consumer behavior.
- *Integration with Blockchain Technology:* The convergence of Generative AI with blockchain technology promises to revolutionize areas like smart

contracts, decentralized finance (DeFi), and enhanced security for financial transactions.

- *AI-driven Personalization at Scale:* Financial institutions will increasingly offer hyper-personalized products and services, catering to individual customer preferences and goals with unprecedented precision.
- *Ethical AI and Explainability*: Growing emphasis on ethical AI frameworks and explainable AI models will ensure that AI-driven decisions are transparent, fair, and accountable.
- *Automated Financial Advising and Planning*: AI could take on a more significant role in financial advising, using complex algorithms to provide personalized investment strategies and financial planning services.
- *Enhanced Risk Management*: Future AI developments could lead to more sophisticated risk management tools, capable of identifying and mitigating potential risks in real-time.
- *Innovative Islamic Financial Products*: AI could be instrumental in developing innovative financial products that comply with Sharia principles and cater to evolving market needs.
- *AI in Regulatory Compliance*: AI technology might play a crucial role in ensuring continuous adherence to Islamic financial regulations, adapting automatically to changes in Sharia law and ethical considerations.

As we look to the future, it is clear that Generative AI will continue to be a driving force in the evolution of the finance sector. Its ability to analyze data, predict trends, and offer personalized services will open new avenues for innovation and growth. However, this journey will also require careful navigation of ethical considerations, regulatory challenges, and the continuous evolution of technology In Islamic finance, Generative AI could be instrumental in developing innovative financial products that comply with Sharia principles and cater to evolving market needs. AI technology might play a crucial role in regulatory compliance, ensuring continuous adherence to Islamic financial regulations.

9. Conclusion

This paper has delved into the evolution of Generative AI in the finance sector, tracing its transformative journey through both conventional and Islamic finance realms. We have witnessed the progressive development of Generative AI, from its initial applications in basic data processing to its current role in revolutionizing automated trading, fraud detection, personalized financial advice, and the development of Sharia-compliant financial products. This evolution of Generative AI has not only significantly enhanced operational efficiency and accuracy but has also pioneered new pathways for personalized customer engagement and innovative financial solutions.

The impact of Generative AI on the financial sector is profound and far-reaching. As the adoption of this technology continues to expand, we are poised to see a finance landscape that is increasingly data-driven, efficient, and customer-focused. In conventional finance, this evolution manifests in more advanced trading algorithms, improved risk management tools, and wider accessibility to financial advice. In Islamic finance, Generative AI offers unique opportunities for innovation within the confines of Sharia principles, enabling the creation of new, ethically-aligned financial products and services.

Looking forward, the future shaped by Generative AI holds promises of greater inclusivity, innovation, and integrity in the financial sector. However, this future also necessitates a careful navigation between technological progress and ethical responsibility. Addressing challenges related to bias, privacy, regulatory compliance, and cybersecurity is crucial for harnessing the full potential of Generative AI in finance.

As we embark further into this AI-driven era of finance, it becomes evident that Generative AI is more than a mere technological advancement; it is a catalyst for substantial transformation. Its continued evolution is set to redefine the landscape of financial services. Nonetheless, this journey must be undertaken with mindful consideration, ensuring that ethical standards and human values remain paramount. The ongoing integration of Generative AI in finance represents not just a technological leap but a step towards a future where financial services are more accessible, efficient, and geared towards the greater good.

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Exploring Cutting-Edge Algorithms in Islamic Banking: Machine Learning and Deep Learning for Enhanced Decision-Making and Risk Management

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Abstract

Purpose – The aim of this research is to explore and analyze the applications of artificial intelligence (AI), machine learning (ML), and deep learning in Islamic banking. It focuses specifically on how these technologies can make a real impact in decision-making and risk management within Islamic finance. This study provides an in-depth understanding of how advanced algorithms, such as machine learning models for customer data analysis and credit risk estimation, as well as artificial intelligence for forecasting market trends and potential risks, can significantly enhance the efficiency and performance of Islamic banking institutions. By doing so, the research intends to redefine the approaches to delivering Islamic financial services.

Methodology/approach – The research methodology follows a qualitative approach, focusing on a comprehensive review of scholarly literature, critical analysis of articles, books, research papers, and industry reports for insights into machine learning and deep learning applications in Islamic banking.

Structure of the paper – The research paper comprises the following sections: Introduction - Definitions and concepts of the technologies - Applications of artificial intelligence and machine learning in Islamic banking - Overview of decision-making and risk management algorithms with examples of their usage - Findings and recommendations - List of references.

Findings – The findings showed that AI algorithms and deep learning and machine learning models can play a significant role in improving decision-making and risk management in Islamic banks.

Originality/Value: This research is pioneering in exploring the application of AI algorithms, deep learning, and machine learning models in Islamic banks.

Implications – This research contributes significantly to understanding the role and impact of machine learning and deep learning algorithms in Islamic banking. The derived results bear crucial implications for banking professionals, policymakers, and researchers, offering insights into how these algorithms can effectively enhance decision-making and risk management processes in Islamic banking institutions.

Keywords – Artificial Intelligence, Islamic Banking, Deep Learning, Machine Learning, Decision Making, Risk Management.

1. Introduction.

Islamic banking, deeply rooted in its commitment to ethical finance and Sharia principles, is undergoing a pivotal transformation. The emergence of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) is shaping a new paradigm in decision-making and risk management, aligning with the sector's anticipated asset boom, projected to surpass $3.69 trillion by 2024.

In an era where the COVID-19 pandemic has accentuated the indispensability of digital transformation, Islamic banking is not immune. Bensley et al. (2020) and

Reddy (2017) highlighted the exigency of enhanced digital engagement—a trajectory echoed in the financial sector at large, as illuminated by Mogaji et al. (2020). AI's contribution to risk management, underscored by its adeptness at deciphering complex datasets to preempt risks and counter fraud, is a testament to its invaluable role in the financial echelon.

According to Malali and Gopalakrishnan (2020), AI's inroads into the financial sector are multifaceted, epitomizing an evolution that is both radical and incremental. Islamic banking, whilst preserving its foundational ethical and legal principles, stands at the cusp of this evolution, aspiring to synergize technological innovation with Sharia compliance. The seismic shift induced by the pandemic has metamorphosed digital engagement from a competitive advantage to an operational imperative, drawing parallels with AI's escalating prominence in risk management as noted by Kruse et al. (2019).

This backdrop sets the stage for our investigation, situated at the nexus of advanced technology and the distinct ethos governing Islamic banking. Islamic finance, as detailed by BNY Mellon (2021) and Hussain et al. (2015), is defined by its ethical propositions and social justice principles. These are not mere theoretical constructs but the very bedrock that underpins the sector's operational framework.

Upon reviewing previous research, it is evident that the primary focus has remained on the applications of artificial intelligence and machine learning within traditional banking environments. The study by Sanil et al. (2021) illuminates the enhancement of banking operations through machine learning but is primarily centered on conventional banks. Various applications of AI in the financial sector, such as improving customer service, recruitment, exception management, and fraud detection, are detailed by Lokuge and Sedera (2016), Branco and Rodrigues (2006), Al-Htaybat et al. (2019), Lytras et al. (2020), Mergaliyeva (2020). Additionally, systematic reviews by Stone et al. (2020), Duan et al. (2019), and Johnson et al. (2019) shed light on AI in decision-making, Big Data challenges, and ethical issues, but the adaptation and alignment with Islamic banking principles remain uncharted

In the dynamic context of the integration of advanced technology into Islamic banking, a distinct gap is evident. This study is committed to bridging this divide, concentrating on the alignment of innovation and technology within Islamic banking's ethical and Sharia-compliant framework. We are dedicated to unveiling new insights that elucidate the nuanced equilibrium between the rapid pace of technological evolution and the steadfast ethical foundations that characterize Islamic finance.

Our primary research question, therefore: "What specific algorithms and applications of ML and DL are shaping the future of Islamic banking, and how do they align with the sector's ethical and Sharia-compliant standards while driving enhancements in decision-making and risk management?"

In this expansive study, we extend beyond a generic exploration of AI and ML in banking. We meticulously examine the bespoke algorithms tailored for and applied within Islamic banking. Each algorithm and application is dissected, with insights

drawn on its technical prowess, adaptability, and alignment with Sharia principles.
As we delve into the depths of algorithmic applications, we seek to unveil the intricate dance between technological innovation and ethical compliance. We aim to unravel the tapestry where codes, data, ethical finance, and Sharia principles interweave, giving rise to a new era of Islamic banking that is as advanced in technology as it is rooted in tradition.

The unfolding narrative of the Fourth Industrial Revolution presents Islamic banking with both opportunities and challenges. It offers a canvas where the strokes of technology can paint a future of enhanced efficiency, precision in decision-making, and robust risk management. Yet, each stroke is measured, evaluated against the unwavering standards of ethics and Sharia compliance that define Islamic banking. Our quest is not a mere scholarly exploration but signifies a pioneering stride towards unveiling empirical insights that will enrich policy, inform practical applications, and contribute to the knowledge pool in Islamic banking in the era of the Fourth Industrial Revolution.

In the upcoming sections of this paper, we'll first clarify essential AI, ML, and DL concepts. We will then highlight their specific applications and the algorithms used in Islamic banking. The paper will further discuss the role of these technologies in risk management and decision-making. The final sections will conclude the findings and offer tailored recommendations for enhancing AI and ML integration while adhering to Sharia principles.

2. Concepts of Artificial Intelligence, Machine Learning, and Deep Learning

In this section, we aim to focus on elucidating and reviewing the fundamental concepts foundational to contemporary technologies like artificial intelligence (AI), machine learning (ML), and deep learning (DL). We aim to offer a clear comprehension of the operational mechanisms of these technologies and their impact in the realm of banking services, with a special emphasis on Islamic banks. The potential capabilities and roles these technologies could assume in enhancing decision-making and risk management processes will be explored.

2.1. Artificial Intelligence (AI)

AI stands at the vanguard of technological innovation, driving transformative impacts across various sectors, including finance. AI involves simulating human intelligence processes by machines, particularly computer systems. This simulation includes learning - the acquisition of information and rules for using that information, reasoning - using rules to reach approximate or definite conclusions, and self-correction.

Different types of AI exist, including narrow or weak AI, designed and trained for specific tasks like voice assistants or image recognition systems. On the other hand, strong or general AI, equipped with broader capabilities, mirrors the performance of intellectual tasks that humans are capable of. However, strong AI currently remains more theoretical than practical (Dunis et al., 2016; Al-Araj et al., 2022; Hatamlah et

al., 2023).
In Islamic banking, AI plays a critical role by enhancing decision-making, improving risk management, and increasing efficiency while adhering to Islamic Sharia principles. Integrating AI promises not only enhanced customer experiences and streamlined operations but also a more precise approach to ethical and sustainable financing.

2.2. Machine Learning (ML)

Machine Learning (ML) technologies are a fundamental pillar in the architecture of today's technological advancements. As a dynamic subset of Artificial Intelligence (AI), ML empowers systems to autonomously learn from their environment. These systems absorb and interpret vast volumes of data, using this information to enhance their operations and decision-making processes. This technological evolution enables industries to enhance their operational effectiveness, making informed decisions based on constantly gathered and analyzed data. Through machine learning, there is a continuous adoption of algorithms that facilitate iterative learning, data interpretation, pattern recognition, and subsequent actions based on these patterns, as detailed by Tatsat et al. (2020).
Additionally, the power of ML lies in its inherent capability to continuously learn and adjust based on new data. This ongoing learning process ensures that its capacity for decision-making is constantly improving, leading to exceptional accuracy. Such capabilities have led to significant advancements in various fields including science, technology, and business.
According to Yao et al. (2018), machine learning methods can vary based on the data and objectives used during training and can be classified into several fundamental categories, as illustrated in Figure 1.

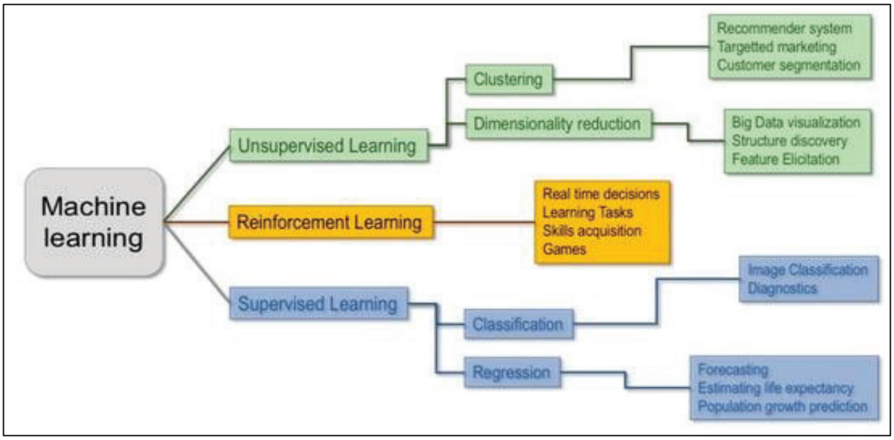

Figure 1. Types of Machine Learning

Source: Seccia et al., 2021.

2.2.1.A. *Supervised Learning*

Picture this as having a teacher-student dynamic. The student is presented with numerous problems, each paired with its solution. With enough practice, the student learns to solve new problems. Similarly, in supervised learning, systems are trained using labeled data. This data acts as a touchstone, guiding the system to develop generalizable rules. It's predominantly leveraged for tasks such as classification and predicting numerical values.

2.2.2. B. *Unsupervised Learning*

Imagine handing someone a jigsaw puzzle without the final image. They'd group pieces based on colors or edges, trying to figure out the larger picture. Unsupervised learning operates on a similar principle. It scours through data, seeking hidden patterns or structures without any prior labels, shining primarily in clustering and exploratory data tasks.

2.2.3. C. *Semi-Supervised Learning*

A harmonization of both supervised and unsupervised styles. Here, the system has some labeled data but also a lot of unlabeled data. It's akin to having some pieces of the jigsaw puzzle already connected, but many aren't. The system uses what it knows to make sense of what it doesn't.

2.2.4. D. *Reinforcement Learning*

Imagine a video game where characters learn from every move, adapting their strategies based on rewards or setbacks. Reinforcement learning is essentially that, but for machines. It's an iterative process of trial, error, and adaptation to reach an optimal outcome.

Machine learning significantly contributes to accelerating technological development and finding solutions to complex problems that were impossible to confront with traditional methods. Moving towards exploiting these technologies in various fields of industry and business is a significant step towards a more innovative and effective future.

2.3. Deep Learning (DL)

Deep Learning (DL), a sophisticated branch of machine learning, is primarily distinguished by the use of multi-layered artificial neural networks (Janiesch et al., 2021). As demonstrated in the accompanying diagram, these networks encompass input layers, a series of hidden layers, and a concluding output layer.

The primary input layer assimilates raw data, analogous to our sensory faculties receiving external stimuli. The following hidden layers conduct intricate computations, progressively refining the data. This multifaceted progression is directed by an array of nodes, termed 'neurons', in every layer, which are interconnected via 'synapses'. These synapses ascribe a weight to the data during its transition from one neuron to its successor. The terminal output layer furnishes a resultant decision or prediction, derived from the comprehensively processed data.

Within the realm of DL, specialized architectures like Convolutional Neural Networks (CNNs) have been formulated, tailored for tasks like image interpretation owing to their adeptness at spatial data discernment (Guo et al., 2016). Conversely, Recurrent Neural Networks (RNNs) are embedded with a semblance to memory, rendering them adept for the analysis of sequential data and time-series.

In the complex field of finance, especially within Islamic banking, DL offers unparalleled analytical capabilities. It excels at dissecting intricate data structures and identifying subtle patterns that might be missed by traditional analysis methods. As Islamic banking continues to evolve, DL tools promise a new age of sophisticated data interpretation, ensuring that outcomes are not only technologically sound but also in harmony with the core principles of Sharia compliance.

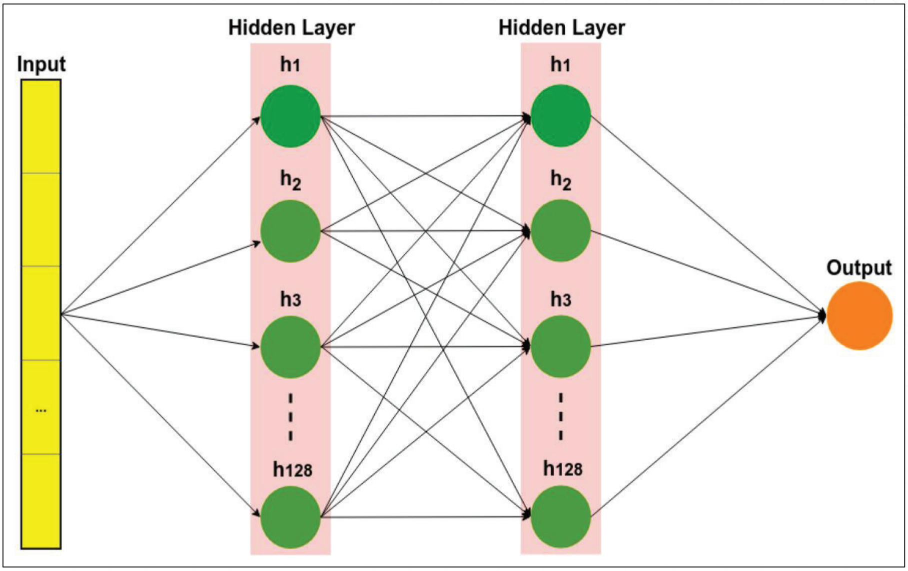

Figure 2. Architecture of a Deep Learning Neural Network.

