INSTITUTE OF DEVELOPMENT AND TECHNOLOGY MANAGEMENT

ARTIFICIAL INTELLIGENCE TECHNOLOGY APPLICATION AND OCCUPATIONAL SAFETY IN DOWNSTREAM PETROLEUM INDUSTRIES IN GREATER ACCRA

JOHN PANYIN ABBAN

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THESIS SUBMITTED TO DEPARTMENT OF DEVELOPMENT RESEARCH, INSITUTE OF DEVELOPMENT AND TECHNOLOGY MANAGEMENT IN FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR OF PHILOSOPHY DEGREE IN DEVELOPMENT STUDIES

SEPTEMBER, 2023

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in Institute of Development and Technology Management or elsewhere.

Candidate's Signature………………… Date……………………………...

John Panyin Abban

Supervisors' Declaration

We hereby declare that the preparation and presentation of this thesis were supervised in accordance with the guidelines on supervision of theses laid down by Institute of Development and Technology Management.

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ABSTRACT

The downstream petroleum industry in Ghana is one among many sectors characterised by the convergence of numerous hazardous exposures that can potentially cause serious catastrophe and work-related accidents. Several studies have been conducted separately on the applications of artificial intelligence technology, occupational safety, the effects of artificial intelligence on safety, and technology and occupational safety. The general objective of the study was to analyse artificial intelligence technology application and occupational safety to improve occupational safety in downstream petroleum industry. The study applied the quantitative research approach. The study relied on primary interval data obtained through questionnaire administration. The data were processed with tools from STATA 15. Data were analysed using descriptive, correlation and synthesis frameworks and descriptive statistics, regression techniques. The results of the study showed that predictive analytics of the environment was found to be the most common area of AI technology application in the downstream petroleum industry, followed by cyber security and compliance with safety rules. Technology attitudes, trust, social norms, and technology adoption culture were observed to be significant determinants of AI acceptance in the downstream petroleum sector. The primary effect of AI technology application in the downstream petroleum sector appears to be precision in decision. A novel framework for model AI technology application for improved occupational safety comprising of the following system characteristics: inputs, AI-based models, occupational safety modes, and efficiency indices. The study findings have implications for how occupational health and safety within the downstream petroleum sector is addressed.

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DEDICATION

To my Parent, Siblings, Wife and Children for their prayers and support during my schooling.

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CHAPTER ONE

INTRODUCTION

Rationale of the Study

Globally, according to PwC (2015), Artificial intelligence (AI) is projected to contribute up to $15.7 trillion to the global economy by 2030, making it the most significant commercial opportunity in today's fast-changing economy. Such developments are a golden opportunity for Africa and many developing nations like Ghana, which they cannot afford to take for granted. Although Africa missed the opportunities of the second and third industrial revolutions (Enaifoghe, 2021), things can be different for the continent this time around. However, in as much as artificial intelligence is a source of great excitement, it is also a source of great apprehension (PwC, 2015).

Technological advancements since the Industrial Revolution, such as the steam engine, electrification, and automation, have significantly boosted industrial productivity (Rubmann et al., 2015). However, post-1970s innovations were relatively incremental until the emergence of Industry 4.0, the current wave of digital industrial technology. AI is a key driver of this fourth industrial revolution (Ajah & Chigozie-Okwum, 2019). Today, Artificial Intelligence propels this transformation, facilitating automation, data-informed decisions, personalization, safety improvements, and advanced R&D.

AI, as a result, has become a focal point of discourse in technological advancement worldwide (Russell et al., 2010). AI refers to the simulation of human intelligence processes by machines, such as learning, reasoning, problem-solving, perception, and language understanding (Russell et al., 2010). The rapid development of AI technologies is transforming various sectors globally, including healthcare, education, transportation, and energy (Russell et al., 2010; Schwab, 2017). In healthcare, AI is being used for disease diagnosis, patient care, drug discovery, and personalized medicine. Machine learning algorithms can analyze vast amounts of medical data to identify patterns, thereby assisting in early disease detection and treatment recommendations (Jiang et al., 2017). In education, AI enables personalized learning by adapting content to individual learning styles and pacing. It is also used in automated grading and plagiarism detection.

In the energy sector, specifically the downstream petroleum sector, AI applications are revolutionizing operations, maintenance, and decision-making. Machine learning optimizes refining operations by predicting catalyst performance and controlling product quality, while also reducing energy use (Nekrasov et al., 2022). Predictive maintenance anticipates equipment failures, reducing downtime and enhancing safety (Gourley, 2021; Jarrett, 2022). AI improves supply chain efficiency by forecasting demand and optimizing logistics (Ivanov et al., 2016).

As evinced from above, AI is redefining the boundaries of what machines are capable of accomplishing (Russell et al., 2010; Schwab, 2017). This redefinition is largely controlled by AI technology acceptance; and that is because acceptance of AI determines how fast it will spread, and once it is accepted new areas of applications for the technology will naturally be sought. The findings made by Ismatullaev and Kim (2022) lend credence to the preceding. Ismatullaev and Kim’s (2022) study provides a comprehensive analysis of factors influencing the acceptance and adoption of AI technologies. Their systematic review of 85 peer-reviewed articles reveals that both technical and human factors play crucial roles in the acceptance and use of AI-based technologies. Specifically, the study found that users' attitudes, trust, and perceptions about AI technology can be enhanced by improving transparency, compatibility, and reliability, and by making tasks simpler. This suggests that the acceptance and subsequent application of AI in occupational safety in the downstream petroleum industry in the Greater Accra region could be influenced by these factors. Technological factors were also found to be key in mitigating human issues such as distrust, skepticism, and inexperience, particularly among users with lower intention to use and lower trust in AI systems.

Roberts et al. (2021) stressed the importance of understanding psychological factors that influence technology adoption, focusing on decision-makers in organizations who are considered the 'gatekeepers' of new technologies. In their study involving the offshore oil and gas industry, they used thematic analysis of interviews with 37 stakeholders to identify six categories that encompass 15 psychological factors (i.e., Risk aversion, Innovativeness, Trust, Technology attitudes, Fear of technology failure, Personal incentives, Perception of certainty, Risk perception, Technical knowledge, Memory of previous experience, social norms, Social influence, Collaboration culture, Leadership, Technology adoption culture) influencing these decision-makers. These categories were: personality, attitudes, motivations, cognitive factors, social factors, and organizational factors, which they organized into a Psychological Technology Adoption Framework. This framework, the first to focus solely on the psychological factors related to technology adoption decision-makers, could guide interventions for successful technology uptake in the oil and gas industry and similar sectors.

In their 2022 study, Park et al. explored the acceptance of Intelligent Information Technology (IIT), which is based on AI and intelligent network communication technology. They found a generally high acceptance rate for IIT and identified six key factors influencing this acceptance: positive image of technology, voluntariness, performance expectancy, radical innovation, experience of use, and relative advantage. Furthermore, they discovered that psychological factors and risk perception, along with technological factors, significantly influenced individuals' decisions regarding IIT acceptance. Building on the idea of the significant role risk perception plays in technology acceptance, it is worth noting how AI itself can contribute to mitigating risks in specific contexts.

Furthermore, AI aids in identifying safety and environmental risks, prompting swift incident responses (Kuglitsch et al., 2022). Occupational safety and health at downstream petroleum sites is not exempted. Occupational safety in the context of the petroleum sector refers to the measures and practices implemented to protect the health, well-being, and safety of workers employed in the petroleum industry. This includes ensuring a safe working environment and minimizing the risks associated with the various activities involved in the sector, such as exploration, drilling, refining, processing, and transportation of petroleum products. However, in the context of the downstream petroleum sector, occupational safety is limited to the refining, and the distribution of petroleum end-products to consumers.

The intersection of AI and occupational safety is an emerging area of study and practice globally (Bahr, 2014). With the rapid development and adoption of AI, there is growing recognition of its potential to enhance occupational safety (Bahr, 2014). The ability of AI to process large volumes of data, identify patterns, and make predictions or decisions surpasses human capabilities in speed, accuracy, and consistency (Russell & Norvig, 2010). This potential is multi-faceted and encompasses hazard identification, risk assessment, training and education, and the enhancement of personal protective equipment (PPE) (ILO, 2019).

In the context of the downstream petroleum industry, AI plays a significant role in improving workplace safety (Khan & Yairi, 2018). Predictive maintenance powered by AI can foresee equipment malfunctions, preventing accidents caused by equipment failure (Khan & Yairi, 2018). AI-powered drones and robots can be utilized for inspections and operations in hazardous environments, reducing workers' exposure to harmful conditions (Environmental XPRT, 2021; Percepto, 2021). Real-time monitoring and alert systems powered by AI, such as wearable technologies, help detect abnormalities and reduce response time in the event of an accident (Kritzler et al., 2015; Patel et al., 2022). These technologies help detect awkward postures, forceful exertions, vibrations, repetitive tasks, physical fatigue, mental stress, mood, emotions, safety compliance, and rest breaks (Patel et al., 2022). By creating a smart and connected workplace with human-in-a-loop models, workers gain enhanced situational awareness, field visibility, and remote supervision.

However, the global development and adoption of AI also bring about significant challenges (Mittelstadt et al., 2016). Ethical concerns, including privacy, security, and potential misuse, are at the forefront of AI discourse (Mittelstadt et al., 2016). The impact of AI on employment and labor markets is also a contentious issue, with fears of job losses due to automation (Arntz et al., 2016). Reliability and security of AI systems used in occupational safety must be ensured to prevent accidents and hazards (Mittelstadt et al., 2016). Despite the challenges, governments, businesses, and academic institutions recognize the transformative potential of AI and are investing heavily in research and development (Lee, 2018). The United States and China are leading in AI research and implementation, with efforts directed towards economic and strategic advantages (Lee, 2018).

In the downstream petroleum sector, maintaining occupational safety is of paramount importance due to the inherent hazards involved (Khan & Yairi, 2018). AI can improve safety measures through applications like predictive maintenance and real-time monitoring systems (Keleko et al., 2022; Theissler et al., 2021). Virtual reality, and augmented reality, incorporating AI technologies, enhance safety training programmes (Corvino et al, 2019). However, challenges such as data security, job displacement, and the need for investment and a skilled workforce must be addressed. (Arntz et al, 2016)

Lu et al. (2019) underline the digital and intelligent transformation taking place in the oil and gas industry, driven by Industry 4.0 technologies, including AI. The major finding from their study is that "Oil and Gas 4.0," characterized by data-driven intelligence systems, can bring about significant benefits to the sector. This can be achieved through enhancing the digital and intelligent capabilities of the industry, thereby revolutionizing operations in the upstream, midstream, and downstream sectors. For instance, the downstream sector can benefit from the application of these advanced technologies through intelligent refineries, which may potentially increase efficiency, reduce costs, and significantly improve occupational safety. However, despite its potential benefits, the study also recognizes that "Oil and Gas 4.0" is still in its infancy, and there are challenges to be faced. These challenges can range from technical aspects, such as the need for advanced digital infrastructure and skilled personnel, to broader issues like regulatory frameworks and data security.

Deif & Vivek, (2022) contribute valuable insights on the application of AI technologies, particularly machine learning (ML) and computer vision, in the downstream petroleum industry. Their findings dovetail with observations of Lu et al.'s (2019) on the potential of Industry 4.0 technologies in the oil and gas sector. Deif and Vivek (2022) pinpoint several key areas where ML algorithms have proven more effective than traditional models. In the refining process, ML has shown promising results in predicting accidents related to repair and maintenance, thereby improving occupational safety. Additionally, these algorithms have facilitated the prediction and estimation of various chemical processes, enhancing both efficiency and safety during product recovery. They also found that Machine learning (ML) and hybrid models have been effective in improving predictability and accuracy in the downstream sector's demand and consumption forecasting, leading to more efficient operations and enhanced safety. As an added bonus, computer vision technology has been proven to be useful in preventing accidents and human mistake in the workplace by keeping tabs on refinery activities.