Source. *Dang et al., 2020.*

3. Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Islamic Banking

Machine learning (ML) and deep learning (DL) technologies are revolutionizing the banking service sector by introducing innovative and efficient solutions. These advanced technologies combine accuracy and speed, addressing complex and multi-dimensional challenges. In the realm of Islamic banking, this technological evolution aligns with a unique trajectory that emphasizes continuous service improvement and adherence to Sharia standards.

In this section, we will explore the detailed applications of ML and DL in Islamic banks and their significant impact on the industry. Specifically, we will examine how these technologies are used to analyze big data, enhance data security, and develop personalized financial services. Furthermore, we will discuss their crucial role in strengthening decision-making processes and risk management. A key focus will be on how ML and DL integrate with the principles of Islamic Sharia, paving the way for innovative and ethical financial solutions.

3.1. Fraud Detection

With the permeation of e-commerce into all aspects of modern life, the use of credit cards as primary means for transactions has surged. However, an unprecedented rise in credit card fraud incidents, a complex crime exploiting the flaws of current security protocols, has been witnessed (Zhang et al., 2019). The existing security infrastructure, characterized by static and linear methods, struggles to adapt to the dynamic and complex nature of modern financial crime.

Machine learning and artificial intelligence technologies are increasingly significant in counteracting multifaceted fraud threats. They provide not only computational power but also an adaptive, intelligent character capable of analyzing complex, non-linear, and large-volume data in real-time, offering predictive insights and analyses far surpassing traditional fraud detection mechanisms (Abdallah et al., 2016; Bolton and Hand, 2002).

In practical application, machine learning and artificial intelligence rely on specially designed algorithms to identify and respond to patterns indicating fraudulent activity within massive datasets. These algorithms are not static; they learn and evolve, adapting to new patterns and techniques used by fraudsters. Their evolution lies in their ability to detect the subtlest anomalies in transaction data, allowing for immediate actions, reducing the time needed to counter attacks, and mitigating potential damages.

Building on the capabilities of machine learning, there's a deeper connection to be explored. Deep learning, a specialized branch of machine learning, employs neural networks to process transaction data. These networks excel in handling sequential data, offering insights into complex patterns and behaviors often indicative of sophisticated fraud attempts. For instance, Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM) have proven particularly effective in processing sequential data, making them invaluable tools for analyzing transaction sequences to detect potential fraud (Zhang et al., 2019; Abdel-Hamid et al., 2014).

Within the realm of credit card transactions, deep learning algorithms analyze each transaction as a data point, evaluating transaction behaviors, merchant categories, spending patterns, and other relevant variables. They can identify unusual patterns and discrepancies in real-time, triggering alerts for further investigation or immediate action. For Islamic banks, the adoption of AI and ML in fraud detection goes beyond operational efficiency; it is a vital step towards upholding the integrity and ethical standards intrinsic to their operations. The immediate, adaptive, and predictive nature of AI and ML aligns with the risk-sharing principles and ethical standards of Islamic finance. This ensures each transaction is compliant with financial regulations and adheres to the strict ethical guidelines that define Islamic banking services.

3.2. Takaful (Islamic insurance)

In Islamic banks and associated Takaful insurance companies, artificial intelligence (AI) and machine learning (ML) technologies can be effectively utilized to enhance the quality and efficiency of services. AI-powered virtual assistants provide instant support to customers, guiding them towards Takaful insurance products that align with their individual needs and preferences, while adhering to Islamic Sharia principles. ML technologies enable the analysis of customer behavior patterns, the development of customized products, and the provision of precise pricing based on each client's specific risk profile (Hassan & Abraham, 2016).

Moreover, these technologies bolster fraud detection mechanisms and elevate the customer experience, increasing customer satisfaction and confidence in Takaful insurance products. The reliance on AI and ML allows Takaful insurance companies affiliated with Islamic banks to offer accurate and efficient insurance solutions, underpinned by precise analytics and real-time information that informs decision-making processes and product development (Verma, 2022).

This integration of ML technologies with Islamic banks contributes to the offering of innovative and tailored Takaful insurance services, meeting dynamic customer needs while respecting Islamic principles and values. The utilization of AI ensures the alignment of personalized, data-driven solutions with the ethical and moral standards upheld in Islamic finance, marking a significant stride in the amalgamation of modern technology and traditional values.

3.3. Implementation of Machine Learning in Identifying Anomalies within Islamic Banking Financial Statements

In the realm of financial services, particularly in dissecting complex financial statements, ML algorithms offer an innovative approach to identify, analyze, and rectify anomalies (Rezaee, 2005; Albrecht et al., 2015). Unlike traditional methods, ML is adept at maneuvering through large, unstructured datasets, offering insights and flagging inconsistencies that are often missed by manual inspection (Perols, 2011), a transformation well-documented in existing literature. Rezaee (2005) and Albrecht et al. (2015) elucidate how ML algorithms facilitate the identification, analysis, and correction of anomalies within financial statements. These mechanisms prove superior to traditional methods, especially in handling voluminous and intricate data as supported by Perols (2011). He underscored the efficiency of ML in unearthing inconsistencies that are typically overlooked during manual inspections.

The detection of anomalies, be they inadvertent errors or indicators of fraud, is well-articulated by Green and Choi (1997) and Lin et al. (2003). These works emphasize the role of ML in thoroughly examining financial data to reveal discrepancies that might otherwise remain undetected. The methodology propounded by these authors, though not specifically contextualized for Islamic banking, forms the foundational framework that can be adapted for this sector.

Transitioning to Islamic banking, the application of ML warrants a tailored approach given the distinct operational and ethical precepts guided by Sharia law. The exclusion of interest-based transactions and the emphasis on ethical and transparent dealings accentuates the need for a specialized mechanism of anomaly detection. Every financial statement is not just a representation of fiscal data but is inherently tied to the adherence to Sharia principles, a scenario where the insights provided by Lokanan and Sharma (2018) become profoundly relevant.

Though Bell and Carcello (2000) and Skousen et al. (2009) did not focus on Islamic banking, their insights on anomaly detection can be extrapolated to align with the foundational ethical standards of Sharia. Each anomaly, in this context, is not merely a financial irregularity but potentially indicative of a deviation from the mandated ethical guidelines intrinsic to Islamic financial institutions.

In a scenario where Kirkos et al. (2007) and Perols (2011) offer advanced algorithms for anomaly detection, Islamic banking can benefit by customizing these tools to integrate Sharia compliance checks. Each flagged anomaly would then be evaluated, not just in terms of financial validity but also for its alignment with Islamic ethical and legal precepts.

In essence, while the referenced works are not explicitly oriented towards Islamic banking, the core principles and applications of ML they present are highly adaptable. By customizing and integrating these principles, Islamic banking can harness ML to enhance both its financial integrity and unwavering adherence to Sharia principles, achieving a harmonious blend of technological innovation and ethical finance.

3.4. Robo-advisory services:

In the modern financial ecosystem, robo-advisory services have emerged as a transformative innovation, exemplified by their capacity to meld intricate technology with sophisticated investment strategies. Abraham et al. (2019) have underscored the prowess of robo-advisory in tailoring financial advice through complex algorithms. These are engineered to sift through vast and multifaceted data, crafting investment paths aligned with individualized client objectives and risk tolerances.

Woodyard and Grable (2018) complement this narrative, highlighting the efficiency, cost reduction, and expeditious nature of robo-advisors. These attributes collectively contribute to refining the investors' journey through the intricate corridors of financial markets, imbuing a level of precision and accessibility previously unattained.

Phoon and Koh (2017) have emphasized the central role of quantitative data and algorithms in this innovation, rendering robo-advisory a magnet for investors aiming for dependable, innovative, and personalized investment channels. Their transparent, analytical, and unbiased nature stands as a testament to their proliferating adoption.

When this lens is turned towards Islamic banking, the incorporation of robo-advisory morphs into a nuanced narrative. It's not merely a technological asset but a conduit through which the balance between operational efficiency and strict adherence to ethical and religious tenets is navigated. Bhatia (2021) has opined that the foray of Islamic banks into robo-advisory unveils a spectrum of opportunities to elevate service delivery, instilling a personalized touch, amplified efficiency while ensuring the stringent adherence to Sharia principles.

The algorithms that power robo-advisory services are inherently adaptable, a feature that Islamic banks can leverage to tailor these digital advisors to echo the ethical and legal resonances of Sharia principles. Every investment strategy, thus crafted, is a reflection of a meticulous balance between financial acumen and ethical adherence.

Woodyard and Grable (2018) elucidate the potential for a precise amalgamation of financial automation with Sharia compliance. In this context, robo-advisory services become instrumental in steering investments strategically, aligning assets and opportunities with the foundational ethos of Islamic finance.

In essence, the narrative of robo-advisory in Islamic banking is a tale of strategic alignment, where technology and ethics converge. This union promises not just enhanced service delivery but a future where Islamic finance is intricately woven into the global tapestry of financial innovation. Every algorithm, investment strategy, and client interaction is a testament to a world where the boundaries between technological advancement and ethical finance are not just blurred but are seamlessly interconnected.

3.5. Predicting customer deposits

The predictive modeling of customer deposits utilizing machine learning represents a transformative innovation in the banking sector. This technology, in essence, supports banks in navigating the intricacies of financial behaviors and economic indicators to enhance their financial stability and service delivery (Banke and Yitayan, 2022; Derbali, 2022).

Machine learning applications are particularly instrumental in parsing through complex, multifaceted data sets, facilitating predictions of customer deposits with heightened accuracy and efficiency (Leo et al., 2019). By utilizing algorithms like Multiple Linear Regression (MLR) and Artificial Neural Networks (ANNs), banks can integrate a systematic approach to analyze historical data, macroeconomic variables, and banks' annual reports to forecast deposit trends (Patway et al., 2021).

Customer deposits are integral for the financial health of banks (Dilrangi et al., 2018), and the fluidity of these deposits can be critically analyzed using machine learning. Complex algorithms like ANNs are adept at handling the myriad of variables impacting deposit behaviors, offering actionable insights that are crucial for liquidity management, risk mitigation, and the enhancement of service offerings. ANNs' capability to process non-linear, intricate relationships within vast datasets allows banks to predict deposit trends, ensuring that strategies are aligned to meet anticipated trends (Muslim et al., 2020).

In the context of Islamic banking, these technologies are refined to ensure that financial predictions align seamlessly with Sharia principles. Algorithms in Islamic banking are tailored to offer predictions that are not only quantitatively accurate but also qualitatively infused with ethical integrity. This integration ensures that Islamic banks navigate the delicate balance of fostering financial innovation while upholding the strict tenets of Islamic finance.

A testament to this integration is the bespoke application of machine learning algorithms that are fine-tuned to respect the nuances of Islamic finance. These algorithms are designed to analyze customer deposit behaviors, economic indicators, and other relevant data within the framework of Sharia principles. Consequently, Islamic banks are not just beneficiaries of numerical accuracy but are stakeholders in a system where financial predictions and ethical considerations are harmoniously intertwined.

3.6. Combating money laundering

Addressing money laundering in the vast realm of cryptocurrency requires innovative strategies beyond conventional Anti-Money Laundering (AML) approaches. The inherent features of cryptocurrencies, such as decentralization and anonymity, pose significant challenges to classical AML frameworks (Canhoto, 2021; Lorenz et al., 2020). In light of these complexities, Machine Learning (ML), particularly supervised learning, is emerging as a compelling solution, enabling the in-depth analysis of vast datasets and the identification of potential money laundering patterns.

However, the transition to ML-based AML for cryptocurrency is not straightforward. A prevailing concern is the 'black box' phenomenon associated with many ML models, which implies a lack of transparency in their decision-making processes (Jullum et al., 2020). The real challenge lies in creating models that effectively identify suspicious activities while also meeting the transparency standards required by regulations.

ML algorithms, like logistic regression, random forest, support vector machines, and decision trees, have demonstrated their capacity to distinguish illicit transactions, each with its strengths and shortcomings (Alarab et al., 2020; Chen et al., 2018). For instance, while decision trees provide transparency, they might be susceptible to biases; support vector machines excel in handling diverse variables but might be constrained by vast datasets.

To effectively leverage ML in cryptocurrency AML, a balanced approach is crucial. This involves optimizing detection accuracy, ensuring model transparency, and adhering to regulatory standards. Moreover, as Pettersson & Angelis (2022) highlight, a comprehensive strategy incorporating ongoing research, multi-stakeholder collaboration, and regulatory adjustments is essential to adeptly respond to the challenges of cryptocurrency-based money laundering.

Finally, it's pertinent to underscore the alignment of these advanced AML efforts with the ethos of Islamic banking, which inherently prohibits and combats money laundering as part of its adherence to Sharia principles. The infusion of machine learning into AML, especially in the intricate landscape of cryptocurrency transactions, doesn't just signify a technological evolution but resonates deeply with the foundational ethical and legal precepts of Islamic finance. This alignment exemplifies the confluence of innovation and ethics, marking a pathway where technological advancement and ethical banking are not mutually exclusive but are collaborative partners in fostering a financial ecosystem defined by integrity, transparency, and innovation.

3.7. Sentiment analysis

Text Classification (TC) is a branch of machine learning that focuses on assigning predefined labels or categories to text, making it easier to manage and analyze. This practice is instrumental in harnessing the potential of unstructured data, especially in the business and financial sectors where vast volumes of such data are generated regularly.

One core application of TC is sentiment analysis. For instance, businesses utilize algorithms like Naive Bayes, Logistic Regression, and Support Vector Machines to process customer reviews and feedback. These algorithms analyze text data to discern the underlying sentiments, be they positive, negative, or neutral (Hartmann et al., 2019). This information is invaluable for businesses to adapt and refine their services, products, and customer engagement strategies. By comprehensively understanding customer sentiments, businesses can proactively address concerns and enhance positive experiences.

In the financial sector, TC is particularly influential in real-time analytics. Algorithms like Random Forest and Gradient Boosting can be used to process and categorize vast datasets, including financial news, reports, and investor feedback (Zhao et al., 2020). For instance, an investment firm might use TC to automatically categorize news articles related to specific stocks or sectors. These categorized datasets can be analyzed to gain insights into market sentiments, trends, and potential investment opportunities or risks.

To further illustrate, consider a scenario where a financial institution employs the LSTM (Long Short-Term Memory) neural network to process and categorize real-time news feeds. By doing so, they can immediately identify market sentiments and trends, enabling rapid response to market changes, optimizing investment strategies, and mitigating risks.

In essence, TC transcends being a mere technological tool; it is an asset that transforms unstructured textual data into actionable, structured insights. It's instrumental in decoding the sentiments embedded in text data, offering real-time insights into customer feedback and market trends. These capabilities don't just enhance the immediacy and relevance of business responses but also shape strategic decision-making, aligning them with current trends, sentiments, and expectations.

3.8. Analyzing User-Generated Content for Banking Reputation Management

Financial institutions, including banks, are increasingly adopting artificial intelligence (AI) as a tool to glean insights from User-Generated Content (UGC) to manage and enhance their online reputation. In today's digital era, social media and other online platforms are replete with a plethora of customer reviews and comments. AI emerges as an instrumental asset for dynamically monitoring and analyzing this vast content in real time (Gensler et al., 2015).

Specific AI technologies, notably Convolutional Neural Networks (CNN), have proven adept at meticulously extracting and processing crucial information from UGC. These technologies unveil insights into customers' likes, dislikes, and sentiments, offering a window into the public's perception of banks' offerings (Li and Li, 2013). By efficiently filtering through large volumes of data and distinguishing between irrelevant content and insightful information, CNN supports banks in making informed, strategic decisions.

Additionally, the capability of AI to analyze data in real time ensures swift responses to customer feedback, both positive and negative (Presi et al., 2014). This immediacy not only fosters enhanced customer service but also supports banks in tailoring their offerings to meet customer expectations and enhance their overall experience (Salminen et al., 2018; Rantanen et al, 2020).

However, the utilization of AI in this context is not without its hurdles. The presence of fake accounts, automated bots, and malicious behaviors pose a significant challenge, introducing the risk of distorted or unreliable insights (Shu et al., 2017). Consequently, ongoing efforts are directed towards honing AI models to counter these challenges, ensuring the authenticity and reliability of the extracted data and the resulting insights.

In the context of Islamic banking, this AI application is of substantial significance. Islamic banking, grounded in Sharia principles, places a premium on ethical and transparent dealings. Analyzing UGC enables these banks to gauge public perception and ensure their operations align with the ethical standards expected by their clientele.

Consider an example where an Islamic bank has recently launched a new digital financing product. AI is employed to scrutinize and analyze UGC across social media and online forums. Customers are actively discussing the accessibility, terms, and ethical implications of this new offering.

The CNN is particularly instrumental in sieving through the large volume of comments and reviews, categorizing positive, neutral, and negative sentiments and presenting a comprehensive analysis to the bank's management. It becomes apparent that there are misconceptions and ambiguities about the Sharia-compliance of this digital financing product.

Armed with this real-time data, the bank promptly engages in a strategic communication campaign to clarify the Sharia-compliance aspects, addressing specific concerns raised in the UGC. Educational content is shared online, and customer service is enhanced to provide personalized clarifications.

This instance underscores the power of AI in not only gathering insights but also empowering Islamic banks to be responsive and adaptive. The analyzed data becomes a catalyst for improving and refining the digital financing product, ensuring it not only complies with Sharia principles but is also perceived as such by the public. This harmonious blend of technology and ethics is integral to upholding the bank's reputation and ensuring the clientele's trust and satisfaction.