Kuranchie et al. (2019) assert that workers in the oil and gas sector may encounter various hazards, including benzene, toluene, ethylbenzene and xylene, hydrogen sulphide emissions, hydrocarbon leaks, fires, falling objects, blowouts, and explosions (Liu et al., 2020; Inkpen, 2010). In Ghana, General Reinsurance Africa Ltd.'s (2012) report highlights that the most critical and perilous incidents in the oil and gas industry are explosions, frequently causing worker fatalities and equipment destruction within the affected area. Oppong's (2014) found that Ghanaian oil and gas employees often experience occupational injuries, such as contusions, cuts, and lacerations on their legs, hands, fingers, and eyes. In the face of these disastrous events, industries in Ghana, including the oil and gas sector, grapple with significant challenges such as inadequate safety infrastructure, insufficient funding for safety systems, numerous unqualified occupational health specialists, poor monitoring mechanisms for work-related accidents and injuries, and a scarcity of health and safety data. Amid these obstacles, workers continue to be the primary victims of the majority of hazards, injuries, and workplace accidents.

The downstream petroleum business in Ghana is one of the many industries that is defined by the convergence of a large number of hazardous exposures that have the potential to create catastrophic events and accidents at work (Achaw & Boateng, 2012). Estimations indicate that in 1852, Ghana experienced 15,702 work-related accidents and fatalities, with a death rate of 20.6 per 100,000 employees across all sectors (Oppong, 2014). This figure represents the total number of workers who lost their lives in accidents. Between 2000 and 2008, occupational injuries and workplace accidents resulted in costs of GHC 2,719,651.92 (approximately $530,000) for Ghanaian businesses (Liu et al., 2020). Furthermore, Amponsah-Tawiah & Dartey-Baah (2011) emphasized that these incidents impose an annual financial burden of around GHC 543,930.38 ($60,000) on employers and GHC 302.96 (about $60) for each occurrence.

Achaw and Boateng (2012) emphasize that employees in this sector face heightened risks of exposure to dangers like hydrocarbon spills, falling debris, fires, explosions, blowouts, and hydrogen sulphide gas emissions (Liu et al., 2020; Inkpen, 20107). As per a 2012 report by General Reinsurance Africa Ltd., explosions are deemed the most hazardous and devastating incidents in Ghana's oil and gas industry. Such explosions typically lead to worker fatalities and extensive damage to equipment within the blast radius..

Insufficient OHS mechanisms for monitoring work-related accidents and injuries, as well as a scarcity of health and safety data, are identified as significant obstacles faced by industries in Ghana, including the burgeoning oil and gas sector. Additionally, inadequate safety infrastructure, limited financial support for safety systems, an abundance of underqualified occupational health experts, and suboptimal OHS accident and injury monitoring mechanisms have been cited (Inkpen, 2010). In addition, employees bear the brunt of the majority of hazards, injuries, and work-related accidents that occur within their professional environments.

With regard to the aforementioned issues, numerous initiatives have been undertaken to address occupational health and safety challenges. An examination of the literature suggests that the primary tools for managing occupational health and safety are largely regulatory and legislative. As stated in the National Energy Policy document, the government's objective is to safeguard both workers and facilities for dependable and cost-effective petroleum product distribution (Ministry of Energy Ghana, 2010). In 2005, the National Petroleum Authority Act (NPA Act) Act 691, was enacted by Parliament, which tasked the National Petroleum Authority (NPA) with the responsibility to regulate, supervise, and monitor activities in the downstream petroleum sector (NPA Act, 2005). The Act also instituted the Unified Petroleum Pricing Fund (UPPF), which aims to ensure a consistent supply of petroleum products throughout the nation (Amponsah & Opei, 2017).

A variety of related legal measures have been implemented across different sectors to govern both employers and employees. Regulations specific to the oil industry encompass the Ghana Labour Act 2003 (Act 651), the Petroleum and Minerals Regulations 1970 (LI 665), the Workman's Compensation Law (1987), the Radiation Protection Instrument LI 1559 of 1993 (amending the Ghana Atomic Energy Act 204 of 1963), the National Road Safety Commission Act 1999 (Act 567), and the Environmental Protection Agency Act 1994 (Act 490) (Abban, 2020). These legislative frameworks operate under separate government institutions rather than a unified directive. Despite the presence of policy guidelines and efforts to organize the downstream petroleum sector, there is no reference to sophisticated early warning systems. That could be because the framers of the above laws did not foresee a time when artificial intelligence will become a critical tool and part of the infrastructure that the state could use to make sure workers, especially oil and gas workers, are safe.

Recognizing the evolving role of AI in ensuring worker safety, it becomes particularly pertinent when considering sectors integral to the local economy, such as the downstream petroleum industries in the Greater Accra Region. Downstream petroleum industries are vital to the economy of the Greater Accra Region's economy, as they play a significant role in the distribution, storage, and marketing of petroleum products. These industries include refineries, storage facilities, transportation networks, and retail outlets such as filling stations. As a result, there is a high concentration of petroleum-related infrastructure and activities within the Greater Accra Region, which makes it an ideal study area for researching the application of artificial intelligence technology and its impact on occupational safety.

The region's well-developed infrastructure and transportation networks enable efficient movement of petroleum products from import terminals and refineries to storage facilities and end-users. This interconnected system, however, also presents numerous potential hazards and safety challenges for workers involved in the downstream petroleum sector. These challenges may include accidents during transportation, fires or explosions at storage facilities, or occupational hazards at refineries and retail outlets.

Given the importance of the downstream petroleum industry to the economy of Greater Accra Region's economy and the potential safety risks associated with this sector, it is crucial to explore the role of artificial intelligence (AI) technology in improving occupational safety. AI technology has the potential to revolutionize various aspects of the industry, such as automating repetitive tasks, improving monitoring systems, and enhancing risk assessment and decision-making processes. The implementation of AI in the downstream petroleum sector can potentially lead to a reduction in accidents and injuries, as well as improve overall safety performance.

Problem Statement

Various research have been carried out on the applications of artificial intelligence technology, occupational safety practices, the effects of artificial intelligence on safety, and technology and occupational safety (Coole, Evans & Medbury, 2021, Qzkiziltan & Hassel, 2021, Habli, Lawtonb & Porterc, 2020, Yi & Wu, 2020, Zigiene, Rybakovas & Alzbutas, 2019, Balooshi, 2018, Pabby & Kumar, 2017,). However, very few studies studies Niehaus et al., 2022; (European Agency for Safety and Health at Work, 2021; Pishgar et al., 2021; Wang & Chung, 2021 have attempted to draw a link between artificial intelligence applications and occupational safety practices. This has necessitated the present study. Wang & Chung (2021) looked at the application of AI in safety-critical systems without emphasis on any particular industry. The study did not conceptualize a model AI technology application for improved occupational safety in any safety-critical industry such as the downstream petroleum sector. The present study, thus, attempts to fill that gap. Furthermore, Niehaus et al., (2022) discussed the impact of AI-based systems on the automation of tasks and the subsequent shift in opportunities and challenges for occupational safety and health. The study presented the perspective that maintaining workers' autonomy in the face of increasing automation is a fundamental aspect of humane working conditions. Notwithstanding, Niehaus et al.'s (2022) study failed to identify the specific roles and tasks where AI assistance is most beneficial. The present research would attempt to fill that gap. Addressing such a gap could provide valuable insights into how AI can be best utilized in the downstream petroleum industries in Greater Accra to improve occupational safety.

A further review of literature by researchers on AI technology and occupational safety reveals that there have not been studies on the potential for application of AI technology in the occupational safety practices of downstream petroleum industries in Accra (Vuki Cevi c et al., 2021, Karakhan & Alsaffar, 2019, Peper, 2017, Borhani, 2016, Skibniewski, 2015, Zhang et al., 2013;). The study therefore analyzed the potential for the application of artificial intelligence technology in occupational safety practices of downstream petroleum industries in Accra.

Objectives of the Study

The general objective is to analyze artificial intelligence technology application and occupational safety to improve occupational safety in downstream petroleum performance in the Greater Accra Region.

The Specific objectives of the study are to:

1. Describe the state of AI technology application and occupational safety in the downstream petroleum sector within Greater Accra Region.

2. Examine determinants of AI technology application in the downstream petroleum sector.

3. Evaluate effects of AI technology application on occupational safety in the downstream petroleum sector within the Greater Accra Region.

4. Synthesize a model AI technology application system for improved occupational safety.

Research Questions

1. What is the state of AI technology application and occupational safety?
2. What are the determinants of AI Technology application in occupational safety within the Greater Accra Region's downstream petroleum industry?
3. How does AI technology application affect occupational safety in the downstream petroleum sector within the Greater Accra Region?
4. Is there an AI technology application model that can be designed for improving occupational safety systems in the downstream petroleum industry in the Greater Accra Region?

Significance of the study

This study was undertaken to establish the technology options that are in place to enhance effective and efficient safety within the petroleum downstream subsector in Ghana. The study was significant because it helped identify which technologies or systems are used to manage reputation damage, cost overruns, revenue losses, delays, quality failures, health and safety incidents, contractual disputes, regulatory non-compliance, and stakeholder dissatisfaction in operational activities. The study has also contributed to adding to the limited literature available on occupational safety and technology management, as it relates to artificial intelligence. The study is also important for developing and implementing effective policies and legislation for the petroleum sub-sector. The study is also important because it helps us understand what is wrong with the petroleum industry in Ghana.

Study Scope

Geographically, the study was limited to the Greater Accra Region of Ghana. Theoretically, the present study analyzed the artificial intelligence and technology management options for improving occupational safety standards within the downstream petroleum sector specifically the petroleum distribution chain of the Accra Metropolis. The scope of the study was limited to the areas of application of AI technology in occupational safety practices, and determinants of AI acceptance and application in occupational safety practices. The study also looked at the impact of AI application on occupational safety practices.

Limitations of the Study

This investigation encompassed downstream petroleum firms in Ghana. However, due to time and financial limitations, the researcher selected GOIL, TPGL, and PFDC as representative samples for the diverse segments of the country's downstream petroleum industry. Additionally, data scope for the study was confined to the aforementioned companies because of accessibility considerations, covering nearly all sectors. It is important to note that these constraints are not believed to have significantly impacted the credibility of the information provided within the study.

Organization of the study

This study is structured into eight distinct chapters. Chapter one serves as the primary introduction, laying the groundwork for the research by offering sufficient background information. This context enables the reader to grasp the study's purpose and intended outcomes. Chapter two reviews previous research pertinent to the topic, focusing on the research objectives. It includes excerpts from books, journals, and other relevant sources that aided in conducting the study and supporting the main findings and recommendations. Chapter three outlines the data collection, organization, and analysis processes, detailing the various methods and instruments employed to gather and evaluate data to yield valid outcomes. Chapter four provided the analysis on the state of AI technology application and occupation safety. While Chapter five presented the analysis results on the determinants of AI technology application, Chapter six presented analysis results on the effects of AI technology application on occupational safety in downstream petroleum. Chapter seven covered the modelling of AI technology application for improved occupational safety. The final chapter, Chapter eight, presented the summary of findings, conclusions from the study, and recommendations based on the findings of the research.

CHAPTER TWO

LITERATURE REVIEW

Introduction

The chapter reviews literature on the major concepts of the study and related theories. The conceptual framework of the study is also discussed. The chapter is divided into three broad sections namely theoretical review (section 2.1), conceptual review (section 2.2) and empirical review (section 2.2). Section 2.2 discussed five different theoretical frameworks vis-à-vis technology acceptance model (section 2.1.1), unified theory of acceptance and use of technology (section 2.1.2), psychological technology adoption framework (section 2.1.3), agency theory (section 2.1.4), and stakeholder theory (section 2.1.5).

The second broad section, conceptual review focused on reviewing major concepts undergirding the study (section 2.2.1) and discussing the conceptual framework (section 2.2. The major concepts that were reviewed were in section 2.2.1 were artificial intelligence (section 2.2.1.1), occupational safety (section 2.2.1.2), occupational safety practices in fuel filling stations (section 2.2.1.3), causes of health and safety hazards in the petroleum downstream industry (section 2.2.1.4), occupational safety management (section 2.2.1.5), effectiveness of AI and technology management options in occupational safety (section 2.2.1.6), challenges of adoption of AI and technology management in occupational safety (section 2.2.1.7), technology adoption in oil and gas (section 2.2.1.8), and factors influencing technology acceptance (section 2.2.1.9). Finally, the third broad section, titled empirical review, presents a discourse on some selected empirical studies.

Theoretical Review

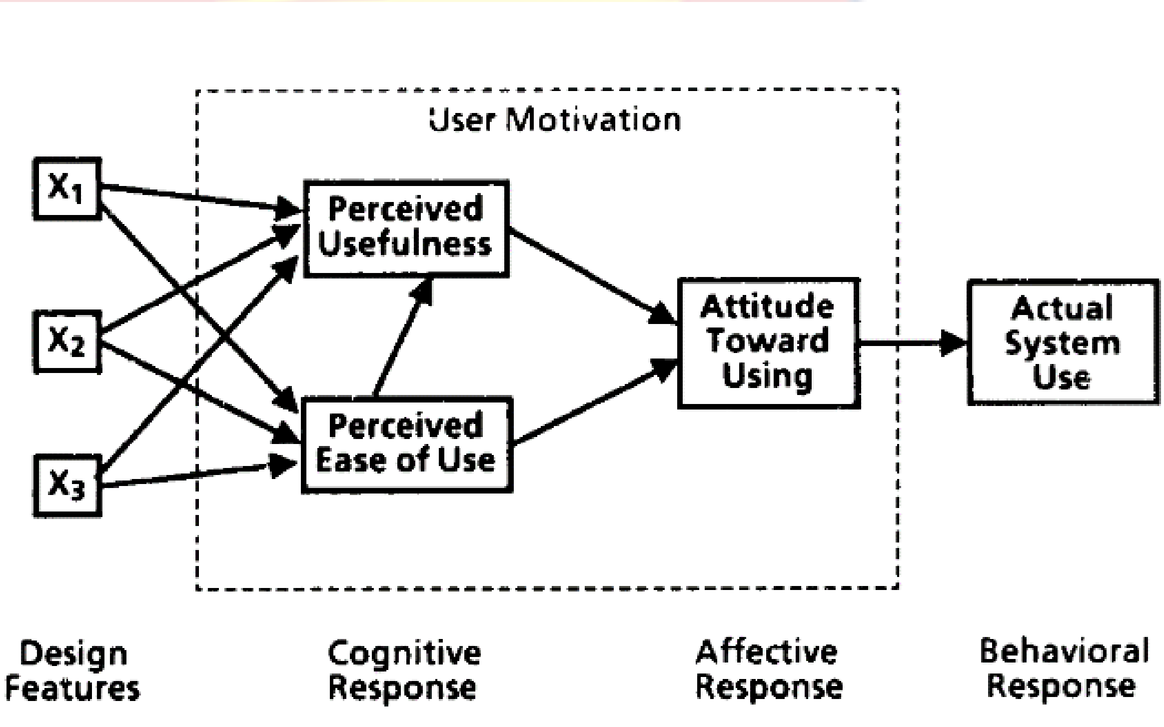
With the introduction of any new technology there is an associated risk, especially for an extremely risky sector like the petroleum sector, where one mistake can cost a lot of lives. For that reason, theories, or models, such as agency theory and stakeholder theory, which are relevant to risk management would also be discussed here. For example, when introducing new technology like the AI into operations of a business, it is vital that all key stakeholders be brought on board and their views and inputs solicited, otherwise risk of failure may be quite high; and that is where a theory like the stakeholder theory comes into play.

But first, we begin with a discussion of the AI acceptance theories/models vis-à-vis Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology.

Technology Acceptance Model

Because technology is being implemented everywhere in an effort to boost organizational performance, researchers have begun looking into how people embrace new technologies. The primary objective of the vast majority of the hypotheses and models that have been developed to explain people's attitudes toward new technologies and their levels of involvement with them is to determine the elements that influence these outcomes (Park et al., 2022). In most cases, technology acceptance models have been suggested at the organizational level after a great deal of discussion regarding the various factors that need to be taken into account in order to properly adopt technology in organizational settings. For instance, in order to describe the principles of technology acceptance at the organizational level, Davis's Technology Acceptance Model (hence referred to as TAM) was proposed (Davis, 1985). When looking to understand how people adopt new technology, Davis' technology adoption model is a great starting point (Na et al., 2022). Figure 1 below presents Davis' technology acceptance model.

Figure 1: Technology Acceptance Model



(Source: Davis, 1989)

Potential users are believed to have an impact on whether or not they utilize the system in question, according to the model (Davis, 1985). Perceived utility and perceived ease of use both influences how people feel about using technology like artificial intelligence. The perceived utility of a product is directly linked to its perceived simplicity of use. Perceived utility and user friendliness are directly influenced by design characteristics. According to the Fishbein paradigm, external variables like design characteristics don't directly affect attitude or behavior. Instead, they affect these variables indirectly through perceived usefulness and perceived ease of use, which in turn affects these variables (i.e., design characteristics such as AI).

System use is defined as the direct and specific use of a certain system by an employee within their work environment. According to Fishbein and Ajzen (1975), Use is a recurrent, multiple-action criterion that is specific with respect to the target (defined system), action and context (in a person's job), but non-specific with respect to time. Attitude is the degree of evaluative affect that an individual identifies with utilizing the target system in his or her employment (M. A. Fishbein & Ajzen, 1975). According to Ajzen and Fishbein, a behavioral criterion should be defined in such a way that the definition and assessment of attitude are in line with it (1977). This term describes how strongly a person believes that making use of a specific system will improve his or her job performance. If a person believes that using a system will not need any physical or mental effort, that is what is meant by "perceived ease of use."

It is predicted that perceived ease of use has a substantial direct effect on perceived usefulness. This is due to the fact that, all other things being equal, higher job performance (i.e., greater usefulness) for the user will arise from using a system that is easier to use. If a user is able to become more productive in the portion of his or her job that is devoted to physically utilizing the system, then the user will become more productive overall. This is because a non-trivial portion of a user's total job content is committed to physically using the system per se. Therefore, aspects of the system, such as how easy it is to use, could have a knock-on effect on the utility of the system.

Unified Theory of Acceptance and Use of Technology

The TAM is a simple and descriptive model that has been utilized in a significant number of contexts up until quite recently. Perceived usefulness and perceived ease of use are the primary variables that are used in TAM. These variables are linked to the attitude regarding usage and the intention regarding usage action, respectively. Venkatesh & Davis (2000) included subjective norms, image, and job relevance in their study because TAM was criticized for focusing solely on the user's perceptual and utilitarian judgement toward information technology. This criticism came about because TAM was criticized for focusing solely on the user's perceptions of the utility of the technology. They introduced an Extended Technology Acceptance Model 2 (which will be referred to as TAM2 from here on out), in which they incorporated many external variables into the model, such as output quality and outcome demonstrability. They also added experience and voluntariness.

Despite the fact that a lot of studies on tech adoption have used TAM2 as their primary method, these studies have limitations in that they overlook other key criteria (I. Park et al., 2022). Consequently, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (hereafter abbreviated as UTAUT) by including new explanatory variables after conducting an empirical evaluation of the variables that had been employed in various TAM research. This was done in order to unify the findings of previous research. Explanatory power is at a level of 70% for the UTAUT model, which is made up of new variables that contribute to the explanation. During the UTAUT study, new factors such as performance expectancy, effort expectancy, social influence, and enabling environments were utilized. In this model, the interactions between these new variables, behavioral intention, and use behavior were controlled by gender, relationship, experience, and voluntary use. Specifically, the model looked at how these four factors interacted with one another.

Since information technology and its applications not only exist in organizations but are widely used in society, they need a theoretical model that can explain acceptability from the point of view of not only members of the organization but also the general public. This suggests that a technology acceptance model is needed at the individual level in a social context, not at the organizational level in organisational life. As a result, Venkatesh et al. (2012) suggested a Unified Theory of Acceptance and Use of Technology 2 (UTAUT2, hereafter). In this model, hedonic motivation, price value, and habit variables are applied to independent variables and used as control variables (I. Park et al., 2022).

A theoretical model is needed that can explain acceptability from the point of view of not only members of the organization but also the general public, because information technology and its applications are not only present in organizations but are widely used in society. This is because information technology and its applications are not only present in organizations but are also widely used in society. This leads one to believe that a model for the acceptance of technology is required at the individual level within a social setting and not at the organizational level within the life of the organization. As a direct consequence of this, Venkatesh et al. (2012) proposed a Unified Theory of Acceptance and Use of Technology 2 (UTAUT2, hereafter). In the UTAUT2 model, the hedonic motivation, price value, and habit variables are used as both independent variables and control variables.

For developing an understanding of the strategies for risk management, companies and government need to identify various models and theories. Successful implementation of theories and models in risk management process helps in managing risk factors due to use of artificial intelligence. In this context, this study provides assessment of two theories that business can incorporate while developing risk management strategies. That is the analysis of stakeholder theory and agency theory.

Psychological Technology Adoption Framework

The above theoretical model was proposed by Roberts et al., (2021). Evidence from O&G industry bodies led to the development of this theoretical model, which suggests that psychological factors like risk aversion, problem with technology leadership and responsibility (OGA, 2018), and a resistance to change are significant contributors to the sluggish pace at which new technologies are adopted (OGA, 2018). To fill this void, Roberts et al. (2021) analyzed the existing research to determine what psychological aspects might affect oil and gas companies' decisions to adopt new technologies. Five types of psychological elements were mentioned in the small number of research that even investigated them. Personality traits (such as aversion to risk), attitudes (such as trust), social influences (such as peer pressure), cognitive processes (such as how one interprets risk), and institutional settings were all considered (e.g., culture). Articles tended to focus on structural and interventional considerations rather than on the individuals who might be influencing the adoption or rejection of new technology. However, neither the innovation literature nor the oil and gas literature, nor the research relating to similarly conservative industries, appears to provide a complete framework outlining the fundamental psychological elements that impact technology adoption decisions (Roberts et al., 2021); hence, the psychological technological adoption framework (the components of which are discussed in much detail in Chapter 5, specifically section 5.2.1.2). Furthermore, because the present model is psychological in nature, much emphasis is placed on the mind and behavior with the individual being the fundamental analytical unit. This focus influenced by Roberts et al. (2021) framework development and framed data collection and analysis for the present study. The psychological technological adoption framework, as proposed by Roberts et al. (2021) comprises six factors namely personality factors, attitude factors, motivation factors, cognitive factors, social factors, and organization factors.

Agency Theory

Agency theory, which originated in the early 1970s, has been a significant foundation for understanding the relationship between principals and agents within organizations (Eisenhardt, 1989). Developed by economists Michael C. Jensen and William H. Mackling, agency theory was formalized in their influential 1976 paper, "Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure" (Jensen & Meckling, 1976). The theory has been further developed and expanded by other scholars, such as Stephen A. Ross and Barry M. Mitnick (Ross, 1973; Mitnick, 1973).

At its core, agency theory assumes information asymmetry, goal divergence, differing risk preferences, and the need for incentives to align the interests of principals and agents (Eisenhardt, 1989). These assumptions have enabled the theory to provide valuable insights into various aspects of organizational governance, such as executive compensation, performance measurement, and board structures (Jensen & Meckling, 1976; Fama & Jensen, 1983).