3.9. Loan Eligibility Prediction

The ascension of Artificial Intelligence (AI) and Machine Learning (ML) in the domain of financial lending has introduced an unprecedented level of precision and efficiency. Traditional mechanisms, which once governed the assessment of borrowers' creditworthiness, are being progressively enhanced and in certain scenarios, supplanted by intricate AI and ML models, facilitating an agile and refined process of loan (or "financing" in the context of Islamic banking) approval (Rawate and Tijare, 2017).

Neural Networks (NN) are pivotal in this metamorphosis, with specific types like radial basis NNs and decision trees becoming instrumental in amplifying the accuracy of credit-risk assessments (Sudhakar and Krishna Reddy, 2014). The complex yet imperative process of loan approval, ingrained with an exhaustive analysis of applicants' financial integrity, is experiencing a significant uplift from the integration of AI and ML technologies (Hamid and Ahmed, 2016; Iqbal et al., 2021).

The novel SBCO-based deep neuro fuzzy network classifier exemplifies the pinnacle of this technological integration. By amalgamating Swarm Search and Bee Colony Optimization, this model elevates the precision and reliability of loan eligibility predictions, underscoring a notable advancement in the decision-making process of financial institutions (Odeh et al., 2011; Singh et al., 2021).

In the distinct landscape of Islamic banking, this technological integration transcends conventional benefits. As a researcher, I argue that given Islamic banks' operational ethos of ethics, transparency, and risk-sharing, encapsulated in products like Murabaha, Mudarabah, Musharakah, Muzara'ah, and Musaqat, the infusion of AI and ML in predicting financing eligibility becomes profoundly pivotal. These banks are not mere custodians but are intricately involved in risk-sharing paradigms with their clients.

Herein, AI and ML models are not luxuries but necessities. They augment the banks' capacity to make informed and ethical financing decisions, balancing the intricate dance between upholding Sharia principles and ensuring financial prudence. In this context, every decision to extend financing is a testament to the bank's commitment to ethical financial engagements, ensuring that every financing approval aligns with both the client's capacity and the overarching Sharia principles.

Conclusively, the ongoing transformation in the realm of financing eligibility prediction, fueled by AI and ML, is of profound significance to Islamic banks. It embodies an era where the dual imperatives of Sharia compliance and financial stability coalesce seamlessly. These innovative technologies ensure that the intricate balance between ethical considerations and financial robustness is not only maintained but is also optimized, heralding a future of ethical, efficient, and prudent Islamic banking practices.

3.10. Stock Price Prediction

The COVID-19 pandemic has precipitated a substantial transformation in the financial sphere globally, necessitating a shift in the analytical tools and methodologies traditionally employed for market analysis and predictions. In this altered landscape, the prominence of machine and deep learning techniques, notably LSTM (Long Short-Term Memory) and KNN (K-Nearest Neighbors), has been accentuated (Alkhatib et al., 2013; Li et al., 2017).

Amid the pandemic, a surge in market volatility worldwide was observed, underscoring the critical role of technological innovations, especially AI and machine learning. In this context, KNN emerged as a robust tool for forecasting stock prices, demonstrating superior performance compared to LSTM and the ARIMA time series model (Fischer and Krauss, 2018; Borovkova and Tsiamas, 2019).

The adaptability and strength of machine and deep learning technologies have been underscored in these studies. The algorithms' proficiency in managing intricate relationships in numerical data and offering precise and pragmatic forecasts has been illuminated. Consequently, a broader spectrum of stakeholders, including investors, analysts, and policymakers, have augmented their reliance on these predictive models during tumultuous times (Moghar and Hamiche, 2020; Khattak et al., 2021).

The flexibility and adaptability of LSTM and KNN, especially in adjusting to rapidly evolving data during the pandemic, is emphasized. These models are instrumental not only in decoding current market dynamics but also in projecting future trends, playing a pivotal role in strategic planning. The depth and dynamism of analyses enabled by these technologies equip stakeholders with data-driven insights rooted in stringent analytical standards (Li et al., 2017; Selvin et al., 2017; Lachaab & Omri, 2023).

Considering Islamic banks, these technological advancements hold paramount significance. Constrained by the principles of Sharia law that prohibit investments in bonds or shares of companies involved in forbidden activities and exclude derivatives, Islamic banks predominantly focus on ordinary stocks. Preferred stocks are typically avoided due to the element of interest.

In this setting, the precision and reliability offered by LSTM and KNN in predicting stock prices are not just advantageous but essential. These AI and machine learning tools facilitate the navigation through complex financial markets while adhering to the ethical and legal confines intrinsic to Islamic banking. It embodies a philosophy where technological innovation is harmoniously intertwined with moral and ethical principles, fostering a resilient, ethical, and forward-looking financial environment.

3.11. Automation and Chatbots

Automation is evidently a perfect match for the finance sector. It alleviates the pressure induced by repetitive, low-value tasks on human employees by efficiently handling routine, everyday processes. This liberation allows teams to focus on high-value work, resulting in significant time and cost savings (Tatsat et al., 2020).

The integration of machine learning and AI into the automation landscape elevates the support for employees. Armed with relevant data, algorithms like Decision Trees, Neural Networks, and Support Vector Machines play a pivotal role. They provide comprehensive data analysis, aiding finance teams in making complex decisions. In specific scenarios, these algorithms can even suggest optimal actions for employees to validate and implement.

AI and automation, enhanced by algorithms like Random Forest and Gradient Boosting, are adept at identifying errors in the financial sector. They curtail the time spent between the identification and rectification of errors. Consequently, human teams are more efficient, their reporting is expedited, and the accuracy of their work is augmented (Tatsat et al., 2020).

AI chatbots, often powered by Natural Language Processing (NLP) and Machine Learning algorithms, are increasingly instrumental in supporting finance and banking customers. The surge in live chat software's popularity in finance businesses marks chatbots as the subsequent evolutionary step, often utilizing algorithms like LSTM (Long Short-Term Memory) for enhanced customer interaction and service (Adams & Clark, 2023).

In the specific context of Islamic banking, the application of AI and automation takes on an added layer of significance. These banks, grounded in principles of efficiency, rationality, and ethical resource utilization, find in AI a partner that not only aligns with but actively advances these values. Every AI-enabled decision is a reflection of the commitment to a banking paradigm that is efficient, ethical, and just.

The precision and adaptability of AI and machine learning mirror the principles of maximizing resource utility and minimizing waste, inherent in Islamic banking. Every transaction and investment is filtered through a lens of ethical and moral considerations. AI ensures compliance with Sharia law, optimizing resources, enhancing efficiency, and contributing to economic justice and sustainability.

3.12. Human Resources Management (HRM)

The inclusion of artificial intelligence (AI) in human resources management (HRM) is a notable advancement, fundamentally changing the conventional approaches and choices made in HR. AI in HRM stands out for its real-time data evaluation, foresight analytics, and task automation capabilities, amplifying the operational speed and quality of HR (Pereira et al., 2021). These improvements not only streamline HR activities but also elevate the experience for employees, promoting greater participation and output.

Yet, the swift embrace of AI in HRM introduces ethical dilemmas, particularly linked to decision-making algorithms (Duggan et al., 2020). Given the often enigmatic and intricate nature of AI systems, dissecting their ethical foundations and consequences is crucial (Charlwood & Guenole, 2022). Crafting moral protocols and instructions is essential to guarantee that AI's role in HRM is clear, just, and answerable. Tackling these ethical issues is key to upholding faith and virtue in AI-integrated HR activities and affirming their positive impact on the organizational environment and employee health (Hermann, 2021).

Regarding hiring, AI aids in refining the recruitment workflow, expertly navigating through extensive applicant groups and evaluating candidacy based on diverse criteria. Nevertheless, ethical questions surrounding justice, prejudice, and openness are associated with this technology. The ethical examination of algorithmic choices is essential to avoid unintended bias and to confirm that the process of selecting candidates remains impartial and just (Prikshat et al., 2021).

4. Deep Learning and Machine Learning: A Comprehensive Overview of Decision-Making and Risk Management Algorithms

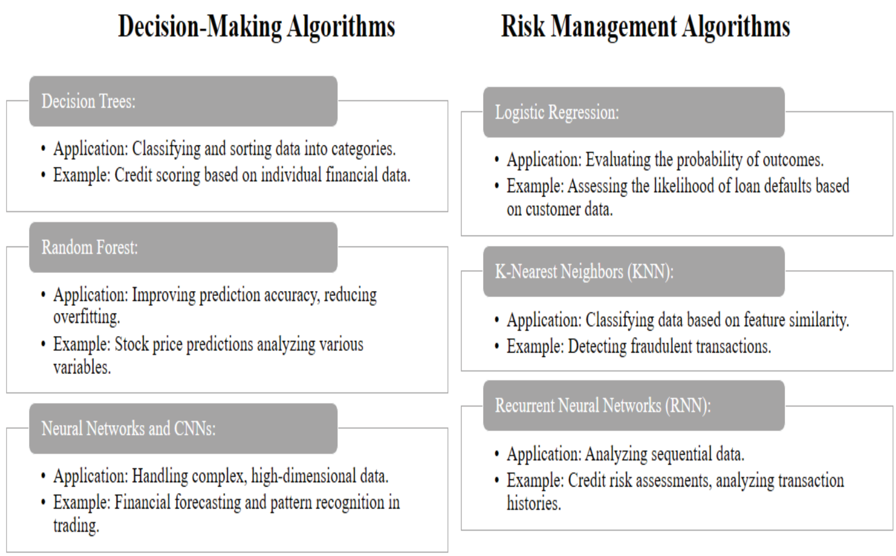

Figure 3. decision-making and risk management algorithms with examples of their usage Generated by the author.

The incorporation of machine learning (ML) and deep learning (DL) in decision-making and risk management has redefined the dynamics of the financial sector. These cutting-edge technologies have introduced a level of precision, efficiency, and intelligence that was once beyond reach. Figure 3 offers a panoramic view of various algorithms and their application examples, underscoring their pivotal roles.

4.1.Looking Ahead: The Intersection of Machine Learning, Deep Learning, and Islamic Banking

As the contours of Islamic banking are being reimagined in the wake of emerging technological trends, we envisage a landscape where the confluence of machine learning (ML) and deep learning (DL) with traditional Sharia principles is not only possible but serves as the vanguard of ethical finance.

4.1.1. Revolutionizing Decision-Making Processes

In the envisioned future, ML algorithms like Decision Trees and Random Forest could potentially offer a refined approach to evaluating complex Sharia-compliance criteria. The integration of these algorithms could transcend existing paradigms, offering precision in ensuring that every financial decision and transaction adheres to Islamic jurisprudence.

Neural Networks and CNNs hold the promise of optimizing Mudarabah and Musharakah contracts. These advanced technologies might potentially be tailored to adapt to the dynamic nature of market conditions, ensuring that profit and loss sharing ratios are optimized while maintaining strict adherence to Sharia principles.

4.1.2. Risk Management

The speculative future of Islamic banking beholds a refined art of risk management, where Logistic Regression and K-Nearest Neighbors (KNN) play pivotal roles. These tools, embedded within the constraints of Sharia laws, could offer a unique amalgamation of tech-driven efficiency and moral banking. Their strategic application promises enhanced identification of credit risks and financial anomalies, ensuring ventures are Gharar-free and ethically sound.

4.1.3. AI-Driven Sharia Compliance Monitoring

AI systems could revolutionize the way Islamic banks ensure compliance with Sharia law. By continuously monitoring all banking operations, these AI systems can instantly identify and address any deviations from Sharia principles. These systems would be dynamic, adapting to any updates or changes in Sharia law, thus ensuring ongoing adherence to Islamic ethical standards. This continuous, real-time monitoring will enhance the integrity and trust in the bank’s operations, reassuring customers and stakeholders of the bank’s commitment to Sharia compliance.

4.1.4. Ethical Oversight in the Technological Age

As Islamic banking ventures into the profound depths of AI, the future landscape is anticipated to be marked by a stringent ethical oversight mechanism. Every algorithm and predictive model would potentially be gauged and refined to ensure unwavering alignment with the tenets of Islamic finance. This meticulous integration could set a benchmark for global banking, epitomizing the harmonious coexistence of cutting-edge technology and stringent ethical standards.

In this speculative integration, Islamic banks are envisaged not merely as financial entities but as pioneering institutions where technology and ethics converge seamlessly. This integration promises a future where decisions are characterized by data-driven precision, risk management echoes the intricate dance between tech efficiency and moral banking, and every financial forecast and personalized solution is a testament to the harmonious melding of technological innovation and Islamic values.

As the Islamic banking sector approaches a pivotal transformation, there exists a potential not only for a comprehensive redefinition of its operational paradigms but also for establishing a groundbreaking model. In this model, finance transcends its traditional role as a vehicle for economic prosperity and emerges as an unequivocal force for global well-being.

5. Conclusion

This scholarly investigation concludes with an in-depth exploration of the integration of artificial intelligence, machine learning, and deep learning within the Islamic banking landscape. Our multifaceted analysis unmistakably demonstrates that these advanced technologies have catalyzed an unprecedented transformation, particularly in decision-making and risk management.

Our findings reveal that AI, ML, and DL together form a synergistic blend that enhances the analytical capabilities and effectiveness of Islamic banking operations. Their application in customer data analysis has led to more personalized banking experiences, while in credit risk estimation and market trend forecasting, they have increased accuracy and predictive insights. Nevertheless, these advancements are not without their challenges. Ethical, privacy, and security considerations are pivotal and crucial for the broader acceptance and integration of these technologies.

The research has highlighted the nuanced impacts AI and ML have had on the sector. However, it's critical to acknowledge the constraints and limitations that remain. Key concerns include data privacy, ethical algorithm development, and the urgent need for a regulatory framework as dynamic and adaptive as the technology it seeks to govern.

5.1. Recommendations

To successfully navigate the integration of AI and ML, a strategic approach rooted in ethical and operational excellence is essential. There is a clear need to establish

and enforce robust ethical standards that align AI applications with the core values of Islamic banking. Enhancing security and privacy is not just an operational necessity but a fundamental pillar to build trust and protect stakeholders' interests.
The regulatory landscape requires agility and adaptability, creating an environment where innovation can flourish within the confines of ethical and legal frameworks. Additionally, empowering the workforce with the necessary skills and knowledge to navigate the evolving technological landscape is crucial for effectively harnessing the potential of AI and ML.

5.2. Future Work

The future of AI in Islamic banking, rich with promise, also presents complex challenges. Research going forward should prioritize the development of ethical frameworks tailored to the moral and ethical underpinnings of Islamic finance. Customized models that simultaneously address technical and ethical aspects of Islamic banking are essential.

Additionally, the potential impact of quantum computing, blockchain, and other emerging technologies on Islamic banking's risk assessment, customer service, and decision-making processes warrants thorough investigation. Future studies should delve into the ramifications and integration possibilities of these technologies with existing AI and ML systems.

This research, while extensive, marks the beginning of a deeper exploration into the intersection of AI, ML, and Islamic banking. The ongoing integration of these technologies is a dynamic narrative, presenting a spectrum of opportunities and challenges. It underscores the need for continued inquiry, ethical vigilance, and creative adaptations. Collaborative efforts among technologists, scholars, and policymakers are crucial to navigate Islamic banking towards a sustainable, ethical, and efficient future in the AI era.

Standing at the forefront of a technological renaissance, Islamic finance is poised to navigate a path shaped by both tradition and innovation. The harmonization of technological advancements with ethical, moral, and legal considerations will be key to guiding Islamic banking's sustainable evolution in the age of artificial intelligence.

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Role of AI in Shariah Audit Analytics

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Abstract

Shariah audit plays an important role in ensuring the compliance of all business areas with the Shariah principles. The purpose of this paper is to provide an overview of possible technical solutions for Shariah audit automation using artificial intelligence (AI) and data analytics. The existing activities in Shariah audit are carried out manually and most of them include repetitive tasks. This leads to more time spent on activities such as data collection, sampling, and recording the observations. It also involves repetitive tasks of running the same checklist on hundreds of files for weeks, attempting to identify the same pattern in the entire set of documentation. Using the AI and data analytics, these issues may be resolved. The AI-based audit can help in reviewing 100% of the transactions by training the machine learning model on datasets. It will also increase the accuracy as the machines are not prone to the constraints humans are exposed to e.g., different levels of brain activity at different time periods etc. The time and cost involved in manual auditing shall be reduced resulting in enhanced efficiency. The solution proposed in this paper shall automatically extract the data from MS word, PDF and other formats and export the same to the next step. A control flow shall be developed, by employing natural language processing (NLP), to clean, process and analyze this data. Based on the already-defined rules (serving as the checklist), the system shall automatically identify the potential Shariah issues and raise the flag on that particular transaction. The large language models (LLM) like GPT shall then be used to record and report the observations. With the help of data analytics tools, Shariah auditors shall be able to identify the past trends and patterns in the transactions, customers, and areas. This study is first of its kind as it provides technical details of integrating Shariah audit with artificial intelligence, machine learning and data visualization. Such solutions will result in better Shariah compliance and contribute to an increased public confidence in the products of Islamic financial institutions.
Keywords: Artificial intelligence, audit analytics, Shariah audit automation

1.Background of the Study

The Islamic financial institutions (IFIs) have a fiduciary responsibility to invest the funds, mobilized through various modes, into Shariah compliant avenues. Discharging this responsibility necessitates a robust Shariah governance system that ensures that all the activities of IFIs including mobilization, deployment, profit calculation and distribution are in conformity with the principles of Shariah. The IFIs operating in various jurisdictions around the world have their own Shariah governance structure that provides a comprehensive framework to ensure Shariah compliance in all activities of IFIs functioning in that jurisdiction. Almost all the Shariah governance frameworks around the globe have prescribed the Shariah auditing as an important organ in the overall Shariah governance scheme. As an important pillar and component of the Shariah governance, the Shariah audit function provides reasonable assurance that all the activities of the IFIs comply with the defined Shariah principles. A robust and well-functioning Shariah audit function enhances the soundness of internal control and systems which are in place to ensure compliance of all products, procedures, and agreements with the Shariah principles. Keeping in view the importance of Shariah audit, the Accounting and Auditing Organization for Islamic Financial Institutions (AAOIFI), global standards setting body for IFIs, has issued auditing standards for Islamic finance industry. These standards provide guidance on internal and external Shariah audit functions and processes of IFIs.