However, agency theory also has its limitations. Critics argue that the theory places too much emphasis on conflicts between principals and agents, neglecting the potential for cooperation and mutual benefit (Davis, Schoorman, & Donaldson, 1997). Additionally, the theory assumes that individuals are primarily motivated by self-interest, which may not always be the case (Ghoshal & Moran, 1996). Furthermore, agency theory does not account for the role of organizational culture and values in shaping principal-agent relationships and may not sufficiently address the complexities and nuances of real-world organizations and their governance structures (Perrow, 1986).

Despite these limitations, agency theory remains relevant in the context of artificial intelligence (AI) and occupational health and safety (OHS). As AI systems increasingly become involved in decision-making processes, understanding the principal-agent relationship can help ensure that AI technologies align with the goals and interests of the organization (Bryson, 2019). The design of AI systems may need to incorporate appropriate incentives and monitoring mechanisms to reduce potential risks and adverse consequences related to OHS. Additionally, agency theory emphasizes the importance of trust and transparency in principal-agent relationships (Eisenhardt, 1989). In the context of AI and OHS, ensuring transparent and trustworthy AI systems can help reduce potential conflicts and build trust between AI systems and human stakeholders (Ananny & Crawford, 2018). Finally, understanding agency theory can inform the development of governance structures that effectively manage the relationship between AI systems (agents) and human stakeholders (principals), ensuring the prioritization of OHS objectives (Bryson, 2019).

In short, agency theory offers a valuable framework for understanding the relationship between principals and agents, with significant implications for organizational governance, AI, and OHS. Despite its limitations, the theory remains relevant, providing insights into decision-making, incentives, monitoring, trust, transparency, and governance in the context of AI and OHS. By considering the assumptions, strengths, and weaknesses of agency theory, researchers and practitioners can better navigate the complex landscape of AI systems and their impact on occupational health and safety.

Stakeholder Theory

Generally, the term "stakeholders" refers to entities (institutions, organizations, groups of people, and individuals) that have a "stake" or "interest" in a particular resource, project, or issue (Osei-Tutu, 2013). Depending on the nature of the "stake" held, "stake holding" can be further disaggregated into "primary" and "secondary" categories. When applied to the petroleum industry in Ghana, "stakeholders" include entities (groups and institutions) that have a general interest in the petroleum industry, whether as owners of the resource; or as investors in its exploitation; or as having a general interest in assisting in making the resource beneficial to a majority of the Ghanaians (Osei-Tutu, 2013). The term also refers to those who are affected by the policies, decisions, and actions governing the exploitation and utilization of the proceeds from petroleum resources. However, the notion of "stakeholder" does not necessarily delineate the mandates or roles of each stakeholder in the policy making process. The term that best captures policy roles is "actors"—a notion which, apart from indicating the fact of having a "stake" in something, also suggests active interaction between different groups of stakeholders who either have decision-making power and/or are in a position to influence a policy process through several channels. Thus, in discussing the petroleum and local content policy processes, we may identify "key actors" as individuals or institutions that have the power to make policy decisions or control the policy making process. "Influential actors" are individuals and organizations who seek proactively to influence the policy and decision-making processes (Osei-Tutu, 2013).

Stakeholder theory, which has its roots in the mid-20th century, emerged as a response to the recognition that organizations have responsibilities that extend beyond their shareholders (Freeman, 1984). R. Edward Freeman, who is often credited with the origin of stakeholder theory, provided a foundation for the concept in his 1984 book "Strategic Management: A Stakeholder Approach" (Freeman, 1984). Other key proponents of stakeholder theory include Max B. E. Clarkson, Thomas Donaldson, and Lee E. Preston.

At its core, stakeholder theory posits that organizations must consider the interests of a variety of stakeholders, rather than focusing solely on their shareholders (Freeman, 1984). Stakeholders encompass any group or individual that can be affected by or has the ability to influence an organization's objectives. The theory further asserts that long-term organizational success is contingent on effectively managing relationships with these stakeholders and that ethical considerations play a crucial role in organizational decision-making processes (Donaldson & Preston, 1995; Amis et al., 2020).

There are several strengths associated with stakeholder theory. Firstly, it encourages a more comprehensive view of organizations, taking into account the interests of multiple groups and leading to more ethical and responsible decision-making (Freeman, 1984). Secondly, by effectively managing stakeholder relationships, organizations can achieve long-term success and sustainability (Clarkson, 1995). Lastly, stakeholder theory promotes open communication with stakeholders, fostering trust and cooperation (Freeman et al., 2010).

However, the stakeholder theory is not without its weaknesses. Balancing the interests of multiple stakeholders can be challenging and may lead to conflict and decision-making paralysis (Donaldson & Preston, 1995). Furthermore, the theory lacks clear guidelines for prioritizing stakeholder interests, making it difficult to implement in practice (Mitchell et al., 1997; Menezes & Vieira, 2022). In some cases, stakeholder theory may be employed as a public relations tool, rather than genuinely addressing stakeholder concerns (Bridoux & Stoelhorst, 2014).

Stakeholder theory is particularly relevant to AI and OHS as it acknowledges that the development and implementation of AI technologies can have significant consequences for a variety of stakeholders, such as employees, regulators, customers, and the public. By taking stakeholder interests and concerns into account, organizations can ensure that AI applications in OHS are developed and deployed responsibly, ethically, and with a focus on protecting and promoting the well-being of employees and the public. Moreover, stakeholder theory can provide guidance for organizations in engaging with relevant parties in the development and implementation of AI technologies, ensuring that diverse perspectives and concerns are considered in the decision-making process (Mittelstadt et al., 2016; François et al., 2020).

In sum, stakeholder theory has made a significant contribution to the understanding of organizations' responsibilities and the importance of considering multiple stakeholders when making decisions. Despite its weaknesses, the theory remains relevant and valuable, particularly in the context of AI and OHS, where the impact of new technologies on various stakeholders must be carefully considered. Organizations can use the principles of stakeholder theory to develop and implement AI applications in OHS responsibly and ethically, ensuring the well-being of employees and the public and fostering trust and cooperation among all parties involved.

Review of Major Concepts

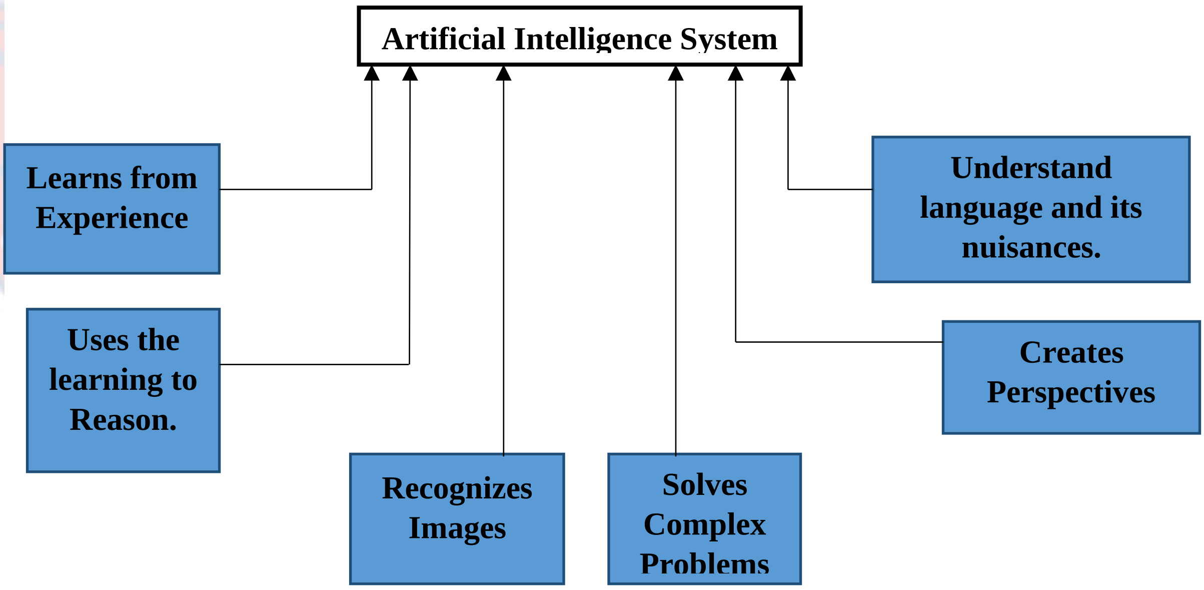
Artificial Intelligence Technology Application

Artificial Intelligence

Artificial intelligence is changing the world. In as much as the third industrial revolution was driven by electronics and computers, the fourth industrial revolution is being driven by artificial intelligence, and we are in the fourth industrial revolution (Mykhailychenko, 2019). The first public test of artificial intelligence against human intelligence was the chess game, which has long been seen as an illustration of intelligence.

Artificial intelligence, known also as machine intelligence, refers to intelligence exhibited by machines, as opposed to natural intelligence demonstrated by humans and animals. In computer science terms, any agent that can 'sense' its environment, regardless of what is being used to do the sensing, and on the basis of that 'sensory' information make specific moves that enhance the likelihood of attaining its targets can be considered as intelligent (Baum, 2020). Kumar et al. (2021) described artificial intelligence as the imitation of intellect in machines designed to carry out tasks that normally demand human intelligence or input. Figure 2 depicts the six components of an artificial intelligence system. An artificial intelligence system learns from experience, uses the learning to reason, recognizes images, solves complex problems, understand language and its nuances, and creates perspectives.

Figure 2: Artificial Intelligence System



(Source: Baum, 2020)

Artificial Intelligence Technology

The world has changed and continue to do so. Rapid advances in civilization have often been spurred by technological breakthroughs. The discovery of electricity changed the world back then ushering in new innovations. Now, once again, new technologies such as blockchain, 3D printing and, Internet of Things, machine learning, and artificial intelligence, have emerged and are disrupting industries. The big companies are embracing these changes and are “riding the wave.” In 2017, CEO Sundar Pichai said Google would be "AI first" (Burns et al., 2022).

Technology has conventionally been described as the use of scientific knowledge in the generation of products and services, or the achievement of goals via the use of tools and processes. “Technology” as a terminology has its roots in the Greek word tekhnologia which means "systematic treatment" and tekhnē which translates as "art, craft" and logia "-ology" in the sixteenth century (Mykhailychenko, 2019). Based on the above, artificial intelligence technologies are, therefore, the scientific knowledge, tools, processes, or techniques used in producing ‘artificial intelligence.” Choubey & Karmakar (2021), in a study, identified nine artificial intelligence techniques namely linear regression (LR), decision tree (DT), support vector machine (SVM), Bayesian belief networks (BBN), Artificial neural network (ANN), Principal component analysis (PCA), Gradient Boosted Machine (GBM), Genetic algorithm (GA), and Fuzzy logic (FL). The frequency of utilization of the above artificial intelligence technologies can be visualized from the plot shown in Figure 2.

Linear regression establishes a linear link between a dependent variable and independent variable(s). Decision tree: It is possible for a DT to execute classification and regression tasks at the same time. Boolean tests of a single characteristic or a collection of attributes form the basis of the DT algorithm's construction. Each node has a root node (also known as a parent node), and each node has an associated action. Graphical representations allow individuals to see the probable outcomes of any decision they make. Support vector machines: they are primarily used for categorization or classification purposes, but as support vector regression, SVM can also be utilized to do regression tasks. Artificial neural network: An ANN (artificial neural networks) is a nonlinear data modelling tool that can handle a high number of inputs and execute complex functions. It consists of an input layer, at least one or more hidden layers, and an output layer. In the input layer, each input is given equal weight. The bias values of the input layer and the concealed layer are distinct. There are three layers in a neural network: a hidden layer, an input layer and an output layer.

Principal Component Analysis: PCA is a preprocessing approach for reducing the dimensions of high-dimensional data so that modelling tools can be used to examine it more easily. Dimensionality reduction approaches create a linear combination of the original qualities in order to determine the ideal attributes or eliminate part of the features. The data is transformed linearly by rotating the feature space so that the data is aligned with the direction of maximum variance. Gradient boosted machine: GBM Model, like Random Forests, is a technique for improving the predicting power of decision trees (Maucec & Garni, 2019).

GBM grows ‘trees’ from information provided by the predecessor, whereas the random forest approach grows ‘trees’ in parallel. Each ‘tree’ in GBM fits into the revised version of the original data. Genetic algorithm: As stated by Liu et al. (2018), GA solves problems by mimicking human cognition. There are six stages to this algorithm: startup; assignment; selection; crossover; and mutation. These artificial intelligence technologies or techniques are what power artificial intelligence technology applications.

Artificial Intelligence Technology Application

Certain experts within the supply chain attribute its rapid and continuous advancement to the influence of artificial intelligence and technology management. Company managers often invest in technology to mitigate risks and minimize disruptions (Tang & Zimmerman, 2013). The acceleration of supply chain progress is primarily due to technology implementation, which significantly streamlines operational processes. Li-xia et al. (2014) note that since the early 1980s, this development has gained prominence with the expansion of enterprise technology management, information technology, and e-business. However, the adoption of artificial intelligence has resulted in numerous changes and enhancements (Laudon and Laudon, 2012).

Information technology is crucial for introducing efficiencies that can improve organizational performance and boost profits. Western countries' managers also employ information technology to achieve sustainability and competitive advantages over rivals (Drnevich & Croson, 2013). In Ghana, petroleum industry supply chain managers have started to compete by building brand equity, loyalty, and recognition through technology (Kim, Cavusgil, &

Cavusgil, 2013). This competition is beneficial, as managers strive to satisfy customers and increase market share. Advancements in modern technology in Ghana will alter how organizations operate within the supply chain sector (Lee, Kelley, Lee, & Lee, 2012).

The growing connection between supply chain management and technology has gained attention due to the rapid response to market demand, coordination of cooperatives, and emphasis on customer satisfaction (Li-xia et al., 2014). Supply chain coordination involves at least two processes, which could be business and information-related (Ivanov & Sokolov, 2013). Each component of the supply chain should be optimized internally to influence the overall system. The integration of new technologies into standardized businesses should aid in improving the supply (Devos, Hendrik, & Deschoolmeester, 2012). To achieve success, Ghanaian businesses need to develop efficiency and reliability indicators within the supply chain (Tabor, 2012).

Significant investments in supply chain technology by organizations have led to improvements in their financial performance. Companies such as Walmart have devoted resources to IT, creating a sophisticated, highly automated logistics distribution system that enables information sharing and efficient distribution across all channels (Li-xia et al., 2014). Walmart's IT systems are designed for collaboration and provide feedback mechanisms for better decision-making, which in turn affects business performance. This approach offers Walmart the opportunity to gather valuable data and learn from past experiences. Ghanaian petroleum industries would benefit greatly from adopting technologies similar to those employed by Walmart. Walmart's supplier selection process is unique, as choosing suppliers can be risky, with many firms opting for the lowest bidder (Tang & Zimmerman, 2013). However, the supplier with the lowest bid may not provide the best service or prevent supply chain disruptions. To accelerate their growth, Ghanaian companies will require adaptive methods to ensure the delivery of high-quality products (Aubry, Sicotte, Drouin, Vidot-Delerue, & Besner, 2012). Taticchi, Cagnazzo, Beach, and Barber (2012) suggest that managers must be flexible and innovative to achieve desired outcomes.

Ardichvili et al. (2012) analyzed the policies and strategies employed by business leaders in Brazil, Russia, India, and China. It is projected that these four countries will dominate the global economy by 2050. Information technology has played a significant role in driving these economies, impacting various sectors such as manufacturing, agriculture, and service industry improvements. IT has enabled countries to compete effectively across continents with relative ease. Loosemore and Chandra (2012) argued that incorporating IT into supply chain management has facilitated the development of strategic models that enhance productivity and minimize disruptions. Managers in Ghana's petroleum industries must recognize the potential of IT and its ability to foster innovation for product and service differentiation (Bendoly, Bharadwaj, & Bharadwaj, 2012).

Focusing on value chain IT investments, integration systems facilitate an optimal flow from one process to another (Kim et al., 2013; Tallon, 2011). This integration adds value to business delivery, enhancing customer satisfaction. Effectively coordinated integration and collaboration within supply chains reduce uncertainty and improve performance across various chains (Denese, 2011). In this dynamic environment, speed becomes crucial. The pace and accuracy of information flow offer a competitive edge for a firm over its competitors. Efficient information flow enables companies to (a) react more promptly to competitor actions, (b) better comprehend customer needs, and (c) generate more innovative ideas for new products (Li & Lui, 2011).

Rapid delivery of information and products to the market is essential for establishing a competitive advantage (Porter, 1998). Collaboration with IT plays a significant role in helping supply chains achieve this advantage in terms of speed (Richey, Adams, & Dalela, 2012). The swiftness of information and collaboration assists companies in making timely business decisions. The utilization of machine learning and artificial intelligence allows more organizations to gather data for just-in-time decision-making (Rutz et al., 2012).

In the past, offering lower prices was an attractive strategy; however, this approach is no longer the preferred method for attracting new customers. Ghanaian businesses must acknowledge this shift and adapt with the support of IT. Tallon (2011) emphasized the importance of aligning IT with business strategy, as it creates value and impacts profitability. Aligning IT with business strategy should enable a company to establish a sustainable competitive advantage. Li-xia et al. (2014) followed the evolution of the global economic environment and the implementation of IT in making supply chains critical in the information age. The aim is to ensure that both enterprises and academia recognize the value of managing supply chain activities and utilize IT services to address Ghana's supply chain challenges. In certain circumstances, IT investments can help companies recover rapidly after a disruption, particularly when significant data is stored off-site in case of interruptions. Specifically, Ghana's oil governance regime has faced challenges since production began in 2010. A summary of the main challenges follows in the subsequent paragraphs.

In 2010, when Ghana commenced its significant oil operations, the nation lacked a comprehensive set of guidelines for the oil industry. Many components of the robust regulatory framework were established later on. For example, in 2010, there were no exhaustive provisions concerning local content usage or the employment of locals by international corporations. A few guidelines existed in the previous Petroleum Exploration and Production Law, 1984 (PNDC Law 84); however, local community content was notably absent. This omission drew criticism from communities near the oil field, such as the Western Regional House of Chiefs. These communities were the first to experience the adverse social and economic impacts of extraction. Moreover, other outstanding legal instruments include regulations for the Petroleum Revenue Management Act, regulations for the new Exploration and Production law, metering regulations, and the Strategic Environmental Impact Assessment of the Voltaian Basin. The entire governance framework also suffers from poor sequencing; for example, the Petroleum Revenue Management Act was passed before the Petroleum (Exploration and Production) law. This issue is further exacerbated by weak institutional collaboration, resulting in poor geological data collection, inadequate revenue collection, and insufficient integration of the oil and gas sector into the broader economy.

Concerning revenue management, the 2015 Annual Report of PIAC highlights several troubling instances of mismanagement. For example, some extraction companies were not paying their surface rentals, and the government was accused of misusing petroleum revenues on numerous social intervention projects without transparency in the selection process. Additionally, the government was urged to refrain from overspending the allocated budget from oil revenues and ensure strict adherence to the required parliamentary approvals for funding government projects. The committee also expressed concern about the funds not being utilized for capacity building and recommended that a substantial portion of the petroleum revenues be directed towards the agricultural sector to enhance productivity, considering its strategic importance to Ghana's people. PIAC has made several recommendations to address these issues, but instances of non-compliance persist.

One issue in Ghana's governance regime is the failure to adhere to essential provisions in the nation's legal instruments for the oil sector. For example, the Petroleum Revenue Management Act requires all revenue reporting agencies to adopt uniform reporting standards. However, a report from the Ghana Extractive Industries Transparency Initiative (GHEITI) revealed that there was no standardized format for documenting crude oil lifting in 2014. On the other hand, the Petroleum Revenue Management Act, 2011 (Act 815), mandates the Investment Advisory Committee to establish a benchmark for oil revenue returns; for 2015, no such benchmark was in place. Furthermore, considerable discrepancies were observed in the amounts reported for royalties, carried interest, and participating interests. Lastly, concerns have arisen about the transparency in granting licenses to organizations involved in the exploration process and the non-compliance of certain oil companies with Ghana's local content regulations. The new Petroleum (Exploration and Production) Act, 2016, addresses some of these issues.

Moreover, there were barriers to achieving complete transparency in information reporting about the oil industry. For instance, the Petroleum Commission is obligated to maintain an online repository containing information such as block ownership, oil block coordinates, block allocations, and annual payments. At present, this online repository is not available. Nonetheless, measures have been taken to address these concerns, including the Petroleum Commission's initiation of efforts to establish the online repository. In other words, information on license issuance and the entire licensing bidding process is now being made public.

Additionally, there are worries about the impact of the oil industry on the nature of political governance in Ghana. Some policy analysts are apprehensive that the oil sector may exacerbate the already problematic state of contemporary Ghanaian politics and political culture, characterized as divisive, hostile, and bitter (Gyimah-Boadi & Prempeh, 2012). Within the constraints set by Ghana's constitution, the ruling party controls the Presidency and Parliament and makes appointments to crucial ministries, departments, and even agencies that are legally independent. A prime example is the President appointing executive directors and board members of the Economic and Organized Crime Office—an institution authorized to investigate financial crimes involving state losses. A similar organization, the Commission of Human Rights and Administrative Justice (CHRAG)—which has the constitutional and statutory mandate to probe corruption, office abuse, and human rights violations—has been rendered ineffective due to insufficient resources. Consequently, conflicts of interest and self-dealing are commonplace among public officeholders.

In conclusion, there is apprehension regarding the failure to adhere to crucial recommendations from organizations responsible for regulating the oil industry. The Ghana Extractive Industries Transparency Initiative (GHEITI) identifies numerous outstanding recommendations, with a few lacking detailed information on their progress. It is worth noting that the majority of these recommendations aim to enhance revenue management and introduce transparency into the oil industry's operations.

The primary efforts to address some of the challenges mentioned above are evident in the new Petroleum (Exploration and Production) Act, 2016, as well as in certain existing laws. For example, the local content law tackles issues related to the utilization of local resources and the employment and training of local individuals in the oil sector. Additionally, the law mandates a minimum equity requirement for companies applying for a license and compliance with the Insurance Act, 2006 (Act 724). A commitment to open contracting has been demonstrated; a committee was formed to develop regulation within the Petroleum Revenue and Management Act; an infrastructure development fund was established to support investment in infrastructure; a national oil spill contingency was created; the Companies Act of 1963 was amended to include provisions for beneficial ownership; and separate guidelines were developed for conducting Environmental and Social Impact Assessments. The revenue management law also provides clear stipulations on how petroleum receipts should be disbursed and/or utilized. Furthermore, the new Petroleum Law consolidates concerns related to finance and environmental protection.

AI Innovative Acceptance and Implementation

In modern times, the challenge for 21st century industries lie in their ability to innovate in the face of an extremely changing market in which competitive positions are constantly evolving (Stank et al., 2019). The globalization of the economy brings more and more competition and more information to be compiled to meet the challenge (Queiroz Maciel, Pereira Susana Carla, Telles, & Machado Marcio, 2019; Rachinger et al., 2019; Stank et al., 2019). But, in a world where information is a strategic asset, it is clear that the organization's ability to manage this information is crucial to its competitiveness (Kuusisto, 2017; Rachinger et al., 2019). Innovative AI is fundamentally reshaping organizations' business and organizational processes. They have already changed the overall relationship between AI and the rest of the organization. This new way of managing information has become both a challenge and a tremendous opportunity for industries, but seizing this opportunity requires a "change in culture, mindset, and skills" (Devaraj & Kohli, 2003; Nwamen, 2006; Turulja & Bajgoric, 2018).