Traditionally, the auditing function has largely relied on human professionals who execute all the processes of auditing. The audit professionals make audit plans, set the sampling criteria, obtain the required data, perform the audit, draft and finally submit the report providing reasonable assurance on the operations of IFIs. The quality of audit is maintained and ensured by complying with the international standards on auditing and Shariah auditing issued by the standard setting bodies like the International Auditing and Assurance Standards Board (IAASB) and AAOIFI. The rapidly evolving world of technology has, however, revolutionized the traditional practices in almost all industries. Like all other industries, the financial services and auditing industry have also been affected by modern technological solutions, particularly artificial intelligence (AI). Although the concept of machine or artificial intelligence started erupting in the 1950s, the applicability of AI has increased rapidly in recent years (Buntak et al., 2021). The AI-based solutions have already replaced human workforce in many processes including repetitive and non-repetitive tasks. The automation and use of data analytics in traditional business processes have enhanced the operational efficiency and led to more informed decisions that rely on vast amounts of data. The processes of auditing executed in various stages of audit are no exception and are prone to the impact of AI-driven solutions. A new field named audit analytics or data-drive audit has emerged which has transformed the auditing and offered new ways to improve the audit quality (Carataș et al., 2018). The large audit firms and related global organizations like ACCA, EY and KMP are exploring the opportunities to take advantage of modern disruptive technologies in improving the audit quality.

2. Problem Statement

Although the traditional Shariah audit provides reasonable assurance to various stakeholders of IFIs that operations and activities of IFIs are in conformity with the principles of Shariah, it lacks the use of modern disruptive technologies and relies heavily on human-performed processes. From sampling to finding observations to reporting, all the tasks are usually performed by the human professionals working in the Shariah audit team. This reliance on human professionals leads to human errors, reduced sampling universe, more time consumption, less reliance on data, and others. Some of the tasks which are of repetitive nature also have an effect on the productivity of the audit team. Utilizing automated solutions for such repetitive tasks can significantly reduce time consumption, freeing up valuable resources and time that can then be redirected towards more productive activities. Similarly, data analytics and machine learning can help in identifying patterns otherwise hidden from human observation.

The task of performing Shariah audit depends on the skills and competencies needed to detect the anomalies and find the deviations from the guidelines and Shariah principles defined by the standards, regulatory instructions and Shariah board/committee. Such settings are where artificial intelligence and data science can play their role. Leveraging the AI in auditing can not only improve the audit quality but it can also lead to charging less audit fees. The deficiencies in the competence of the Shariah auditors observed by some researchers can also be fulfilled by employing data analytics and machine intelligence techniques. This technical paper highlights the role of AI in improving the quality of audit which, in turn, shall enhance the overall Shariah compliance environment in IFIs. In particular, this paper explores the machine learning and natural language processing (NLP) methods that could be used to read, extract and process the data from the transaction documents executed in various products e.g. murabaha, istisna` and salam etc. These tasks of processing the transition documents can also be automated by designing and deploying the automated workflows. By defining and executing the triggers for these workflows, the entire process of auditing the transaction documents and finding the observations related to Shariah non-compliance can be automated. The machine learning model trained on formats and templates of transaction documents can extract the field-based data using optical character recognition (OCR). The observations recorded during the previous step can be written to a report in a pre-defined template. Such solutions can not only bring automation in the Shariah audit activities but also enhance the Shariah compliance by removing the element of human error to which traditional audit processes are exposed too. Another great benefit offered by these solutions will be that almost 100% of the transaction shall be able to be audited by machines compared to the existing model of auditing where only a fraction of transactions, chosen on sample basis, is reviewed and audited.

3. Related Literature

Fedyk et al. (2022) analyze the resume data of more than 300,000 employees of the 36 large audit firms to measure the investment of these audit firms in the AI workforce. Their results show that when audit firms invest in AI and build AI workforce, the quality of audit is improved and manual tasks performed by humans are replaced by machines. They also report that investing in AI also helps in reducing the fees and enhancing the efficiency of audit. The research by Aitkazinov (2023) also shows that utilizing AI based solutions can enhance the audit quality by automating the repetitive tasks, fast-processing the large amount of data and revealing the patterns and insights hidden from human observation. Integrating AI in audit processes can also help in establishing a continuous monitoring and anomaly detection system to proactively identify, assess and report the risk. A similar study has been conducted by Saat (2021) who reports that using modern AI tools increase the ability and skills of audit professionals to perform high-level and complex audit activities. Audit firms and professionals need to equip themselves with understanding and utilizing machine intelligence to execute various activities (Carataș et al., 2018). In addition to use of AI in auditing of private entities, AI based systems have been introduced and implemented in the public domain too. For instance, the Indian government has expressed its plans to implement an AI based tax audit system to identify and reduce the inefficient practices in the taxation system including evading the tax and poorly managing the tax collection and reporting. Implementing such systems shall decrease reliance on human workforce and eliminate errors and inefficient practices (Et al., 2021).

One of the challenges faced in using AI for auding the transaction documents used in various modes of IFIs is that such documents come in varying layouts and have unstructured data. The traditional technology techniques are not good for reading and extracting data from such documents and are mostly rule-based. However, AI provides a better solution for extracting and processing the data from unstructured documents and automating the whole process. After training the model on a large dataset of different layouts of documents, the task of assessing the transaction documents can be made easy by deploying such a model (D. Baviskar et al., 2021). For an efficient AI document processing models, the quality of the dataset on which the model has been trained is very important. Lack of data validation techniques and low-quality image can also affect the performance of models trained to extract the data from unstructured documents such as invoices and purchase orders. Di. Baviskar et al. (2021) provide a high-quality dataset consisting of multi-layout invoices with unstructured data which can help in feature extraction and entity recognition. Another area related to data extraction from unstructured documents is the classification of text. The classification model based on NLP has various applications in various industries which produce or gather large amounts of text data. Kowsari et al. (2019) present an overview of text classification and feature reduction models with their application in solving the real-world problems. In addition to general NLP-based models, some domain specific models have also been developed by the researchers and experts. One example is the use of AI in legal tasks including tokenization of legal agreements, prediction of judgement, and question answering from the legal agreements. Xiao et al., (2021) have worked on developing a pre-trained language model (PLM), using NLP techniques, to understand the Chinese legal agreements and extract information from them.

4. Use of AI in Shariah Audit of Islamic Financial Institutions

Before we explain the proposed solution based on AI and data science for Shariah auditing in IFIs, it is appropriate to present an overview of the processes and documents involved in different types of financing transactions. For the simplicity of analysis, we shall focus on only murabaha transactions as this contract is used globally as a financing mode.

4.1. Transaction Process and Documents in Murabaha

Murabaha is a sale transaction in which the seller discloses the cost he incurred for acquisition of the goods as well as the profit he is going to charge on sale from the buyer. In IFIs, murabaha is used, along with wakala or agency, as a financing product to meet the working capital and inventory requirements of the clients. Below is a sample process of how murabaha is used to finance the purchase of raw material required for production, value addition or onward sale by the client.

- At the first stage, Customer offers to the IFI asking authorization from IFI to act on its behalf to purchase the required commodity.
- IFI accepts the offer made by the customer and authorizes him to purchase the commodity on behalf of IFI.
- Customer places a purchase order with the supplier.
- Payment is made to the supplier either directly by IFI or through the customer.
- Supplier delivers the commodity as per the agreed sale agreement.
- Customer informs IFI that it has successfully purchased and taken into possession the commodity as per agency contract.
- Customer makes an offer to IFI that it wishes to purchase the commodity from IFI on murabaha basis and quotes purchase price.
- IFI accepts the customer`s offer and agrees to sell the commodity to customer on murabaha basis.
- Upon execution of murabaha sale contract, ownership of commodity is transferred from IFI to the customer. Customer is liable to pay the sale price of murabaha as per the terms and payment schedule agreed in the murabaha sale contract.

The documents in executing murabaha transaction may be divided into two categories:

- Transaction documents
- Supporting documents

4.1.1. Transaction Documents

The transaction documents are those agreements which initiate a contract or transaction. For instance, an agency agreement or murabaha sale document is a transaction document. They initiate the agency and murabaha contract, respectively.

4.1.2. Supporting Documents

These documents don`t initiate the contract rather they serve as an ancillary or supporting documents. They are required to support the execution of a transaction. A sales invoice in murabaha, for example, is a supporting document. This endorses that the commodities have been purchased from the supplier.

The responsibility of the Shariah auditor involves assessing both types of transaction documents. We shall now describe these two types of documents in more detail. This may be noted that the names of these documents are at the discretion of each institution. Each institution in various jurisdictions has its own convention of naming these documents.

4.1.3. Agency Offer

This document is the first step in executing murabaha in IFIs. Through this document, the customer offers the bank that he be appointed as an agent of the bank to purchase commodities. In this document, the necessary details about this agency are provided. This includes the description of the commodity, supplier details, mode of payment to supplier, expected price and delivery data of the commodity etc.

Along with this transaction document, some other documents (supporting documents) are also provided. For example, the quotation from the supplier or the proforma invoice. These supporting documents provide assurance that the details stated by the customer in agency offer documents are correct.

4.1.4. Acceptance to Customer`s Agency Offer

After reviewing the agency offer as well as the related supporting documents, the bank may accept the customer`s offer and appoint him as an agent to procure the goods as per the details mentioned in the agency offer and related documents. Generally, no other supporting document is required at this stage.

4.1.5. Declaration of Delivery of Goods

Once the customer procures the goods from the supplier, he sends an intimation of the same to the bank. This is not a transaction document, per se, because no new contract is initiated by this document. This document is confirmation of performing the duties assigned to the agent. At this stage, the bank requires supporting documents to confirm purchase and delivery of goods. To evidence the purchase of goods, sale contract with the supplier, invoice and evidence of payment to the supplier (pay order issued in favor of supplier, LC, import contract documents etc.) are provided by the customer. For confirmation of delivery, shipment documents (truck receipt, bill of lading, airway bill etc.), gate pass of the premises of delivery place (showing the delivery of goods at the said premises) and inventory reports of the premises are normally provided.

4.1.6. Offer to Execute Murabaha Sale

Once the goods are delivered and the bank has taken the ownership and possession of the same, the customer offers to purchase the same goods on murabaha basis from the bank. No extra supporting documents are usually required at this stage. This is because the existence of goods and their suitability for murabaha sale has been ascertained in previous steps.

4.1.7. Acceptance to the Customer`s Offer for Murabaha

After examining the offer made by the customer, the bank accepts the offer thereby concluding the murabaha sale contract between the bank and the customer. No other supporting document is generally required at this time. The security documents, to secure the due payments by the customer, are already executed before the murabaha transactions.

4.2. Risks in Murabaha

There are various risks associated with murabaha transactions. Some risks are common while the others may vary depending on the jurisdiction, institution and the commodity. There are many types of risks involved in murabaha; credit risk, price risk, Shariah compliance risk, to name a few. In this section, we shall largely focus on Shariah compliance risk. The below table shows the risks at each stage as well as the implications. The Shariah audit examines the controls put in place to mitigate these risks and records the observations.

Murabaha Stage	Risk	Implication
Prior sale contract between the client and the supplier.	The client orders/enters into a sale contract with the supplier before being appointed agent of the bank to purchase the goods.	Murabaha shall not be executed on such goods since they are already purchased by the client.
Purchase of Shariah non-compliant Goods by the Agent	The client, as an agent of the bank, purchases Shariah non- compliant goods.	Purchasing Shariah non-compliant goods is not permissible and murabaha cannot be executed on such things.
Delay in shipment of goods/non-shipment of goods	The funds are disbursed but the bank is not intimated about delivery of goods.	This may result in consumption of goods by the client before murabaha. In this case, murabaha would not be possible.
Consumption of Goods by the client before execution of murabaha_	The goods are consumed before the execution of murabaha. This can happen for a number of reasons including non-intimation of delivery of goods to the bank (as mentioned in above point), or delay in accepting the murabaha offer made by the client.	Murabahah cannot be executed on such goods because existence of goods at the time of murabaha sale is a mandatory condition for validity of sale.
Not mentioning the cost in murabaha	The cost of acquiring the goods by the bank is not mentioned in murabaha agreement.	Murabahah is a fiduciary transaction in which the seller must disclose the cost to the buyer. However, if the cost is not mentioned the sale remains valid (provided all sale conditions are met) though it will not be a murabaha sale.

5. Shariah Audit of Murabaha Transactions

In order to assess the control environment and provide reasonable assurance on Shariah compliance of murabaha transactions, the Shariah audit engagement involves the following steps:

- Sampling and data collection
- Reading and understanding the information from the documents
- Running the checklist to identify the gaps and observations
- Recording and reporting the observation

Now, we analyze the traditional audit process and activity involved in each of the above steps and provide an overview of an alternative approach to execute each step using AI.

5.1. Sampling and Data Collection

The Shariah audit department is provided with the list of all the murabaha transactions executed during the audit period to enable the department to choose samples from that list. Based on various parameters already defined in the audit manual, a sample of transactions is chosen by the Shariah auditors and the relevant department is asked to provide the transaction documents. Most of the time, this activity is carried out manually and sample selection is done based on the customer types, financing segment, amount of the transaction, subject matter of the transaction etc. The purpose of this sampling is to ensure, to the extent possible, that all variants of murabaha transactions executed in an IFIs undergo the Shariah audit assessment.

With the help of AI and process automation, the entire set of transactions executed during the audit period can be examined to find and identify the possible Shariah non-compliance instances. The sample is selected in a traditional audit because of the time and human resource constraints; it becomes practically difficult or impossible for Shariah audit personnel to examine all the transaction documents. Another issue with reviewing large amounts of transaction documents is managing and querying the data. The machines, on the other hand, are not constrained by these limitations. An automated workflow can be designed that, when triggered, will fetch all the transaction documents and transfer the same to the next step in the workflow for data extraction and processing. In organizations where the transaction documents are stored electronically, the automated workflow can be integrated with the internal database of the organization. This shall help in direct querying and fetching the required documents from the database instead of asking a specific department to provide the transaction documents. Such integration will ultimately lead to ongoing, continuing monitoring of the transactions as well as saving dozens of hours in each audit period which are spent on asking, retrieving and submitting the documents by the relevant departments to the Shariah audit unit. Auditing 100% of the transactions shall truly transform the audit spectrum and cause to increase confidence of all the stakeholders

in Shariah compliance of the practices and operations of IFIs.
There are many platforms available online which help in designing the automated workflows. They have templates which are commonly used in various industries, or one can create and design their own customized workflow. If information security guidelines of an IFI or the regulatory requirements do not allow using such online and cloud based automated workflows, an automated solution can be developed in-house or purchased from a vendor that will run on internal servers of the IFI to maintain the privacy and security in document querying and processing.

5.2. Reading and Understanding the Information from the Documents

This is the most critical task where artificial intelligence can be leveraged to improve the audit quality, efficiency and productivity of the audit department. In a traditional manual Shariah audit, the transaction documents submitted by the auditee are read and reviewed by the auditor. As explained above, there are different types of documents executed and/or submitted at each stage in murabaha in a sequence. Sequence breaking or mismatching information may lead to Shariah non-compliance of the transactions. For instance, if the client has already established a purchase contract with the supplier for the same goods he intends to get financed by the bank, the bank cannot finance such goods through murabaha. So, when the Shariah auditor finds from examining the supporting documents provided by the client that the goods had already been purchased by the bank before the bank had appointed the client to procure the same, this observation shall be highlighted by the auditor. The murabaha executed in this transaction shall stand invalid as the bank is not allowed, as per the Shariah principles, to sell the goods it does not own to the client. This shows that the Shariah auditor does not review the documents in isolation rather the overall context and sequence are considered by him/her while reviewing the transaction documents. Examining the documents in this way requires careful review and attention which, sometimes, can be compromised due to by-default human nature or constraints. The above activity performed manually in traditional Shariah audit can be outsourced to an AI based solution which shall read, extract and process the data from the transaction documents. Before we provide an overview of such a solution, there are some challenges and issues which need to be discussed.

5.2.1. Data Types

There are two types of data which are usually reviewed during an audit; one is numeric and the secondi is non-numeric. The numeric data means the amounts involved in a murabaha transaction which include the cost of acquiring/purchasing the goods, bank`s desired profit rate, quantity of goods, financing amount, sale price of murabaha contract, break-up of cost and profit etc. The non-numeric data, on the other hand, involves text and data-time data. This includes the information present in transaction documents e.g. agency offer date, agency approval date, invoice date, possession date, description and specification of goods, place of delivery, estimated delivery time, supplier details, payments terms with the supplier, description and quantity of the goods possessed by client acting as an agent of the bank, description of goods in murabaha sale contract etc. The processing of first kind data by the machines is relatively easy as computers are considered better and superior to humans in number crunching. The real challenge is handling and processing the second type of data e.g., non-numeric and text because such data is usually created and structured in an unstructured form. Most of the data created during the murabaha and other contracts is in unstructured format and contains text. Our discussion in this technical paper shall be more focused on this text data contained in the transaction documents.