Furthermore, AI innovations continue to contribute to the benefits of AI in organizations. As part of an organization's ecosystem, AI can have an impact, particularly on performance, on the relationships between organizations and their customers, prospects, and partners (Kelly, Karthikesalingam, Suleyman, Corrado, & King, 2019; Rubin Victoria et al., 2010). Rubin Victoria et al., 2010; Kelly et al., 2019).Given the rapid technological advancements, particularly in the field of AI, the idea of entrusting more complex tasks to machines no longer seems as farfetched as it was several years ago. As a set/combination of several different IT configurations and capabilities in different areas of an organization's business, AI has already proven its effectiveness in automating monotonous repetitive tasks usually performed by specialists like human resources administrators, salespeople, and small contractors (CIGREF, 2018; Pwc, 2019; Rachinger et al., 2019).

Maintenance of Data

Maintenance of data refers to the ability of AI to collect, store, process, and disseminate information within and between organizations (Abijith & Wamba, 2012; Kim et al., 2011). Data as fuel for AI technologies is used by algorithms to produce reliable, fresh, available, complete, relevant, dynamic, transmittable, up-to-date, intelligent, and fast information. Thus, the higher the capacity and ability to derive the informational effects of AI and its technologies, the more effectively and quickly the organization can make quality decisions that in turn affect the financial and managerial stability of organizations (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013). Other benefits of proper maintenance of data induced by AI include administrative tasks such as renewed organizational control over resources; enhanced coordination between and within organizations; and rapid staff responsiveness.

AI Infrastructure

AI infrastructure System flexibility refers to the combination of all technological assets (software, hardware, and data, etc.), systems and their components, network and telecommunications installations, and applications that are necessary for the implementation of an AI system capable of performing tasks (Kim et al., 2011; Liu et al., 2013; Wamba et al., 2017). The flexibility of deploying AI infrastructure for organizational operations allows the organization's staff to rapidly support various system components and adapt to changing business conditions and business strategies, such as economic pressures, strategic alliances, acquisitions, global partnerships, or mergers (Abijith & Wamba, 2012; Bhatt et al., 2010; Kim et al., 2011). Multiple key elements must be brought together to ensure the success of AI in an organization. They include data, combined talent (IT and AI), domain knowledge and technologies, key decisions, external partnerships, and a scalable infrastructure. The first four elements represent the fuel and scalable infrastructure, which is the engine without which nothing can work. A better IT infrastructure allows organizations to use IT resources effectively and efficiently, so as to support structural restructuring through the deployment of AI technologies. A self-configuring, self-healing, and self-optimizing infrastructure will prevent problems before they occur, promote strategic business process innovation, and help to proactively improve performance and optimize available resources (Kim et al., 2011; Liu et al., 2013; Wamba et al., 2017). Therefore, we can conclude that AI infrastructure flexibility has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level.

AI Staff Skills and Competences

AI personnel expertise is seen as the professional skills and knowledge of AI-related technologies, business functions, and relational (or interpersonal) domains required by the organization's staff for modeling and/or using intelligent behavior in a computer or other technology to accomplish the tasks assigned to it (Ha & Jeong, 2010; Hamet & Tremblay, 2017; Jiang et al., 2017; Kim et al., 2011). It is important for an organization's IT staff to have a combination of skills—awareness, ownership, integration, management of AI technologies, and knowledge of IT elements that would allow for more effective management of the AI resources at their disposal. Therefore, the creation of business value by organizations depends on the effectiveness of AI strategic alignment with their strategy; and the latter improves if staff have the right combination of skills. However, the expertise of AI staff becomes an intangible asset for organizations when IT staff understands how the organization's strategies are mixed with IT and AI skills (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013). As a result, businesses with competent AI staff are more likely to meet the demands of ever-changing dynamic environments by aligning AI with strategies and developing dependable and cost-effective intelligent systems.Therefore, we can enunciate the proposition that AI personnel expertise has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level.

Managing AI Business Process

An organization's management capability is the ability of an organization and its staff to administer or to model intelligent behavior on a computer or technology to create added value for the organization's sustainability (Ha and Jeong, 2010; Hamet and Tremblay, 2017; Kim et al., 2011). The potential of AI management capacity is specific to "strategic planning, strengthening relationships within and between organizations, investment decision-making, coordination, and control." Kim et al. (2011) have demonstrated in their study that control, which depends on the expertise of the staff, has an influence on infrastructure flexibility. AI management skills have a big effect on AI skills, which in turn have a positive relationship with the impact of AI at the process level.

Performance Improvement at the Process Level

In organizations, performance improvement at the process level is usually measured using key performance indicators concerned with efficiency, capacity, productivity, quality, profitability, competitiveness, effectiveness, and value (Santos & Brito, 2012). These key process performance indicators are used to monitor the organization's outputs. In other words, they make it possible, through the collection of relevant information, to monitor the evolution or innovation of the process during and after the introduction, adoption, and integration of an information technology or of a repository of best practices by an organization (Nwamen, 2006). These indicators provide information that allows the manager to make decisions that will improve the efficiency and effectiveness of the process.

It is commonly accepted that AI is a vector of performance development in a company (Abijith & Wamba, 2012; Kim et al., 2011). However, whether their impact on the performance of business processes also evolves remains an open issue and a major concern for researchers. Yet, the available literature suggests some relevant approaches to evaluate the impact of AI technology capabilities on business processes. For instance, Mooney et al. (1996) identified three complementary factors of increased organizational performance, namely reduction in risk; recognition of threats and prevention of hacking; smarter and safer fuel stations; and precision in decision making. Since part of our study focuses on the influence of AI on business performance, these four areas will be discussed in detail.

For an organization or industry to increase its performance, it must focus on the need to reduce the number of risks it encounters or is likely to encounter. Reduction in risk is a prerequisite to business growth and development (Makradakis, 2017). The implementation of AI and technological management will aid an industry or organization to minimize risk. Since risk is based on technologies, processes, techniques, and tools being visible to a company, it is important for industries to implement effective tools and techniques for organizational development. As mentioned by Fillat and Garetto (2015), risks that are underwater are linked to risks above the waterline. Effective risk management based on techniques, tools, processes, and technologies enables a company to reduce the risk associated with underwater operations.Nowadays, every industry relies on technology for business processes. From this, it can be emphasized that effective technological management is an important aspect of business that requires attention. In this context, businesses need to develop strategies for risk management based on technological failure, security, and privacy. The evaluation of processes for effective management is aided by effective risk analysis based on organizational processes and technological techniques.

To overcome these obstacles, reap the full benefits of AI adoption, and avoid problems further down the road, it is imperative for boards and senior management to develop a meaningful understanding of the technology, including its existing and potential uses within their organizations, and take a firm grip on the implications of AI from a risk perspective. In this context, effective risk management, far from being an inhibitor of innovation, is in fact pivotal to a firm's successful adoption of AI (Bigham et al., 2018).

With the recent increase in cybercrime and its negative repercussions on businesses, it is prudent for industries to look out for business threats and how to prevent one's business ideas or information from being hacked into. This can be effectively and efficiently done with the application of AI in technological management. Also, to survive in a global competitive business world like we have today, managers need to be vigilant for pop-up dangers that can harm their business (Shah, 2018). A stolen business idea is tantamount to a business losing profit margins. Incorporation of cognitive technologies and evaluation of structured data processes are a few strategies that a company adopts in order to work in an organized way while maintaining business confidentiality. In the context of modern business processes, maintaining data confidentiality and security of business details is a crucial point in order to retain market value. Furthermore, AI risk analysis enables the detection of fraud processes in an organization (Omolo, 2014).

The use of AI in technology management breeds smarter and safer fuel stations, void of accidents and explosions. Business managers must be precise in their decisions in order not to confuse themselves and their customers. Customers feel safe dealing with people who are straightforward and concise in their decisions (Agrawal & Goldfarb, 2018). Adopting AI, at an organizational level, can improve the productivity and efficiency of crucial decision-making (Knight 2015). Studies indicate various advantages of implementing AI in organizations, yet organizations still face difficulties in adopting AI technologies (Chui & Malhotra 2018). One of the reasons behind these difficulties is the failure of organizations to understand where and how to implement AI. Another reason is the failure of organizations to extract insights at an enterprise level to best implement the business strategy for AI adoption (Andrews, 2017).

Empirical Review

Artificial Intelligence (AI) has penetrated almost every sector in the world, bringing unprecedented transformations and innovations. In this review, the empirical evidence of its application in various domains is the focus. In the healthcare sector, AI applications have revolutionized patient care and management. For instance, Esteva et al. (2017) demonstrated the use of a deep learning algorithm to identify skin cancer, performing on par with dermatologists. In another study by Rajpurkar et al. (2018), AI was effectively used in interpreting medical images, significantly improving diagnosis accuracy and time efficiency.

In the realm of environmental science, Rolnick et al. (2019) highlighted the potential of AI in addressing climate change. AI applications in climate modeling and prediction, renewable energy optimization, and carbon capture technology have shown significant promise in promoting environmental sustainability. Transportation and logistics sectors have seen a profound transformation with AI application. Voulodimos et al. (2018) outlined the role of AI in improving vehicle navigation, traffic management, and the development of autonomous vehicles.

In the financial industry, the use of AI for predictive modeling in stock markets, credit scoring, and fraud detection has been studied extensively. Huang et al. (2020) demonstrated how AI algorithms significantly outperform traditional models in predicting stock prices. Lastly, in the oil and gas industry, AI has emerged as a potent tool for enhancing safety, reducing cost, and increasing efficiency.

The study by Rahmanifard and Plaksina (2022) presents a comprehensive review of the application of Artificial Intelligence (AI) in optimization problems in the petroleum exploration and production industry. Their study classifies AI methods into four key categories: evolutionary algorithms, swarm intelligence, fuzzy logic, and artificial neural networks. Their review sheds light on the impressive performance of AI methods in optimizing crucial objective functions for industrial decision-making in petroleum engineering.

The authors provide a detailed, systematic analysis of AI optimization techniques in the petroleum industry. Notably, their exploration of evolutionary algorithms, including Genetic Algorithms and Particle Swarm Optimization, reveals these techniques' efficacy in addressing complex optimization problems in oil reservoir characterization and production optimization.

Swarm intelligence techniques, like Ant Colony Optimization and Bee Algorithm, according to their findings, have been extensively used to solve optimization issues in drilling, reservoir simulation, and production systems. Fuzzy logic is used primarily for uncertainty analysis in reservoir characterization, while artificial neural networks have found extensive application in production optimization and reservoir modeling.

The authors point to an emerging trend of hybridization or combination of various AI techniques to solve complex optimization problems, resulting in superior solutions. They found that these hybrid models outperform the individual models in terms of precision, reliability, and robustness. An additional contribution of the Rahmanifard and Plaksina (2022) study lies in its extensive mapping of the geographical regions where these developments in AI application in the petroleum industry have been taking place. This regional analysis provides an important insight into the global distribution of advancements in this area.

Even though Rahmanifard and Plaksina's 2022 study doesn't spell out its own shortcomings, we can tease out a few potential limitations when we consider the nature of their research, a literature review or survey. Firstly, the study aspires to be a comprehensive review of AI optimization techniques in petroleum exploration and production. Yet, due to the sheer magnitude and fast-evolving pace of this field, it's possible that not all techniques and applications were captured. Another potential pitfall could be selection bias, a common issue in literature reviews. The researchers' selection of studies may unintentionally skew the results, either overlooking some relevant studies or favoring those that align with their own perspectives.

Additionally, as a literature review, the study doesn't bring any new experimental or primary data to the table. Its findings hinge on the analysis of pre-existing literature, potentially putting a cap on the ability to draw fresh, novel conclusions. Time also factors in as a possible limitation. The study's findings are up-to-date only until the time the literature review was conducted.

Considering the relentless pace at which AI research progresses, it's feasible that some latest developments may not have made the cut.

Lastly, the study takes a gander at the geographical distribution of AI advancements in the petroleum industry. But, accessibility and availability of data could differ across regions, which might result in a regional analysis that isn't quite complete or is skewed.

Despite these potential limitations, it's important to remember that recognizing these areas of weakness doesn't devalue the study. Rather, it lays out a map for future research to navigate and cover these gaps.

In sum, AI has revolutionized multiple sectors by offering advanced solutions for complex problems, significantly enhancing operational efficiency, accuracy, and economic benefits. However, challenges, such as data security, ethics, and bias, still need addressing to ensure the sustainable and equitable use of AI technologies.

Occupational Safety

Definition and Specification

Occupational safety and health (OSH) is a domain that cuts across several others and it mainly deals with employees' health, safety and welfare. The WHO in defining occupational health looked at occupational health as a holistic field centred on safety and health with the principal goal of preventing the incidence of hazards at the workplace. The essence of OSH is to allow an individual to carry out their job in a manner that minimises the risk of injury to their health.

Occupational safety is encompassed within the broader concept of "welfare." The Cambridge Advanced Learner's Dictionary characterizes "welfare" as "well-being." As such, health and safety are integral components of employee welfare, which have been recognized as crucial areas of welfare provision for an extended period. Seddon (2005) describes safety hazards as elements of the work setting that pose the risk of immediate and occasionally violent harm to a worker, such as hearing loss, vision impairment, or the loss of limbs; lacerations, strains, contusions, fractures, burns, and electrocution. In contrast, health hazards are aspects of the work environment that gradually and cumulatively (and often irreversibly) contribute to the decline of an employee's health, for instance, cancer, poisoning, and respiratory illnesses. Common sources include physical and biological hazards, toxic and carcinogenic substances, chemicals, and demanding work conditions (Walters, 2003).

Occupational Safety Standards

Ghana is progressively positioning itself as a symbol of democracy for not only West African nations but also the entire African continent and beyond. Since 1992, the country has sustained a relatively stable democratic environment. Individual and institutional rights and freedoms are upheld according to the constitution. The robust legal system has empowered state institutions and businesses. The legislative branch leverages its experience to expedite legislative processes, providing a legal framework for multinational corporations and industries. Ghana joined the Extractive Industry Transparency Initiative (EITI) to ensure transparency in payments made to the government. Parliament has considered bills related to the oil industry (Manu, 2011).

Regarding the compliance of fuel filling stations with safety, environmental, and workplace standards, there is room for improvement. Management safety practices (Ezenwa, 2001) stem from the "Three Es of safety" – Education, Engineering, and Enforcement. Engineering focuses on creating a safe environment by providing suitable safety facilities and up-to-date equipment for employees. Education furnishes workers with the necessary knowledge of best practices, guidelines, and regulations for safe work. Moreover, enforcing workplace safety policies is vital for motivating employees to adhere to established rules and regulations (Porter & Porter, 2001). Hence, it is the responsibility of management or its representatives to execute workplace policies to ensure safe work practices.

Fuel filling station employees are exposed to hazardous conditions daily, such as armed robbery or contact with harmful petroleum fuel and fumes containing carcinogens (WHO, 2010). For instance, the American Conference of Government and Industrial Hygienist in 2001 recommended an occupational exposure limit of 23 mg/m3 for a 10-hour workday in a 40-hour workweek for VOCs for petroleum industry workers and fuel service station attendants. However, in Ghana, fuel attendants experience continuous exposure to gasoline fumes beyond a typical 40-hour workweek (Udonwa et al., 2009). Exposure to these compounds presents a potential risk for numerous illnesses. At low chronic doses, petrol vapor irritates the eyes, respiratory tract, skin, and neuro-cognitive function (Tu et al., 2004). Exposure to higher concentrations of petroleum vapor containing benzene and other harmful substances can lead to central nervous system (CNS) effects, such as unsteady gait, slurred speech, confusion, or long-term cancer (WHO, 2010). It may also cause rapid unconsciousness, death due to respiratory failure, renal dysfunction, lipid degeneration, and other clinical manifestations (Tu et al., 2004). Frequent exposure to petroleum products is hazardous to workers' health (WHO, 2010). Nevertheless, many filling stations lack safety policies to address the health needs of attendants and other employees in general (Ansah & Mintah, 2012).

Occupational Safety Indices

The primary objective in developing occupational health and safety policies is to ensure employee well-being and safeguard the environment for sustainable growth. As a result, safety specialists and managers make decisions based on an assessment and evaluation of current health and safety management systems to create more cost-effective policies aimed at equipping workers to control or prevent occupational hazards and injuries (Lingard & Rowlinson, 2005). Occupational safety indices serve as valuable tools in this process.

Leading occupational safety indices are performance measurements that help predict injuries and illnesses, enabling workplaces and system partners to examine an organization's health and safety environment, culture, and performance before an injury or disease occurs (Institute for Work and Health, 2021). In contrast, trailing indicators measure performance based on injuries and illnesses that have already transpired. Examples of occupational safety indices include non-fatal injuries and illnesses, work-related hospitalizations, fatal work-related injuries, and elevated blood lead levels. These indices can be utilized to compare the performance of two or more downstream petroleum companies.

Occupational Safety Practices in Fuel Filling Stations

Occupational safety pertains to employees' shared beliefs about the significance of maintaining secure behavior within their work environment (Zohar, 1980). It is a distinct aspect of an organization's social climate, reflecting the perceived priority of safety-related policies, procedures, and practices (Flin et al., 2000; Zohar, 2000; Zohar & Luria, 2005). Payne et al. (2010) describe policies as organizational objectives and methods for achieving them, while procedures offer tactical guidelines for actions related to these goals. Practices involve the implementation of policies and procedures by managers within each workgroup (Payne, 2010: p.806). Thus, "safety practice" can be primarily understood as shared social cognition.

Safety practice has recently emerged as a strong indicator of both subjective and objective organizational safety performance (Bosak et al., 2013; Andreas et al., 2016; Huang et al., 2017). Zohar (2010) suggests that the operationalization of safety practice should focus on the relationships between policies, procedures, and practices concerning safety, taking into account how they compete with other operational demands. It is essential for future research to consider the relative priorities of safety practice, specifically how management balances production and cost demands against organizational safety requirements.

When comparing immediate profit gains to potential accidents resulting in simultaneous production losses, human casualties, environmental pollution, and organizational reputation damage, prioritizing safety over short-term financial gains is economically sensible. To effectively evaluate safety performance, researchers must examine how management chooses between production and cost demands and the requirements of organizational safety policies, procedures, and practices.

A crucial strategy for preventing accidents is continuous vigilance through the use of indicators (Øien et al., 2011). Skogdalen et al. (2011) developed safety indicators to monitor system safety levels, motivate action, and provide decision-makers with the necessary information about where and how to act. Common safety indicators in the petroleum industry include fatal accident rates, lost time injury frequencies, and total recordable injury rates, supplemented by hydrocarbon release statistics (Tamim et al., 2017).

Occupational accidents can be broadly characterized as trips, slips, and falls (Skogdalen et al., 2011), whereas major accidents involve events like major leaks, fires, explosions, or loss of structural integrity that lead to multiple fatalities, significant environmental damage, or property loss (Amyotte et al., 2016). Controversial aspects of safety indicator measurement include whether occupational and major accident indicators should be managed similarly and whether safety indicators should be measured retrospectively or predictively.

There is a growing consensus that traditional occupational accident indicators are insufficient for predicting major hazard risks (Baker, 2007; Skogdalen et al., 2011). Reactive lagging safety indicators use retrospective analysis to measure potential accident-contributing factors, while predictive leading safety indicators involve active monitoring to achieve organizational safety outcomes.

Many studies assess workers' perception of historical safety within an organization using safety practice as a lagging indicator, primarily because retrospective designs are easier to conduct due to data availability (Payne et al., 2010). However, it is crucial to proactively monitor potential contributing factors to major accidents instead of waiting for them to occur before investigating their causes. Despite the apparent importance of leading indicators, academic research in this area remains limited. Several studies (Antonsen, 2009; Kvalheim et al., 2016) criticize the inability of safety practice scores to predict major accidents, yet the link between safety climate indicators and major accidents remains underexplored in the literature.

Payne et al. (2010) found that safety practice perceptions (such as good routine housekeeping, backlog prevention, and timely correction of health and safety issues) were significant predictors of major accidents in the chemical process industry. Additionally, research by Vinnem et al. (2010) and Kongsvik et al. (2011) on hydrocarbon leakage analysis discovered that safety climate results functioned as leading indicators for major accident risks. The 'Swiss cheese model' of accident causation (Reason, 1990) supports the notion that addressing 'failed defenses' is the most promising approach for preventing organizational accidents. Active failures (e.g., errors and procedural violations) and latent conditions (e.g., high workload, time pressure, insufficient skills or experience, and poor equipment) create gaps in defenses. These latent conditions can persist within defenses for an extended period and may be exposed through system auditing or incident occurrence (Reason, 1990; 2016).

Various studies have developed safety practice variables by capturing elements of active failures and latent conditions to measure organizational safety performance (Mearns et al., 1997; Fleming, 2001; Mearns et al., 2001; Mearns et al., 2003; Bayire, 2016). Safety practice perception serves as a distal antecedent of safety behavior, mediated by more proximal drivers of safety performance (Zohar, 2010). This implies that safety practices can be employed proactively to identify latent conditions of major accidents and prevent organizational shortcomings from becoming the root causes of future accidents. Once the measures of failed defenses have been established, it is possible to provide predictive indicators of accident likelihood. Furthermore, it is crucial to develop safety practice scales that are valid and reliable for measuring the predictive conditions of major accident risks.

The research conducted by (Quaigrain et al., 2022) is an in-depth look into the state of health and safety in Ghana's oil and gas industry. The primary objective of this research was to determine how well-versed workers in this high-risk industry were in occupational health and safety. Researchers used primary and secondary resources as part of a positivist and deductive methodology. Data was collected using a structured survey, and multiple linear regression was used to examine how factors like staff knowledge and attitude influenced health and safety compliance.

The study's results were illuminating. Employees in this sector were found to have a strong foundation of knowledge and a constructive outlook on the topic of occupational health hazard management. The majority of workers were also found to follow established safety and health procedures. Although they had the right mindsets towards safety, they did not always put those mindsets into reality per the findings made by Quaigrain and colleagues (2022). Interestingly, female employees outperformed their male counterparts in both knowledge and compliance with occupational health and safety practices. This unexpected finding could warrant further investigation to understand the underlying causes and potential implications.

Based on these findings, the study recommended several practical actions. These include the implementation of appropriate education and training programs that cover the correct usage of machinery and equipment, as well as hazard safety training that is specific to the employee's job requirements. Additionally, there should be more effective dissemination of risk information and stricter enforcement of safety procedures through governance initiatives.

The study is unique in that it explores the influence of employee knowledge on overall health and safety compliance within the oil and gas industry, and its findings and recommendations have significant implications for improving occupational health and safety outcomes within this industry. This research could inform future policy and workplace practices to improve safety conditions for workers in high-risk industries, particularly in developing countries like Ghana.

Quaigrain et al.'s 2022 study on occupational health and safety in Ghana's oil and gas industry has several limitations. These include limited generalizability due to its context-specific focus, potential biases from self-reported data in a structured survey, unexplored reasons for gender differences, a lack of understanding of why knowledge and attitude do not always translate into comprehensive safety practices, and the absence of qualitative data, which could offer deeper insights. A mixed-methods approach and further research could help address these limitations.