5.2.2. Reading the Unstructured Data

So far, one of the significant issues faced in outsourcing the auditing function to machines is that the information present in the transaction documents is in an unstructured way. This makes it difficult for traditional technology solutions to read and extract such information. With the advancement in the capability of machine translation systems and OCR, reading and extracting data from unstructured data has become easy. Machine learning models can now easily scan and process the vast amount of structured and unstructured data. Specifically, the natural language processing (NLP) based AI solutions are being used to extract the information from documents including financial reports, bank statements and legal agreements. These models are not limited to one specific language or computer-generated documents; rather they can read the text data in dozens of languages even if it is handwritten by humans. In the context of murabaha transactions, the unstructured data encountered by the Shariah auditors is usually in the form of PDF documents e.g., offer & acceptance, invoices, declaration of goods delivery, murabaha contract etc. From the perspective of machine intelligence, these PDF files are of different types. Some files have tables with clear borders, others have borderless tables or some files even don`t have tables. In some cases, even the image file (JPEG, PNG etc.), which is the scanned copy of the transaction document, is shared with the audit team. The underlying mechanics for reading and extracting data from each type of file is different which require different techniques for each type of file. To build an efficient text data extraction tool, it is necessary that the AI model has been trained on various formats and types of murabaha transaction documents. For instance, the invoice submitted by one supplier in a murabaha transaction might have a different format from what has been submitted by another supplier in another murabaha transaction.

An IFI can either purchase subscriptions of models already built and trained by the solution providers (like Microsoft and Amazon) or develop its own AI model that utilizes the OCR and NLP techniques in reading the transaction documents and extracting the data. Tesseract is one the most powerful OCR tools sponsored by

Google to extract the text data from images and PDF documents. In Python, one of the most used programming languages to build AI products, the pytesseract library can be used, which is a wrapper for Tesseract, to extract text data. If the transaction document is in image format and has unstructured data, OpenCV can be used with pytesseract to run OCR and extract the required information. With OpenCV, we can define areas for information extraction i.e., the system should look for the invoice date in the top right of the document etc. Similarly, different models and libraries can be used to extract information from table, borderless table and only-text type files. The output file and format of the extracted data can be of any type keeping in view the subsequent processing and requirement. Since the extracted information is, most of the time, required in key-value pairs (invoice no, invoice data, goods description etc.), JSON format is usually selected as the output format for the extracted information. Below are a few illustrations of the information extraction from transaction documents using Python.

```
03-08-2022
We refer to the Master Murabaha Agreement dated 13-04-2022 (the Agreement). We request your approval to
purchase the Goods indicated below as your agent upon the terms and conditions of the Agreement. Please notif
y
us of your approval by facsimile by sending a Transaction Approval to us by no later than the close of busine
ss on
the date five (5) Business Days after the date of this Transaction Notice.
1 Description of the Goods:
(a) Nature of the Goods
Silver Travertine Blocks
(b) Quantity
88.15 Pons ia PRR S55,000-- per Pon (Rs. 1.083.250 -).
(c) Quality
(As per Quotation)
2 Name(s) and address(es) of the Supplier(s):
Stones
3 The Purchase Date:
26-08-2022
4 The Purchase Price:
PKR 4,683,250/-
5 The Value Date:
03-08-2022
6 Approximate date(s) of shipment of the Goods:
24-08-2022
/ Approximate place of shipment of the Goods:
SK Stones (Pvt) Ltd.
Plot 150 Mangopir Road, _- -
Cyate) 7
Gadap Town, ~ S "as
Karachi. g "2
yy Py 2
We
8 The Purchaser's bank account: %
Payment Order in favour of Stone NS 4S x,
* SK Casa, 390, Potohar Road (St.16), 1-9/3 Industrial Area, ISLAMABAD-PAKISTAN
TEL:-0092-51-4859035-38 Fax:-0092-51-4441174
```

Fig 1. Text data extracted from transaction notice (notice for appointment of agent) in a sample murabaha transaction.

```
tom_tros = tom_tros.sort_values(by='Tom Tros')
tom_tros ['Product_name_NL'] = 'Tom Tros'
tom_tros = tom_tros.rename(columns={'Tom Tros': 'Variety'})
tom_tros = tom_tros.reindex(columns=['Product_name_NL', 'Variety', 'Trader', 'Price'])
tom_tros = tom_tros.reset_index(drop=True)
print(tom_tros)
```

```
   Product_name_NL   Variety    Trader    Price
0         Tom Tros      Grof   Harvest      NaN
1         Tom Tros      Grof   Harting        x
2         Tom Tros      Grof    Kraaij      por
3         Tom Tros      Grof   Combilo      NaN
4         Tom Tros      Grof   Witkamp  € 14,00
5         Tom Tros      Grof  Greenery      NaN
6         Tom Tros      Grof    Seelen      NaN
7         Tom Tros      Grof    Seasun      NaN
8         Tom Tros      Grof       STC  € 13,00
9         Tom Tros  Mid/grof   Combilo      NaN
10        Tom Tros  Mid/grof  Greenery      NaN
11        Tom Tros  Mid/grof    Seasun      NaN
12        Tom Tros  Mid/grof   Harting      NaN
13        Tom Tros  Mid/grof       STC      NaN
14        Tom Tros  Mid/grof    Seelen      NaN
15        Tom Tros  Mid/grof   Witkamp      NaN
16        Tom Tros  Mid/grof    Kraaij      NaN
17        Tom Tros  Mid/grof   Harvest      NaN
18        Tom Tros    Middel       STC      NaN
19        Tom Tros    Middel   Witkamp      NaN
20        Tom Tros    Middel    Seasun      NaN
21        Tom Tros    Middel    Kraaij      NaN
22        Tom Tros    Middel  Greenery      NaN
23        Tom Tros    Middel   Harvest  € 27,50
24        Tom Tros    Middel   Combilo      NaN
25        Tom Tros    Middel    Seelen      NaN
26        Tom Tros    Middel   Harting      NaN
```

Fig 2. Text data extracted from a sample invoice in PDF that has structured tables.

```
In [42]: table = extracted_tables[0]  # Assuming the table is at index 0
         display_html(table.html_repr(title="Extracted Table"), raw=True)
```

Extracted Table

Title: No title detected

Bounding box: x1=105, y1=84, x2=1526, y2=2050

	0	1	2	3	4	5	6
0		Domanda					es
1		Nella teoria del ciclo di vita di Erik					
2		Erikson, durante l'adolescenza	integrità e	identità e confusione		generatività e	
3		l'individuo si trova in una fase dello\nsviluppo psicosociale caratterizzata	disperazione	dell'identità	fiducia e sfiducia	stagnazione	
4		dall'antinomia tra:					
5		Secondo Daniel Goleman, la	della creatività	delle competenze	delle competenze	del pensiero	
6		consapevolezza di sé è una capacità:		emotive	relazionali	divergente	
7						è influenzato solo	
8		Nel modello della "prosocial	non è influenzato\ndalla competenza	è influenzato dal	dalla competenza	dalle caratteristiche\ncognitive e dalla	
9		classroom" il rendimento scolastico:	sociale degli studenti	clima di classe	sociale degli\ninsegnanti	motivazione degli\nstudenti	
10		Rispetto al campo delle emozioni e					
11		della loro espressione, l'incapacità di	discalculia	empatia	alessitimia	dislessia	
12		alcuni soggetti di verbalizzare le\nemozioni si definisce:					
13		Wim Meeus afferma che, dalla	bassi livelli sia di	elevati livelli sia di	moderati livelli di	basso impegno ed	
14		combinazione dei livelli di impegno,	impegno, sia di	impegno, sia di	impegno, media	esplorazione in	
15		riconsiderazione dell'impegno, è	esplorazione in	esplorazione in	esplorazione in	profondità ed	
16		possibile individuare cinque stati	profondità, sia di\nriconsiderazione	profondità, sia di\nriconsiderazione	profondità e bassa\nriconsiderazione	elevata\nriconsiderazione	
17		moratorium" indica:	dell'impegno	dell'impegno	dell'impegno	dell'impegno	
18						nati in Italia da	
19		Si definiscono "seconde generazioni"\nminori:	che emigrano da soli	che raggiungono i\ngenitori nel paese di	che migrano insieme\nal nucleo familiare	genitori stranieri, che\nnon hanno vissuto	
20				accoglienza		direttamente la	
21						migrazione	
22			provenienti dalle	psicologiche, per	statistiche, che	che alimentano il	
23		La pedagogia per John Dewey si basa\nsu	dell'educazione e	raccogliere dati utili\nsui soggetti, senza\nnecessità di	offrire numeri e dati\nper	pedagogico,	

Fig 3. Text data extracted from a PDF file with borderless table. The text is non-English (Italian).

```
for table in extracted_tables:
    for row in table.content.values():
        for cell in row:
            cv2.rectangle(table_img, (cell.bbox.x1, cell.bbox.y1), (cell.bbox.x2, cell.bbox.y2), (255, 0, 0),

image_pil = PILImage.fromarray(cv2.cvtColor(table_img, cv2.COLOR_BGR2RGB))
image_pil
```

Out[138]:

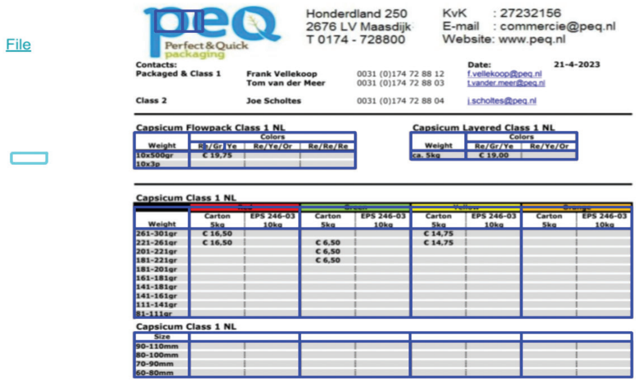

Fig 4. Data extraction from an invoice using Open CV.

```
for table in extracted_tables:
    for row in table.content.values():
        for cell in row:
            print(cell)
```

```
TableCell(bbox=BBox(x1=210, y1=53, x2=242, y2=79), value=None)
TableCell(bbox=BBox(x1=242, y1=53, x2=258, y2=79), value=None)
TableCell(bbox=BBox(x1=258, y1=53, x2=266, y2=79), value=None)
TableCell(bbox=BBox(x1=185, y1=206, x2=250, y2=230), value=None)
TableCell(bbox=BBox(x1=250, y1=206, x2=447, y2=218), value=None)
TableCell(bbox=BBox(x1=250, y1=206, x2=447, y2=218), value=None)
TableCell(bbox=BBox(x1=250, y1=206, x2=447, y2=218), value=None)
TableCell(bbox=BBox(x1=185, y1=206, x2=250, y2=230), value=None)
TableCell(bbox=BBox(x1=250, y1=218, x2=268, y2=230), value=None)
TableCell(bbox=BBox(x1=268, y1=218, x2=292, y2=230), value=None)
TableCell(bbox=BBox(x1=292, y1=218, x2=447, y2=230), value=None)
TableCell(bbox=BBox(x1=185, y1=230, x2=250, y2=251), value=None)
TableCell(bbox=BBox(x1=250, y1=230, x2=447, y2=251), value=None)
TableCell(bbox=BBox(x1=250, y1=230, x2=447, y2=251), value=None)
TableCell(bbox=BBox(x1=250, y1=230, x2=447, y2=251), value=None)
TableCell(bbox=BBox(x1=513, y1=206, x2=578, y2=229), value=None)
TableCell(bbox=BBox(x1=578, y1=206, x2=710, y2=218), value=None)
TableCell(bbox=BBox(x1=513, y1=206, x2=578, y2=229), value=None)
TableCell(bbox=BBox(x1=578, y1=218, x2=710, y2=229), value=None)
TableCell(bbox=BBox(x1=513, y1=229, x2=578, y2=240), value=None)
TableCell(bbox=BBox(x1=578, y1=229, x2=710, y2=240), value=None)
TableCell(bbox=BBox(x1=185, y1=300, x2=250, y2=327), value=None)
TableCell(bbox=BBox(x1=250, y1=300, x2=381, y2=327), value=None)
TableCell(bbox=BBox(x1=381, y1=300, x2=513, y2=327), value=None)
TableCell(bbox=BBox(x1=513, y1=300, x2=644, y2=327), value=None)
TableCell(bbox=BBox(x1=644, y1=300, x2=775, y2=327), value=None)
TableCell(bbox=BBox(x1=185, y1=327, x2=250, y2=439), value=None)
TableCell(bbox=BBox(x1=250, y1=327, x2=381, y2=439), value=None)
TableCell(bbox=BBox(x1=381, y1=327, x2=513, y2=439), value=None)
TableCell(bbox=BBox(x1=513, y1=327, x2=644, y2=439), value=None)
TableCell(bbox=BBox(x1=644, y1=327, x2=775, y2=439), value=None)
TableCell(bbox=BBox(x1=185, y1=458, x2=250, y2=469), value=None)
TableCell(bbox=BBox(x1=250, y1=458, x2=381, y2=469), value=None)
TableCell(bbox=BBox(x1=381, y1=458, x2=512, y2=469), value=None)
TableCell(bbox=BBox(x1=512, y1=458, x2=644, y2=469), value=None)
TableCell(bbox=BBox(x1=644, y1=458, x2=775, y2=469), value=None)
TableCell(bbox=BBox(x1=185, y1=469, x2=250, y2=514), value=None)
TableCell(bbox=BBox(x1=250, y1=469, x2=381, y2=514), value=None)
TableCell(bbox=BBox(x1=381, y1=469, x2=512, y2=514), value=None)
TableCell(bbox=BBox(x1=512, y1=469, x2=644, y2=514), value=None)
TableCell(bbox=BBox(x1=644, y1=469, x2=775, y2=514), value=None)
```

Fig 5. Location of tables in a PDF file detected by the system.

5.3. Custom Rules for Checklist

Once the information has been extracted from the transaction documents, the next step is to process this information and detect the Shariah non-compliance anomaly. The machine alternative for the check list run through by the Shariah auditors are custom rules. For example, we can create a rule in the AI audit system that if the invoice data occurs before the date of agency appointment notice, this shall be treated as an anomaly and the system shall raise the flag in that transaction. Another custom rule may be such that if the goods procured in the first stage of murabaha products are not fully delivered, the murabaha contract shall not be executed for undelivered goods. For classification problems, the decision tree model can also be trained on a large dataset of transaction documents including quotation, invoice and purchase order. These rules can be developed in the system along with the human-in-loop model too. By doing this, the system shall not be making any decision on its own rather it shall be referring the observation to a human Shariah auditor for decision making.

5.4. Recording and reporting the Shariah Audit Observations

After finding the observations, the next step involved in traditional audit is to record and write the observations in the Shariah audit report. The format of the Shariah audit report varies from jurisdiction to jurisdiction and from organization to organization. This activity is also time consuming where the Shariah auditor needs to carefully incorporate the observation along with the related details. By employing AI, a model can be trained, and the activity can be trained so that the observations are written by the system in a pre-defined report. The advancements in generative AI technology have now made it possible for machines to write text like humans. ChatGPT is a great example of this which can write any text content and has trained models on trillions of features. These models are available for use by developers after subscription. The Shariah audit AI system can leverage the ChatGPT and other models to write Shariah audit reports based on the observations found by the system in the preceding step.

6. Conclusion and Recommendations

In order to increase the public confidence in the practices of Islamic financial institutions (IFIs), a robust Shariah audit system is necessary to be developed and implemented. The traditional audit activity involves repetitive and routine tasks, manual examination of the transaction documents, report writing etc. Performing these activities in a traditional manual way is prone to the risks of human error, lagging competency and compromised human judgment. Time and resources investment in routine repetitive tasks leads to unproductivity. With the rapid advancement in the field of automation and artificial intelligence, the Shariah auditing activities can be performed using the sophisticated AI solution. AI can handle unstructured data and extract the text data from transaction documents executed in various stages of Islamic finance products. An AI workflow can be developed which shall automatically read, extract, and process the data, and validate custom rules. The observations found by the system can be passed onto the next step in the workflow where a generative AI model shall be used to write text Shariah audit reports. Employing the AI in Shariah audit engagement shall enhance the audit quality and efficiency and contribute to productivity of time and human resources.

It is recommended to build AI solutions that read the long legal agreements and detect the anomalies in the light of applicable AAOIFI standards, regulatory guidelines and Shariah Board`s pronouncement. The Shariah audit of profit calculation and distribution can also be done using AI and data analytics where the AI system shall validate the calculation and distribution of profit in the light of applicable instructions and guidelines. Although it is a bit early, human judgement and decision making may also be outsourced to the artificial intelligence which shall make unbiased decisions based on the historical data of Shariah Board`s advice and corrective actions.

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Utilising AI-based Chatbot for Maximising Value and Profitability of Islamic Financial Institutions

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Abstract

The global Islamic finance industry has experienced significant growth in recent years, establishing Islamic financial institutions (IFIs) as prominent players in the international financial landscape. To maintain competitiveness and sustainability, IFIs must embrace innovation and explore avenues for maximising their performance. This research aims to investigate the effect of AI-based Chatbots on the value and profitability of IFIs in Organisation of Islamic Cooperation (OIC) countries. The study has employed quantitative methodology, and the data was collected from the Bloomberg database, Thomson Reuters DataStream, and annual reports of 104 IFIs across 44 OIC countries from 2020 to 2022. Utilising the Generalised Method of Moments (GMM), the study analysed the effect of AI-based Chatbots on the value and profitability of IFIs. The results indicate significant relationships in various models: in the Ordinary Least Squares (OLS) model, size is significant for return on assets (ROA), return on equity (ROE), and Tobin's Q (TBQ), while age is only significant for TBQ. In the fixed effect model, age is significantly associated with ROA and ROE, and size is significant for TBQ. In the GMM model, Chatbot, size and age are all significantly associated with ROA, ROE, and TBQ. Policymakers should recognise the importance of a company's age in financial performance and implement tailored strategies for both older and younger institutions. Additionally, the consistent positive relationship between company size and ROA, ROE, and TBQ highlights the need to support growth and scalability in institutions where size plays a significant role. Furthermore, promoting chatbot adoption in institutions where ROA, ROE, and TBQ are critical metrics can yield substantial benefits for financial outcomes.

Keywords: AI-based Chatbot; Profitability; Islamic financial institutions (IFIs); OIC Countries; Dynamic GMM

1. Introduction

Over the course of the past decade, there has been a notable expansion in the Islamic finance sector, mostly attributed to a rise in the demand for Shariah-compliant financial offerings, expanding from a market of USD 200 billion in 2003 to USD 3.95 trillion in 2021. Projections confirm that the global Islamic finance markets will reach a total asset value of USD 5.9 trillion by 2026 (Statista, 2023). This massive growth has not only strengthened the position of Islamic financial institutions (IFIs) as significant participants in the global financial arena, but it has also fueled ingenuity and collaboration within the sector. According to Khan and Rabbani (2021), Islamic finance is important because it offers a morally sound and socially aware alternative to traditional finance. It also supports economic stability, financial inclusion, and fair wealth distribution in a way that is in line with the principles of Shariah (Islamic Law). In an era of constantly shifting financial landscapes marked by volatile market dynamics, changing consumer preferences, and technological advancements, it is essential for IFIs to remain agile and adaptive in order to ensure their long-term sustainability. Innovation plays a fundamental role in this endeavour, as it enables IFIs to develop novel financial solutions that cater to the ever-evolving needs of both Muslim and non-Muslim customers on a global scale while adhering to Shariah principles. The adoption of innovative practices within IFIs can lead to maximising the overall performance of IFIs, which is integral to their continued success and growth in the contemporary financial landscape (Khan & Rabbani, 2021). Enhancing performance is contingent upon increased efficiency, which may be realised by leveraging advanced technology or using a judicious allocation of available resources within the organisation (Bulla et al., 2020). Technical efficiency refers to the inherent capacity of an organisation to produce the highest achievable level of output with a certain combination of inputs (More & Gupta, 2021). In order to optimise the value, profitability, and overall performance of IFIs, it is essential to strive towards a higher level of technological efficiency.

Artificial intelligence (AI) is one of the main underlying technologies within the realm of financial technology (fintech) innovations. The introduction of AI in the financial industry has garnered significant interest in recent times, particularly following the outbreak of the COVID-19 pandemic (Dawood, 2022). In the financial industry, the use of AI has yielded several applications. Notably, AI-powered Chatbots have been implemented to automate business operations for increased operational efficiency. The term "Chatbot" is a portmanteau of the words "chatting" and "robot," and it is mostly used in the sphere of text messaging or messaging platforms with diverse functionalities (Hwang & Kim, 2021). Major financial institutions are now recognising the potential of Chatbots to significantly enhance their performance in terms of value and profitability. Consequently, these institutions are actively involved in initiatives aimed at improving the capabilities of Chatbots. They are allocating substantial financial resources to ensure that Chatbots possess a high level of intelligence in their interactions with users (Khatab, 2020). Remarkably, the global market for Chatbots is projected to achieve a value of USD1.25 billion by the year 2025 (Statista, 2023). However, the integration of AI into Islamic finance has received relatively little attention in the literature.

The motivation for this study is to fill the gap in the literature by conducting an extensive literature review on AI-based Chatbots. The study aims to evaluate and identify significant developments, emerging trends, and major players in the implementation of AI-based Chatbots, including their prominent use cases in enhancing the performance of financial institutions (FIs), with a particular emphasis on their applicability to IFIs. The findings and analysis presented in this study serve as a roadmap for future academics and professionals to develop theoretical frameworks and practical applications for the integration of AI in the Islamic financial industry. This study seeks to provide a scholarly contribution to the advancement and expansion of Islamic finance in the digital era by offering evidence-based insights on the current state of research and suggesting potential avenues for future investigation.

The primary objective of this study is to examine the effect of AI-based Chatbots on the value and profitability of IFIs. To achieve this objective, the Generalised Method of Moments (GMM) will be employed to analyse large datasets retrieved from the Bloomberg database, Thomson Reuters DataStream, and annual reports of the relevant IFIs in the OIC countries to measure their performance using return on assets (ROA), return on equity (ROE), and Tobin's Q (TBQ) as key financial indicators. This data-driven analysis may provide empirically supported insights that can guide the strategic decision-making process for financial institutions seeking to make investments in Chatbot technology.

The subsequent sections of the paper are organised as follows: Section 2 provides a review of the literature on the uses of AI-based Chatbots in the financial industry. Section 3 discusses the hypothesis's development. Section 4 presents the methodology employed to analyse the effect of AI-based Chatbot applications on IFIs. Sections 5, 6, and 7 delineate the elucidation of results and discussion, policy implications, conclusion, recommendation for future research, and limitation of the study, respectively.

2. Literature Review

2.1. Artificial Intelligence in the Financial Industry

Artificial intelligence (AI), as defined by the Financial Stability Board (FSB, 2017), is a collection of theories and algorithms that enable computer systems to complete tasks that conventionally require human intelligence. The emergence of AI may be traced back to the seminal paper "Computing Machinery and Intelligence," authored by Allan Turing in 1950, indicating that the concept of AI is not a new phenomenon. However, recent breakthroughs in the technology have sparked a renewed interest in exploring its potential uses. Artificial intelligence (AI) has seen a substantial surge in popularity, particularly within the financial industry, where it is revolutionising the market for consumer financial services and redefining the way customers engage with the broader financial services ecosystem (Mehrolia et al., 2023; Xie, 2019). This transition can be attributed to multiple factors. Firstly, the growing amount of digital data available and the investments made in AI have played a significant role. Additionally, the advancements in data storage and computational processing capacity, coupled with their reduced costs, have contributed to this shift. Furthermore, the progress achieved in the algorithms employed has also been a contributing factor (Satheesh & Nagaraj, 2021). Lastly, the rapid changes observed in consumers' preferences for digital financial products, which have been facilitated by the integration of AI, have further propelled this shift (Boukherouaa et al., 2021). The utilisation of AI in the provision of financial services can yield major benefits not only for financial institutions but also for society at large (Fernandez, 2019). These benefits include enhanced operational efficiency, reduced costs, improved service quality, greater customer satisfaction and retention, and the promotion of financial inclusion (OECD, 2021; Khatab, 2020). As such, AI is being extensively employed within the financial industry to automate processes, conduct analysis, and facilitate decision-making across a range of domains, including cybersecurity, risk management, fraud detection, sales, internal auditing, financial assistance, asset management, loan administration, and customer relations (Ris et al., 2020). These applications aim to improve financial performance and foster the development of innovative business models (Fernandez, 2019).

The management of customer data is a notable area that is witnessing continual improvements in the use of AI. The majority of present-day AI applications are classified under the umbrella of machine learning (ML). This procedure entails the use of a computer to derive inferences from a statistical analysis of data, whereby the algorithm's performance progressively improves as more information is incorporated (FSB, 2017). It is strengthening the ability of the financial industry to provide superior customer service, thus leading to improved financial performance (Al-Araj et al., 2022; Mor & Gupta, 2021). AI-enabled technologies, including Chatbots, Voice systems, and Text chats, are progressively supplanting traditional customer support services (Fares et al., 2022). There has been a significant increase in the mainstream adoption of Chatbots in particular. This may be driven by their ability to effectively manage basic inquiries and requests, surpassing the efficiency of human agents. Consequently, this enables human agents to allocate their time towards more intricate jobs. (Li & Zhong, 2023).

2.2. Functionalities of Chatbots

A Chatbot is an AI-based computer programme designed to imitate human interactions and engage in real-time spontaneous conversations with users in a controlled environment through self-learning processes. This programme uses Natural Language Processing (NLP), a subfield of AI, that applies mathematical algorithms to comprehend the semantics of human language. By doing so, the programme is able to simulate human-like interactions with users, encompassing both voice recognition and text input in accordance with its officially approved configuration, with the purpose of creating the illusion that the user is momentarily conversing with another individual. (Adamopoulou & Moussiades, 2020). The inception of the Chatbot known as ELIZA took place during the mid-1960s at the MIT Artificial Intelligence Laboratory under the guidance of Joseph Weizenbaum (Weizenbaum, 1983). However, the term "chatterbot" was first coined by Mauldin in (1994). The deployment of Chatbots has seen significant momentum over the last decade, particularly in the wake of the COVID-19 pandemic (Andrade et al., 2022; Mulyono & Sfenrianto, 2022).

The Chatbot platform is created via the development of a user interface that enables users to submit feedback and receive corresponding responses. The application establishes communication with the user by keeping track of the status of the interaction and retrieving past commands to include additional functionality. Artificial algorithms have the capability to construct Chatbots that analyse and categorise customer inquiries, then offer targeted responses to certain queries. The programme employs a dynamic Graphical User Interface (GUI) to provide explanations in real-time, effectively communicating with the user throughout their interactions. (Bulla et al., 2020).

In the presence of a Chatbot, it may not be necessary for a customer to visit a physical location. Instead, they may simply access the website, where a pre-defined Chatbot will begin the process of gathering the necessary data. Once the primary data has been collected, the Chatbot initiates a series of inquiries to ascertain if the individual fits the necessary eligibility requirements and to determine whether it should proceed with further dialogue or cease interaction. If the issue statement is addressed by the Chatbot algorithm, the Chatbot will thereafter continue and provide guidance to the client in accordance with the provided textual instructions. In an alternative scenario, the Chatbot will direct the customer towards an appropriate authority in order to facilitate the resolution of the issue. (Misischia et al., 2022).

One advantage of a Chatbot is its ability to efficiently obtain information from a data warehouse at a much quicker rate compared to its human counterparts. This enhanced speed ultimately leads to improved overall performance. Performance is a crucial factor in the effectiveness of a data warehouse since it relies on a well-designed structure and efficient query engines that are optimised for reading and capable of accommodating incremental changes in the data (Bakkouri et al., 2022). Another key feature to consider is usability, since it is possible that users may lack familiarity with the process of extracting information from source data. However, users are able to manipulate the data using the data warehouse's analytical methodology by transforming, filtering, or slicing it in order to find the desired information. In this manner, customers are provided with a consolidated data source that is subject to AI processing, as opposed to the conventional approach of seeking and comparing information from several sources (Ris et al., 2020). The predominant use of Chatbots has been observed in the role of customer care support agents (Abdulquadri et al., 2021). Numerous studies on Chatbots have been conducted in different areas, including healthcare, education, and banking. The current research focuses on the effect of utilising Chatbots as service agents in the financial industry.

2.3. Adoption of Chatbots in the Financial Industry

Nicholas et al. (2001) introduced the concept of artificial intelligent service agents for financial markets. Since that time, AI-based agents have been created in the form of Chatbots and have gained widespread acceptance among prominent financial institutions across the globe (Agarwal, 2019). Chatbots that are currently implemented in the financial industry are AI-powered automated virtual service assistants that are equipped with ML algorithms at their core, possessing the potential to learn and improve their performance autonomously (Suhel et al., 2020). They are extensively featured across the industry, including the websites, mobile applications, and social media platforms of banks, insurance companies, and other financial institutions. Financial institutions use Chatbots of varying levels of complexity to engage with their clientele. While there might be significant differences in terms of complexity, level of automation, and range of functionalities, all systems in question receive input from users and use programming techniques to generate an output. Chatbots sometimes adopt human identities, use popup features to stimulate user interaction, and are capable of engaging in direct messaging on many social networking platforms (CFPB, 2023).

The rapid adoption of Chatbots by financial institutions for the purpose of delivering customer service can be explained by key characteristics, such as their round-the-clock availability and instant customer support, which can be accessed conveniently through an online messaging system via personal computers, smartphones, and other electronic devices, eroding the need for in-person visits to physical branches for assistance (Agarwal, 2019). Unlike traditional banking methods, Chatbots play a crucial role in optimising operational processes, pushing relevant content to end users, offering tailored recommendations, automating and eliminating human errors in high-frequency tasks that are repetitive or of low value (e.g., responding to frequently asked questions), which are often time-consuming, and ensuring the enhancement of the overall customer experience by fostering continuous improvement, all while requiring minimal setup and seamless integration without the need for human intervention (Sharma et al., 2022; Suhel et al., 2020). According to Gartner (2022), 80 percent of customer inquiries encountered by banks exhibit a recurring nature. These queries have been shown to be effectively addressed via the use of Chatbot technology, resulting in an efficient resolution.

The adoption of Chatbots was primarily motivated by the objective of cost reduction in relation to human customer service agents. They enable financial institutions to boost productivity and improve service quality as well as operational efficiency by minimising the traditional cost associated with customer service while maximising revenue, as improving the customer experience will have a direct influence on profitability. (Misischia et al., 2022). For example, surveys revealed that Chatbots generate about USD8.0 billion per annum in cost savings, resulting in an estimated savings of around USD0.70 per customer interaction when compared to traditional human agent customer service models (Juniper Research, 2017). According to research by Accenture (2018), 57 percent of businesses claimed that Chatbots deliver a high return on investment (ROI) at minimal cost. These advantages collectively contribute to augmenting the value and profitability of financial institutions, positioning Chatbots as indispensable instruments in meeting customer expectations and sustaining competitiveness in the financial industry.

Evidently, studies by Hsu and Lin (2023) and Suhel et al. (2020) found that the integration of Chatbots in the financial industry has the potential to increase customer service quality, productivity, and user satisfaction levels while simultaneously alleviating the burden on human employees. In another study, Chatbots were shown to facilitate the provision of adequate services to individuals residing in geographically isolated regions. This technological advancement not only introduces modern elements but also enhances operational effectiveness and fosters a sense of closeness between service providers and customers (Illescas-Manzano et al., 2021). In addition, Allal-Cherif et al. (2021) highlighted the capability of Chatbots to address complex customer issues that were previously deemed unsolvable. The findings of Hwang and Kim (2021) showed that the implementation of Chatbot services for existing products positively and significantly affects the banks' net income.

Some common applications of Chatbots in the field of finance include account management, customer service, and investment advice (Ris et al., 2020). Irrespective of the use-case, financial institutions are increasingly using Chatbot technology as a means to streamline the banking experience for their clientele. As Chatbots gain increasing familiarity and drive competitive advantage, it is imperative for Islamic financial institutions to expedite the optimisation of their Chatbot strategy. This urgency is necessary to remain relevant in the industry and to meet escalating customer expectations, thereby aligning with the pace set by their conventional counterparts. (Khan & Rabbani, 2021). Despite their potential, the existing body of research on the effect of Chatbots on enhancing the performance of Islamic financial institutions is limited or non-existent. The primary objective of this study is thus to address the existing research gap in the Islamic finance literature in the context of Chatbots.

2.4. Common Chatbot Use-Cases in the Financial Industry

2.4.1. Onboarding customers

Chatbots may be used by new customers to facilitate onboarding processes, including ensuring the successful uploading and subsequent accessibility of all necessary financial records; requesting the recipient to reread the contract and providing a gentle reminder to affix their signature; setting up and exploring a new account; and downloading and engaging with a financial application on users' mobile devices. Chatbots are capable of gathering feedback from new clients on their customer journey and offering services during the onboarding chats for the purpose of doing comprehensive analysis (Adamopoulou & Moussiades, 2020).

2.4.2. Performing transactions

Chatbots can assist customers in performing financial transactions and transfers between accounts. The Chatbot can inquire about the intended recipient of the monetary transaction, posing a query along the lines of "To whom do you wish to allocate the funds?" Once the Chatbot has the recipient's name, it might proceed to get the recipient's account in order to finalise the transaction. This feature is particularly beneficial for those who have visual impairments or limited mobility. Additional instances of transactions include submitting a formal report on the loss of a credit card or any unauthorised transaction; resetting one's account passwords or security questions; changing account holds or financial limits; and applying for a private loan (CFPB, 2023)

2.4.3. Providing financial advice

Chatbots can function as personal money management assistants or financial coaches. They possess the ability to advise and respond to inquiries pertaining to: expenditure patterns observed on a monthly and quarterly basis; budget establishment and management; credit score information; suggested savings strategies; financial statements indicating the amount of funds held by an individual or organisation in a bank account; and guidelines for insurance and taxation. In addition to engaging in conversation, users can request Chatbots to send them transaction alerts or notifications when a certain budget threshold is met or when a promotion is available (Gartner, 2022).

2.4.4. Uninterrupted customer support

In the financial industry, the provision of round-the-clock customer care is seen as essential. Customers have ever-higher expectations for the services they use. Insurance and banking consumers sometimes have a need for immediate assistance and accurate solutions to their inquiries. Chatbots can assist with several tasks, including resolving queries with consistent answers, facilitating updates to customer KYC (Know Your Customer) information, and offering information on new schemes and services at any time of the day. They are designed to efficiently address customer inquiries within a minimal timeframe while also striving to provide an experience that does not make customers perceive their interaction as being with an automated system (Juniper Research, 2017).

2.4.5. Delivering personalised marketing through cross-selling

Chatbots can provide personalised offers to customers by using their profile data or life events. Financial institutions offer a diverse range of services and products, including insurance, loans, mortgages, investment advisory services, wealth management, and other related offerings. Advancements in intent recognition have facilitated the ability of Chatbots to comprehend the needs of customers, assess their behaviour during customer care or onboarding conversations, and recommend supplementary products or offer promotions that are relevant to the customer's current situation. During the process of client onboarding, a Chatbot may use inquiries such as "What was the location of your previous work or residence?" to ascertain if a customer has recently relocated. Subsequently, the Chatbot can provide tailored recommendations for renters insurance that align with the customer's specific needs (CFPB, 2023).

2.4.6. Preventing fraud

Chatbots can keep records of conversations with users and use Natural Language Understanding (NLU) to identify fraudulent conduct or suspicious activities, therefore notifying human agents to intervene. In addition, the extraction of data from Chatbots may serve the purpose of identifying fraudulent patterns and facilitating the training of Chatbots with up-to-date data (Adamopoulou & Moussiades, 2020).

2.5. Examples of Major Financial Institutions Using Chatbots

2.5.1. Bank of America (USA) – Erica

The Bank of America (BoA), as a prominent financial institution in the United States, is actively embracing the use of AI-powered Chatbots within the financial industry. Erica, the virtual financial assistant that is considered to be the most sophisticated and was the first to be publicly accessible, has achieved a significant milestone by surpassing one billion encounters with customers of BoA. The award-winning technology was formally introduced in 2018 and has since assisted around 32 million consumers in fulfilling their daily financial needs. The Chatbot actively contributes to the process of disseminating alerts, provides recommendations on cost-saving strategies for customers, generates reports pertaining to their FICO score, and promotes timely bill payment via the banking application. Erica has proven to be very successful in delivering the necessary information to more than 98 percent of customers (Bank of America, 2022).

2.5.2. Swedbank (Sweden) – Nina

Swedbank in Sweden introduced a virtual assistant named Nina in 2014, which was further enhanced with AI in 2016. This implementation enabled the bank to transition its customer support operations into a collaborative framework, including both robots and human agents. The bank has devised a strategic approach whereby it delegated straightforward inquiries to the chatbot, enabling the customer care staff to concentrate on addressing more intricate matters. Nina has the capability to transfer the client to a customer representative in situations where human intervention is necessary. Nina, with her natural language skills, has enhanced the level of customer satisfaction and achieved a successful resolution rate of 81 percent for first-time client inquiries (Nuance, 2016).

2.5.3. HDFC Bank (India) – Eva

HDFC Bank, the largest private sector bank in India, launched the country's first AI-powered Chatbot named Eva in 2017 that delivers responses within a time frame of under 0.4 seconds with more than 85 percent accuracy. The bank improved its lead generation by 30 times using the Chatbot (HDFC, 2021).

2.5.4. Abu Dhabi Islamic Bank (UAE) – ADIB Chat Banking

Abu Dhabi Islamic Bank launched the first customer care Emirati Chatbot, dubbed ADIB Chat Banking, in the United Arab Emirates (UAE) in 2020. The Chatbot is accessible via the popular instant messaging platform WhatsApp. Powered by AI, ML, and Natural Language Processing (NLP), the Chatbot can comprehend and interact with the Emirati Arabic dialect, classical Arabic, and English languages. The Chatbot meets customers' banking needs in real time and delivers personalised assistance, such as addressing their general queries and providing them with instant access to their account information. It also aids in locating nearby ATMs or branches and informing users about card features and promotional offers (Ghelani et al., 2022). Since its launch, the amount of chat interactions has seen significant growth, surpassing 800,000 instances, and 80 percent of these interactions have been successfully handled by the Chatbot without the need for human interaction, resulting in a deflection of user queries. The use of this strategy has allowed ADIB to achieve a 20 percent reduction in call centre volume, leading to an annual cost savings of USD2.7 million. The bank's customer satisfaction (CSAT) score for a single quarter demonstrates a notable achievement, with an overall score over 90+ from a customer base of 7700 individuals. (Verloop,io, 2023).

2.6. Performance Indicators of Financial Institutions

Customer engagement plays a pivotal role in the financial sector, serving as a primary driver of profitability and revenue generation (Khan & Rabbani, 2021). Improving customer experience through the provision of high-quality services has a direct influence on the performance and profitability of financial institutions (Misischia et al., 2022). Therefore, in order to conduct a comprehensive evaluation of a financial institution's performance, it is essential for the management to juxtapose its performance against the expectations of its clientele. The presence of competing firms within the same sector drives a firm to prioritise service quality, wherein it strives to provide services that either meet or exceed the expectations of its clients. By doing so, the firm is able to cultivate stronger customer loyalty and achieve higher profitability (Pakurar et al., 2019). Several studies have shown that the quality of service provided by financial institutions has a positive impact on their financial performance and profitability (Ijara, 2020; Sumra et al., 2011). Nevertheless, much research has been undertaken to evaluate the qualitative aspects of services, which pose challenges in terms of quantitative performance assessment (Jahan & Islam, 2017). Performance for a business entity often refers to the trajectory of stock prices, profitability, and current valuation (Melvin and Hirt, 2005). Thus, performance serves as a proxy indicator to assess a firm's financial performance, which is mostly measured by non-frontier-based financial ratios, such as profitability ratios (Ercegovac et al., 2020).

Financial ratios, such as return on assets (ROA) and return on equity (ROE), are frequently used as performance indicators to assess the profitability status of financial institutions. The ROA is often considered an essential measure for evaluating performance, mostly owing to its strong direct association with a firm's profitability (Kosmidou, 2008). The ROA is a metric that quantifies the profitability achieved per unit of assets, hence indicating the effectiveness of firm management in using the firm's tangible investments and resources to generate profits (Naceur, 2003). A positive correlation exists between the value of ROA and the profitability of firms, signifying that as the ROA increases, so does the level of profitability. The ROE, on the other hand, is used as a metric for assessing a firm's profitability and effectiveness in generating profits. A firm's management demonstrates more efficiency in producing revenue and growth from its equity funding as the ROE increases. In other words, this metric measures the profitability generated per unit of shareholders' equity (Jahan & Islam, 2017).

Tobin's Q (TBQ) is another commonly used performance indicator that has been extensively utilised in research as a measure of a firm's value. It refers to a traditional measure of the expected long-term performance of a firm (Bozec et al., 2010). Specifically, TBQ is the ratio of a firm's market value to the replacement cost of its assets. This statistic is influenced by the firm's profitability as well as the required rate of return established by financial markets. The ratio may be used for the purpose of forecasting investment expenditure or for mitigating the impact of a firm's present and future profitability. The utilisation of the market value of equity may reflect the firm's potential for future growth opportunities, which may stem from exogenous variables that are outside management control (Shan & McIver, 2011). A high TBQ ratio is indicative of a firm's effectiveness in leveraging its investment to enhance the value of the business, in terms of its higher market value relative to its book value (Kapopoulos & Lazaretou 2007).

Many studies in the finance and accounting literature have used ROA and ROE as primary performance indicators, in tandem with others, to measure the profitability of financial institutions. Caliskan and Lecuna (2020) conducted a study in which they used the ROA and ROE metrics as measures of profitability. The objective of their research was to examine the factors influencing the profitability of the banking industry in Turkey over the period spanning from 1980 to 2017. Similarly, Ercegovac et al. (2020) examined the profitability indicators of banks operating inside the European Union (EU), applying the same measures of profitability, i.e., ROA and ROE. Further research was conducted to examine the correlation between the liquidity and profitability of commercial banks in Nepal. This investigation used Bank Supervision Reports and yearly reports spanning the timeframe of 2013 to 2019. The liquidity indicators used in this study were the credit-deposit ratio (CDR), cash-deposit ratio (CADR), and asset quality (AQ), while proxies for profitability were measured via ROA and ROE. A recent scholarly investigation examined the factors that impact the financial performance of commercial banks in Bangladesh. The study utilised balanced panel data covering the timeframe from 2009 to 2018. Three distinct performance indicators, namely ROA, ROE, and net interest margin (NIM), were employed as proxies for measuring profitability (Mondol & Wadud, 2022).

In the Islamic finance literature, several studies employed TBQ in addition to other performance indicators to measure the value of a financial institution. Mahmuda and Muktadir-Al-Mukit (2023) used financial indicators such as ROA, ROE, earnings per share (EPS), and TBQ to assess the financial performance of seven prominent Islamic banks in Bangladesh. The researchers analysed the annual reports of these banks for the period spanning from 2009 to 2018. In their study, Alyousef et al. (2019) conducted an analysis of the factors influencing bank profitability in Kuwait. They gathered data from a total of ten banks, consisting of five Islamic banks and five conventional banks. The data covered the period from 2009 to 2016. The authors assessed profitability by utilising ROA, ROE, and TBQ ratios as functions of bank-specific and macroeconomic factors (Alyousef et al., 2019).

The above review of past literature suggests that ROA, ROE, and TBQ are the most commonly suggested tools to evaluate the profitability and value of financial institutions. Hence, this study employs ROA, ROE, and TBQ as profitability and value indicators to measure the performance of IFIs in relation to Chatbots.

3. Hypothesis Development

The objective of this study is to investigate the effect of AI-based Chatbots on the value and profitability of Islamic financial institutions (IFIs) in Organisation of Islamic Cooperation (OIC) countries. The proxies used to measure the value and profitability of the IFIs are return on assets (ROA), return on equity (ROE), and Tobin's Q (TBQ). The hypotheses are developed based on the study framework, as seen in Figure 1 below.

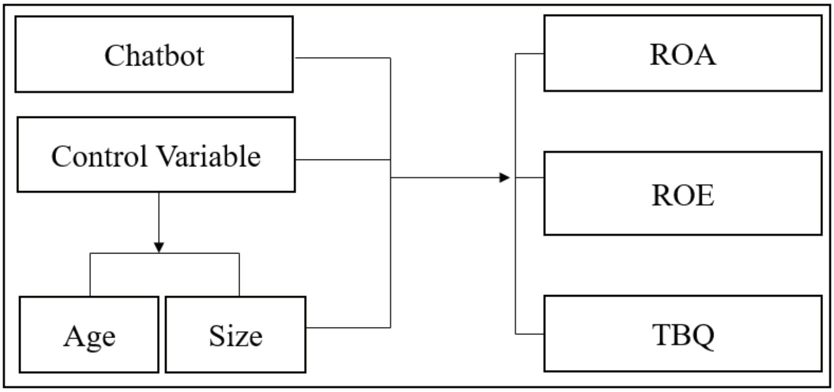

Figure 1. Research Framework

Hypothesis 1: There is a significant positive effect of Chatbot on ROA of IFIs in OIC countries.
Hypothesis 2: There is a significant positive effect of Chatbot on ROE of IFIs in OIC countries.
Hypothesis 3: There is a significant positive effect of Chatbot on TBQ of IFIs in OIC countries.

4. Methodology

4.1.Sample Data

In order to conduct this study, the data was gathered from a comprehensive sample of 419 Islamic banks and Takaful companies that are currently active in 44 OIC member countries. Out of the total sample, it was observed that only 104 Islamic banks and Takaful companies have successfully implemented Chatbot technology. These IFIs were selected to form a panel dataset to achieve the objective of the current research. The data pertaining to the ROA, ROE, and TBQ was collected from the Bloomberg and Thompson Reuters DataStream databases, as well as the annual reports of the selected IFIs. Additionally, data relating to the usage of Chatbot was obtained from the websites of the IFIs, along with their annual reports, covering the period from 2020 to 2022. The number of total customers in each year who availed of the services of the institution or purchased the product using Chatbot is considered a proxy of Chatbot based on the study of Hwang and Kim (2021). The rationale behind considering this specific timeframe for this study is the expedited digitalization of the financial industry during the COVID-19 pandemic in 2020, which resulted in the accelerated adoption of innovative, highly networked, and adaptive operational models, such as Chatbots (Dawood, 2022). This led to a significant surge in the deployment of Chatbots by companies and financial institutions that they may not have otherwise pursued. Hence, it is only logical to analyse data from that time period to fulfil the purpose of the present study.

4.2. Variables

In empirical studies evaluating the relationships between financial performance and AI-based technology, many financial performance indicators have been employed. This study uses return on assets (ROA), return on equity (ROE), and Tobin's Q (TBQ) as proxies for analysing the value and profitability of Islamic financial institutions across OIC countries based on the study of Zhou et al. (2022) and Kumar et al. (2020). Several studies have suggested that the relationship between a company's financial performance and its technology is impacted by a variety of aspects, including the size of the business (in terms of value), its age, and the company to which it belongs (Clarkson et al., 2011; Waddock & Graves, 1997). Previous research has found a link between technology and the size, industry, and age of an organization. Kimbro and Melendy (2010), Peters and Mullen (2009), and Michelon (2011) recently claimed that technology is proportional to the size of a corporation. This study has used the firm's size and age as a control variable that may affect the association between AI-based chatbots and the profitability and value of the institution.

4.3. Model Specification

A dynamic Generalised Method of Moments (GMM) model was employed to perform an econometric analysis of the panel data to assess the effect of AI-based Chatbot on the profitability and value of IFIs. The performance metrics used to measure profitability and value were ROA, ROE, and TBQ. Accordingly, the following equation is formulated for this study:

$$ROAi\text{-}t = \beta 1ROAit\text{-}1 + \beta 2CHATBOTit + \beta 3LSIZEit + \beta 4AGEit + \mu it \quad (1)$$

$$ROEi\text{-}t = \beta 1ROEit\text{-}1 + \beta 2CHATBOTit + \beta 3LSIZEit + \beta 4AGEit + \mu it \quad (2)$$

$$TBQi\text{-}t = \beta 1TBQit\text{-}1 + \beta 2CHATBOTit + \beta 3LSIZEit + \beta 4AGEit + \mu it \quad (3)$$

Where:

"i" is used to denote the firm, "t" represents the time, "ROA" stands for return on assets, "ROE" signifies return on equity, "TBQ" represents Tobin's Q, "LSIZE" represents log size, and "μ" symbolises firm-specific fixed effects that remained unobserved. During the process of estimation, it is possible for three sources of endogeneity to arise. These sources include simultaneity, which occurs when the independent variables serve as a function or as the expected values of the dependent variable. Unobservable heterogeneity is another source, which develops when the dependent and explanatory variables both have an impact on the unobservable factors. Lastly, the current values of Chatbot, which are derived from past financial performance, can be a cause of endogeneity, which is often ignored by researchers (Hill et al., 2020). The GMM estimator was used in past research to eliminate endogeneity (Ullah et al., 2018; Blundell & Bond, 1998). Li (2016), who asserted that GMM has the highest coefficient correction effect, supported this. In addition, under reasonable conditions, the dynamic GMM may correct an upward bias that may be present in the ordinary least squares (OLS) estimation of a dynamic model. If the time "t" is short, it effectively corrects a downward bias in the mean difference estimation of a dynamic model (Li, 2016).

5. Results and Discussion

For empirical analysis, the study applied the Generalised Method of Moments (GMM) method to investigate the effect of an AI-based Chatbot on the value and profitability of Islamic financial institutions (IFIs) in Organisation of Islamic Cooperation (OIC) member countries. Statistical assessments, accompanied by a theoretical and conceptual discussion of the results, were carried out to address the research hypotheses. In addition to the empirical results, descriptive statistics were used for the variables employed in the study, as well as a diagnostic test for best-fit models. Descriptive statistics serve a crucial role in data analysis as they provide a succinct summary of the key characteristics of a given dataset. Moreover, they offer valuable insights that can guide further analysis, such as identifying potential outliers, assessing the diversity within the dataset, and helping to understand the context and significance of the variables being studied.

According to the results shown in Table 1, the ROA variable exhibits a mean value of 4.841 and a standard deviation of 13.228. The range of values for ROA spans from -104.43 to 212.22. Similarly, the ROE has a mean value of 8.253 and a standard deviation of 26.961, encompassing a range from -125.97 to 431.17. The TBQ has a mean value of 1.289 and a standard deviation of 1.415, varying from 0.19 to 12.98. CHATBOT has a mean value of 11087 and a standard deviation of 46886, with a range from 82332 to 29763. LSIZE displays a mean value of 13.395 and a standard deviation of 1.472, ranging from 9.016 to 17.209. Lastly, the variable AGE has a mean of 6 and a standard deviation of 5.103. The range of values for this variable extends from 4 to 22. The descriptive statistics presented provide valuable insights into the measures of central tendency, variability, and range of each variable, facilitating a better understanding of the dataset's characteristics.

Table 1. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
ROA	312	4.841	13.228	-104.43	212.22
ROE	312	8.253	26.961	-125.97	431.17
TBQ	312	1.289	1.415	0.19	12.98
CHATBOT	312	11087	46886	82332	29763
LSIZE	312	13.395	1.472	9.016	17.209
AGE	312	6	5.103	4	22

Table 2 displays the correlation analysis among the variables CHATBOT, LSIZE, and AGE. Firstly, it is seen that CHATBOT has a perfect positive correlation with itself, as expected. The variables LSIZE and AGE also demonstrate perfect positive correlations with themselves. When examining the relationships between variables, it is observed that there exists a weak to moderately positive correlation of 0.230 between CHATBOT and LSIZE, implying that as the utilisation of Chatbot increases, there is a slight tendency for firms to be larger in size. However, it is important to note that this correlation is not significantly strong. Furthermore, CHATBOT and AGE share a weak positive correlation of 0.108. This suggests that older firms are more inclined to use Chatbot to a somewhat greater extent, though this correlation remains relatively weak. Finally, the correlation coefficient between LSIZE and AGE is nearly zero at 0.008, signifying an extremely weak or practically non-existent link between business size and the age of firms. Furthermore, all the VIF values are within the threshold level of 10.

Table 2. Correlation Matrix

Variables	VIF	CHATBOT	LSIZE	AGE
CHATBOT	0.966481	1.000		
LSIZE	0.975106	0.230	1.000	
AGE	0.988460	0.108	0.008	1.000

The results illustrated in Tables 3, 4, and 5 were obtained after conducting the diagnostic tests and model selection tests (the results of the model selection test are shown in Appendix 1). The robust estimation method has been adopted to overcome the issues posed by heteroskedasticity and autocorrelation.

Table 3 shows the results of OLS, fixed effects, and GMM. Each of these techniques provides insights into the relationship between the dependent variable, ROA, and the independent variables CHATBOT, LSIZE, and AGE. In the OLS analysis, the insignificant relationship between CHATBOT and ROA suggests that the observed association between CHATBOT and ROA may be due to random chance rather than a true underlying relationship. In other words, changes in CHATBOT may not reliably predict changes in ROA in this OLS model. Conversely, LSIZE exhibits a notably significant relationship with ROA. This implies that, in this model, a larger IFIs size is reliably associated with higher ROA. This indicates that, on average, larger IFIs tend to have higher returns on their assets. On the other hand, the AGE of the IFIs has an insignificant relationship with ROA. This implies that, within the scope of the OLS model and the data used, the age of the IFIs is not a significant predictor or explanatory factor for variations in ROA. In other words, changes in the age of the IFIs do not lead to a statistically meaningful or discernible effect on the ROA.

Table 3. Estimation results of ROA

VARIABLES	OLS	Fixed Effect	GMM
ROA_{t-1}			0.192*** (0.00396)
CHATBOT	-4.669	-0.829	3.632***
	(3.164)	(3.218)	(0.398)
LSIZE	1.006***	0.168	1.105***
	(0.033)	(1.535)	(0.0473)
AGE	-0.0131	-0.616***	-0.500***
	(0.0534)	(0.164)	(0.0247)
Constant	-6.271	15.09	
	(4.782)	(19.35)	
Sargan Test			0.0410
AR (1)			-2.2603 (0.0238)
AR (2)			1.2335 (0.2174)
Number of Instrument			37
Observations	312	312	286
R-squared	0.016	0.026	
Number of Company	104	104	104

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

In the fixed effect analysis, which employs a panel data approach designed to account for individual company-specific effects, notable shifts in the estimated relationships between variables are observed. Specifically, the relationship between CHATBOT and ROA becomes notably insignificant. Conversely, the relationship between LSIZE and ROA is no longer statistically significant in this model, suggesting that the effect of IFI size on ROA may not hold when accounting for individual IFI variations. Additionally, AGE is statistically significant, suggesting that the age of IFIs is a meaningful predictor of ROA when company-specific effects are considered.

The GMM stands as a robust technique employed to address potential endogeneity and other modelling challenges. Particularly useful when handling dynamic panel data, GMM provides efficient estimates. In this specific GMM model, noteworthy relationships between the variables and ROA emerge. CHATBOT exhibits a statistically significant relationship with ROA. The positive coefficient of 0.192 suggests that, on average, an increase in the CHATBOT is associated with an increase in ROA. In other words, as companies use chatbots more extensively, their return on assets tends to increase. This suggests that CHATBOT usage is positively associated with ROA, and this association is reliable within the context of the model. LSIZE demonstrates a substantial positive relationship with ROA, with a coefficient of 1.105, and this relationship is statistically significant as well. This implies that, in the GMM framework, a larger IFIs is strongly linked to a higher ROA. Conversely, AGE holds a coefficient of -0.500, indicating a negative relationship with ROA, which is statistically significant. This underscores that older IFIs tend to have a lower ROA. In this case, a one-unit increase in the age of the entity is associated with a decrease in ROA by 0.500 units.

Table 4 presents the estimation results of ROE. The OLS analysis reveals several key relationships between the variables. CHATBOT shows an insignificant relationship with ROE, suggesting that changes in CHATBOT may not reliably predict changes in ROE within the context of OLS model. On the other hand, LSIZE demonstrates a substantial and statistically significant positive relationship with ROE, with a coefficient of 1.673, indicating that larger IFIs sizes tend to be associated with higher ROE. AGE is associated with an insignificant relationship with ROE. In other words, changes in the age of the IFIs, within the context of the model, do not lead to a statistically meaningful or discernible effect on the ROE.

Table 4. Estimation Results of ROE

VARIABLE	OLS	Fixed Effect	GMM
ROE_{t-1}			0.0936***
			(0.00175)
CHATBOT	-10.23	-0.432	2.807***
	(6.451)	(6.166)	(0.531)
LSIZE	1.673**	0.395	0.667***
	(0.0677)	(2.941)	(0.0750)
AGE	0.137	-0.876***	0.524***
	(0.109)	(0.0314)	(0.0434)
Constant	-12.22	20.42	
	(9.750)	(37.07)	
Sargan test			0.1046
AR (1)			-1.7495 (0.0802)
AR (2)			-.26674 (0.7897)
Number of Instrument			37
Observations	312	312	286
R-squared	0.016	0.014	
Number of Company	104	104	104

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

In the fixed effect analysis, the relationship between CHATBOT and ROE is insignificant, suggesting that the connection between CHATBOT and ROE may not be reliably established within the context of this fixed effect model. LSIZE displays a coefficient of 0.395, and this relationship is insignificant, implying that the influence of IFIs size on ROE may not hold when accounting for individual company-specific effects. Conversely, AGE has a significant relationship with ROE, suggesting that changes in the age of entities, within the context of the model, lead to a statistically meaningful and discernible effect on the ROE.

In the GMM analysis, the lagged value of ROE is found to have a statistically significant relationship, suggesting that the past performance of ROE can influence the present ROE. Notably, CHATBOT exhibits a statistically significant relationship with ROE; the fact that the relationship is statistically significant implies that changes in CHATBOT usage are associated with consistent and reliable changes in ROE. In other words, the presence or extent of Chatbot usage can be considered an important predictor of ROE in this specific analysis. Conversely, LSIZE is associated with a substantial positive coefficient of 0.667, implying a strong and statistically significant positive relationship with ROE, indicating that larger company size corresponds to higher ROE. In this context, it signifies that for every unit increase in LSIZE, ROE tends to increase by approximately 0.667 units. The positive sign of the coefficient indicates that as IFIs size, represented by LSIZE, increases, ROE also tends to increase. AGE has a significant relationship with ROE. This suggests that age is an important and meaningful factor in explaining changes in ROE.

Table 5 shows the estimation results of TBQ. In the OLS analysis CHATBOT displays a negative coefficient of -0.402, indicating a negative and insignificant relationship with TBQ. The negative coefficient suggests that there is a tendency for a decrease in the CHATBOT to be associated with a decrease in the TBQ. In other words, as CHATBOT usage decreases, TBQ tends to decrease as well. This implies an inverse or negative relationship between CHATBOT and TBQ. The insignificant relationship means that the observed association between CHATBOT and TBQ is likely due to random chance or noise in the data. On the other hand, LSIZE is associated with a positive coefficient of 0.0975, indicating a significant positive relationship with TBQ. The positive coefficient indicates that there is a tendency for an increase in the LSIZE to be associated with an increase in TBQ. In other words, as the size of IFIs increases, TBQ tends to increase as well. This implies a positive relationship between LSIZE and TBQ. Similarly, AGE exhibits a positive coefficient of 0.0171, suggesting a positive relationship, and this relationship is statistically significant. The positive coefficient indicates that there is a tendency for an increase in AGE to be associated with an increase in TBQ. In other words, as IFIs get older, TBQ tends to increase as well.

Table 5. Estimation Results of TBQ

VARIABLES	OLS	Fixed Effect	GMM
TBQ_{t-1}			1.010*** (0.00313)
CHATBOT	-0.402	0.0897	0.112***
	(0.336)	(0.139)	(0.0338)
LSIZE	0.0975***	-0.231***	0.0100***
	(0.0353)	(0.0665)	(0.00257)
AGE	0.0171***	0.00321	-0.0117***
	(0.00568)	(0.00709)	(0.000831)
Constant	-0.172	4.275***	
	(0.508)	(0.838)	
Sargan test			0.1111
AR (1)			-3.283 (0.0010)
AR (2)			-1.0552 (0.2913)
Number of Instrument			37
Observations	312	312	286
R-squared	0.028	0.020	
Number of Company	104	104	104

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

In the fixed effect analysis, CHATBOT is associated with a positive coefficient of 0.0897, indicating a positive relationship with TBQ, although this relationship is insignificant, suggesting that changes in CHATBOT may not reliably predict changes in TBQ within the context of this model. On the contrary, LSIZE exhibits a negative coefficient of -0.231, implying a negative relationship with TBQ. However, this relationship is statistically significant, indicating that larger IFIs sizes may be associated with lower values of TBQ. AGE holds a coefficient of 0.00321, signifying a positive relationship with TBQ; however, this relationship is insignificant.

In the GMM analysis, the lagged variable TBQ is positively significant, with a substantial coefficient of 1.010. This significant relationship underscores the robust influence of past values of TBQ on its current value, suggesting a strong temporal dependency. CHATBOT is associated with a positive coefficient of 0.112, indicating a positive relationship with TBQ. The positive coefficient suggests that there is a tendency for an increase in the CHATBOT to be associated with an increase in TBQ. In other words, as CHATBOT usage increases, TBQ tends to increase as well. This implies a positive or direct relationship between CHATBOT and TBQ. This noteworthy relationship is statistically significant, signifying that increased usage of CHATBOT may be associated with higher values of TBQ. LSIZE also shows a positive coefficient of 0.0100, suggesting a positive relationship with TBQ. Importantly, this relationship is statistically significant, suggesting that larger IFIs sizes might correspond to higher values of TBQ. The positive coefficient suggests that there is a tendency for an increase in the LSIZE to be associated with an increase in TBQ. In other words, as the size of companies increases, TBQ tends to increase as well. This implies a positive or direct relationship between company size and TBQ. Conversely, AGE exhibits a negative coefficient of -0.0117, implying a negative relationship with TBQ, and this relationship is statistically significant, indicating that older IFIs may tend to have lower values. The negative coefficient suggests that there is a tendency for an increase in the AGE to be associated with a decrease in TBQ. In other words, as IFIs get older, TBQ tends to decrease. This implies a negative or inverse relationship between IFIs age and TBQ.

Based on the results, it can be seen that in terms of profitability, while the OLS and fixed effect analysis suggest an inconclusive relationship between the utilisation of Chatbot and ROA. Moreover, there is a consistent positive relationship between firm size and its ROA, as evident in both the OLS and GMM analyses. Furthermore, the role of a firm's age in predicting its ROA becomes more pronounced when taking into account the distinct differences across individual firms, as seen by the results obtained from the Fixed Effect and GMM models. With regard to the association between utilisation of Chatbot and ROE, the GMM analysis highlights that the presence and extent of Chatbot usage can serve as a meaningful predictor of ROE within the context of this specific analysis. Additionally, there is a varying impact of firm size on ROE across different models. A significant and negative relationship is also found between firm age and ROE, as revealed in the Fixed Effect.

As for value creation, the OLS analysis suggests a lack of statistical significance in the relationship between Chatbot utilisation and TBQ, while the GMM analysis highlights a significant and positive association between the two variables. This suggests that harnessing Chatbot technology can potentially boost market value. Moreover, the positive correlation between firm size and TBQ emphasises the importance of fostering business growth and expansion. Conversely, the negative relationship between firm age and TBQ highlights potential challenges faced by older firms in terms of market valuation. The GMM analysis also reflects the strong temporal dependencies in investment decisions.

6. Policy Implications

From an industrial perspective, the findings of this study can be used as a platform for policymakers to evaluate the importance of utilising AI-based Chatbot to maximise the profitability and value of IFIs. It is essential for policymakers to recognise that the effect of Chatbot on ROA and ROE may vary across different IFIs contexts. They should deliberate the promotion and facilitation of Chatbot adoption in IFIs where ROA and ROE are critical performance metrics, realising the potential benefits it may bring to maximise profitability. In sectors characterised by significant firm-specific influences, it is necessary that policymakers prioritise the promotion of competitiveness and innovation among firms of different sizes and foster an environment conducive to business growth and scalability, particularly in sectors where economies of scale are pivotal. They should also acknowledge that the age of a firm can be a meaningful factor in financial performance. Policymakers should explore strategies to support older IFIs in adapting to changing market conditions to remain relevant. In addition, considering the robust influence of historical data on current market valuation, policymakers should prioritise data-driven decision-making processes, empowering IFIs with tools and resources to analyse past performance and market conditions when making investment decisions. This requires the development of industry-specific tailored policies, specialised strategies, targeted initiatives, and support mechanisms for the effective utilisation of Chatbot warranted in sectors to cater to the specific needs of IFIs of varying sizes and establishments, yielding substantial advantages that contribute to their maximising profitability and value.

Nevertheless, it is important to acknowledge that although the utilisation of Chatbot has the potential to maximise profitability and value of IFIs through increased efficiency, it is not without accompanying challenges. The transition from human-centred banking to algorithmic banking will have certain long-term implications that policymakers must actively monitor. Financial institutions that prioritise enhancing customer support through investments seeking to grow their revenue may encounter challenges when relying on automated Chatbot responses. The reliability of these automated systems is contingent upon the prioritisation of features and the allocation of development resources as determined by an IFI. Chatbots are limited in their ability to reply to requests that fall beyond the boundaries of the data inputs they have been programmed with. In such cases, customers may find themselves trapped in repetitive and unhelpful interactions as the Chatbot fails to address their specific concerns due to an inability to activate the appropriate response rules. Consequently, customers may lose confidence and trust in these institutions, particularly if they are unable to get timely access to human customer service. Moreover, a Chatbot with limited syntax might resemble a command-line interface, necessitating customers to possess knowledge of the precise phrases required to get the desired information. This constraint may provide significant challenges for those with a weak command of the English language. Chatbots are often used to carry out phishing attacks on individuals that use popular messaging platforms. These attacks aim to deceive users into divulging their personal or financial details, then coercing them into making fraudulent payments through money transfer applications. The extensive nature of security testing required for Artificial intelligence (AI) systems like Chatbot, necessitates the implementation of stringent testing protocols and the meticulous auditing of any third-party service providers engaged in operational activities.

Therefore, it is imperative for policymakers to have a robust cohort of knowledgeable and skilled practitioners adept at addressing these issues, so they can assist in informed decision-making. They should embrace AI by developing a governance framework that prioritizes human-centred principles. Policymakers need to use industry-specific expertise to advocate for appropriate regulatory mechanisms that effectively meet the dual objectives of minimizing risks associated with AI while harnessing its substantial potential to enhance overall welfare, not only for IFIs but also for the broader economy and society.

7. Conclusion, Recommendation for Future Research, and Limitation

The study has analysed the effect of AI-based Chatbot on the value and profitability of 104 IFIs in OIC member countries from 2020 to 2022. Using a dynamic GMM analysis, the results show that in the OLS model, size has a significant relationship with ROA, ROE, and TBQ, while age is significant only with TBQ. In the fixed effect model, age is significantly associated with ROA and ROE, while size is significant with TBQ. Furthermore, in the GMM model Chatbot, size and age have a significant relationship with ROA, ROE, and TBQ. Policymakers should acknowledge that the age of IFIs can be a meaningful factor in financial performance, requiring tailored strategies and support mechanisms for both older and newer IFIs. Moreover, the consistent positive relationship between IFIs size and ROA, ROE, and TBQ suggests the importance of fostering growth and scalability within IFIs, where size plays a significant role in market performance. Finally, policymakers should consider promoting and facilitating chatbot adoption in IFIs where ROA, ROE, and TBQ are critical profitability and value metrics, recognising the potential benefits it may bring to financial outcomes.

Future research could investigate industry-specific factors, such as customer preferences and market dynamics, to provide a more granular understanding of when and where AI-based Chatbots have the most substantial impact on financial performance. Further research could focus on developing industry-specific guidelines or best practices for integrating Chatbots effectively into businesses. This could involve examining case studies of successful Chatbot implementation in various sectors and identifying common strategies that lead to improved financial outcomes. Researchers could also assess how policy interventions, such as access to funding or innovation support, influence the financial performance of firms based on their size and age. Further research could also investigate the specific attributes of industries where technology adoption has a significant impact on market value. This could involve a sector-specific analysis to identify the key variables and conditions that contribute to higher market value in technology-intensive industries. Developing analytical tools and frameworks that assist industries in leveraging historical performance data and market conditions for investment decisions could be another potential avenue for future investigation. This could involve the creation of industry-specific decision support systems that incorporate both quantitative and qualitative factors to guide investment choices.

This study is limited to the 104 IFIs across OIC countries, and the proxy of profitability and market value used are ROA, ROE, and TBQ, and the data is used from the years 2020–2021. The result may differ from conventional financial institutions if we analyse the effect of Chatbot on longer time periods and a larger sample size using more profitability proxies such as gross profit margin ratio, return on sales (ROS), and net profit margin (NPM).

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Appendix

Appendix 1. Result of model selection tests

Test	Chatbot and ROA	Chatbot and ROE	Chatbot and TBQ
Breusch and Pagan test	Prob = 0.0000	Prob = 0.0000	Prob = 0.0000
Hausman test	Prob = 0.0007	Prob = 0.0030	Prob = 0.0226
Arellano-Bond test	Prob = 0.2174	Prob = 0.7897	Prob = 0.2913

Index