Liu et al.’s (2020) research in the Ghanaian oil and gas industry sought to understand how workers' safety knowledge influences the connection between OHSMFs and worker injuries and accidents. Using a cross-sectional survey design, 699 participants from three state-owned oil and gas companies were selected using both systematic and haphazard methods.

The study used correlation, multiple regression, and bootstrapping techniques to establish a relatively substantial inverse link between OHSMF and occupational accidents and injuries. This shows that there is a correlation between better OHSMF and fewer injuries and accidents on the job. It is noteworthy that safety knowledge was shown to considerably mediate this association, suggesting that OHSMF's influence on safety outcomes was mediated in part by its influence on workers' safety knowledge.

The level of safety awareness, and thus the likelihood of workplace injuries and accidents, was found to be significantly correlated with the amount of safety training employees received. Based on these results, the researchers concluded that the present OHSMF may not be adequate to manage hazard exposures in the industry.

The research calls for increased funding of regular safety training and orientations to improve worker safety awareness. It also urges stakeholders across Ghana's economy to work together for the common good of improving occupational health and safety. The ultimate objective is to lessen the number of oil and gas workers injured on the job.

It is important to note that there are several caveats to the findings of Liu et al. (2020), despite the fact that they shed light on the connection between OHSMFs, safety knowledge, and workplace injuries and illnesses.

To begin with, the sample strategy used in the study could restrict how widely applicable the results are. Non-probability sampling strategies, such as convenience and purposive sampling, were used to acquire the sample. Because of this, it's possible that the sample is not representative of the entire workforce in the Ghanaian oil and gas industry, resulting to bias in the results (Bryman, 2016).

A cross-sectional survey approach was used to collect information for this study as well. As a result, it becomes harder to deduce causes and effects or trace the development of links across time. It's possible that the discovered connections won't hold steady over time. Research designs that follow participants over time will shed more light on the interplay among OHSMF, safety literacy, and workplace mishaps (Menard, 2002).

Researchers relied on participants' own accounts of events like occupational injuries and accidents. This could cause social desirability bias or recollection bias in responses. It's possible that people will forget or underreport accidents and injuries for fear of retaliation (Duffy, Smith, Terhanian, & Bremer, 2005).

Causes of Health and Safety Hazards in the Petroleum downstream Industry

The body of research on occupational safety indicates that the petroleum industry has numerous unique health and safety hazard sources. Ochsner & Greenberg (1998) identified these specific causes.Physical Hazards

Nevertheless, traumatic injuries continue to pose a significant concern, varying from minor to fatal events (DeJoy, 2000). Common causes of such fatalities encompass spills, fires, explosions, accidents involving mobile equipment, and falls from elevated positions. Nachimas & Nachimas (2009) note that the methodical implementation of risk management techniques has led to a considerable reduction in injury frequency rates in developed countries compared to less developed nations where accidents occur more often. They believe that additional progress is needed to achieve rates deemed acceptable by the broader society. Osuala (2003) conducted a review on strategies for controlling physical hazards, which encompassed system safety and risk management within the petroleum industry.Chemical Hazards

In contemporary work environments, over 80,000 distinct chemical products are utilized, and this number continues to rise. Industries with the highest exposure to chemical hazards include those involved in chemical and metal processing, manufacturing of specific consumer goods, textile and synthetic fiber production, and the construction sector. Chemical hazards can be categorized as follows:

- Particles, fibers, fumes, and mists: Carbon Black, Welding Fume, Oil Mist
- Metals and metalloids: Arsenic, Cadmium, Chromium, Mercury, Zinc
- Organic solvents and compounds: Acetone, hydrocarbons, Benzene
- Inorganic gases: Carbon monoxide, Hydrogen sulfide, Sulfur dioxide

Chemicals are also increasingly employed in a wide array of tasks, encompassing non-industrial activities such as healthcare facilities, office work, cleaning services, and cosmetic and beauty treatments. The level of exposure varies significantly. Health consequences may involve metal poisoning; damage to the central nervous system and liver due to solvent exposure; pesticide poisoning; skin and respiratory allergies; dermatoses; cancers; and reproductive disorders (WHO, June 2013).

Biological Hazards

Hale and Hale (2005) claimed that specific biological illnesses are prevalent in petroleum regions in developing nations. For instance, the likelihood of contracting tropical diseases like malaria and dengue fever is quite significant in certain remote petroleum sites. In some occupational settings, there is exposure to around 200 biological agents, including viruses, bacteria, parasites, fungi, molds, and organic dust. The most frequent occupational diseases arising from these exposures include hepatitis B and hepatitis C virus infections, tuberculosis infections (especially among healthcare professionals), asthma (among individuals exposed to organic dust), and chronic parasitic diseases (particularly among agricultural and forestry workers).

Waqar et al. (2023) set out to determine what characteristics are most likely to lead to accidents happening during the building phase of downstream oil and gas projects in Malaysia. The researchers used a combination of qualitative interviews with experts and quantitative techniques including factor analysis and structural equation modelling to compile their findings. The researchers identified multiple sources of potential danger that could lead to accidents on construction sites. Inadequate safety training, lax safety practises, and the lack of a strong safety culture are all major problems. Other contributors include faulty communication, malfunctioning equipment, and insufficient management focus on safety.

These findings have theoretical ramifications since they shed new light on the factors that contribute to mishaps at Malaysia's oil and gas installations. They are also relevant in the real world since the data they provide is used to inform safety regulations in the field. The findings stressed the importance of strengthening safety education and following established procedures. The research offered a number of recommendations for how to make the downstream oil and gas construction sector in Malaysia safer and cut down on accident rates. Safety management should be a top priority in all organisations, and that means taking preventative measures, doing regular audits and reviews, and providing all personnel with extensive training. A safety culture, defined by open lines of communication across departments and a zero-tolerance stance for dangerous behaviour, should be instituted whenever possible. There was also talk about the importance of company, contractor, and regulatory body cooperation, as well as ongoing research into potential safety issues.

This study highlighted the importance of a comprehensive, preventative safety management plan in the downstream oil and gas construction sector in Malaysia. Businesses can improve their safety performance, reduce accidents, and help create a more secure and sustainable industry by adopting the suggested reforms.

The study in focus, concerning accidents within Malaysia's downstream oil and gas construction sector, presents several limitations which can potentially undermine the conclusiveness and wider applicability of its results. Firstly, the limited sample size of industry professionals consulted poses a critical constraint. This small representation might not accurately mirror the reality of the entire Malaysian sector, potentially leading to skewed conclusions. For research to yield more robust and widely generalizable results, a significantly larger and more diverse sample would be instrumental.

Secondly, the study's geographical scope is strictly limited to Malaysia. While it may present a comprehensive analysis within this context, the extension of these findings to other countries' oil and gas sectors becomes problematic. This is because of inherent differences in regulations, work conditions, and cultural practices among nations, which inevitably impact safety protocols and risk factors.

Occupational Safety Management

The primary objective in formulating occupational safety policies is to safeguard employees and preserve the environment for sustainable development. Consequently, safety professionals and managers make decisions based on the assessment and evaluation of existing occupational safety management systems, aiming for more effective and cost-efficient policies that equip workers to control or prevent occupational hazards and injuries (Lingard & Rowlinson, 2005). Channing (2008) indicates that the establishment of occupational safety practices became crucial in the wake of numerous workplace catastrophes and harm to human life. The 1980s witnessed several environmental and social incidents, including the American oil tanker Exxon-Valdez's collision with Bligh Reef, resulting in a significant oil spill in Alaska's Prince William Sound, and an explosion on an oil and gas production pipeline near Aberdeen (Peattie, 2008).

Dabup (2012) contends that the primary purpose of occupational safety practices is to ensure proper control over risks to workers, the general public, and the environment. Dabup (2012) further elaborates that effective management of occupational safety and environmental protection, essential for employee well-being, enhances a company's reputation and contributes to high-performance teams and cost benefits. This claim is supported by Erickson (2011), whose findings suggest that the treatment of employees is the most predictive factor in occupational safety performance.

Effectiveness of AI and Technology Management Options in Occupational Safety

The integration of artificial intelligence (AI) into business operations has significantly advanced the development of businesses. It has not only altered the way companies conduct business processes but also elevated their performance levels. Bharathy and McShane (2014) assert that businesses have adopted a novel approach to achieve success through the incorporation of AI. This method facilitates an enhanced level of work processes within companies. The effective adoption of AI in businesses has considerably contributed to their development. Machine learning and its application have simplified tasks and business processes (Mok et al., 2014). Moreover, the communication and networking capabilities of industries have become more efficient and rapid due to AI advancements, subsequently leading to the improvement of business efficacy.

The successful integration of AI alongside human intelligence has a considerable impact on a business process's productivity. Kleiman et al. (2013) point out that the performance of industries, as well as the evaluation of strategies through the effective implementation of AI systems, has facilitated the development of business processes more efficiently. Glendon et al. (2016) indicate that businesses have experienced growth in specific areas, with increased productivity and enhanced company performance. This encompasses:

Custom Research and Planning Supports

The incorporation of AI in various industries and governmental sectors has resulted in tailored research efforts and strategizing. This fosters a swifter and more efficient process for organizations, ultimately boosting business productivity. As previously noted, the personalization of government procedures and the enhancement of planning contribute to the proficient management of business operations.

Project Management and Development

The progression of AI technologies and their successful integration into business operations have facilitated the growth and management of projects. Mok et al. (2014) noted that evaluating the precision of systems and technological instruments according to project needs fosters efficient management and the triumphant conclusion of project tasks, ultimately contributing to the enhancement of business processes.

Effective Strategic Alternative Simulation

Evaluating the various options that companies must embrace to improve their performance has become significantly more straightforward due to the successful incorporation of technological instruments. Moreover, this has also provided advantages to organizations in terms of elevating business productivity. Identifying the appropriate strategic choice for a business aids in formulating tactics tailored to the specific needs of the enterprise.

Development of IP Strategies, Business Development Plans and Valuation

Advancements in business strategies and intellectual property (IP) approaches are achievable through the incorporation of technological research by organizations. Industries' thorough evaluation of AI systems, in accordance with project requirements, aids in the formulation of suitable business plans. Consequently, this results in enhanced business performance. As noted by Kleiman et al. (2013), the appropriate development of business plans and IP strategies contributes to increased business productivity while simultaneously decreasing the likelihood of market failure.

Advisory and Consulting Services

With the successful integration of AI technology, consulting and advisory services have become more efficient and accessible for businesses. AI enables seamless communication among organization members and facilitates effective networking processes. By incorporating AI, companies experience enhanced business capabilities and increased adaptability (Glendon et al., 2016).

Challenges of Adoption of AI and Technology Management in Occupational Safety

In recent years, the petroleum industry has faced numerous obstacles. To address the growing global energy demand and reduce hydrocarbon production costs amidst heightened competition, the oil sector must adopt proactive strategies while adhering to environmental regulations and social responsibilities. Significant challenges include price fluctuations (Regnier, 2007), shareholder pressure for value creation (Ramos et al., 2017), complex drilling and production processes (Gupta & Grossmann, 2017), increasing oil and gas demand (BP, 2017a), critical HSE compliance (Neill, 2017), protecting the social license to operate (Tomlinson, 2017), corporate social responsibilities (Banerjee, 2017), fiscal regime fluctuations, R&D and innovation (Hall & Vredenburg, 2003), data and knowledge management (Bratianu & Bolisani, 2015), and unstable NOC-IOC partnerships (Whitson, 2009).

These challenges impact major petroleum producers when implementing sustainable development policies. Petroleum production, refining, and transportation are industries known for causing pollution due to high pressure-high temperature underground reservoir conditions and the use of chemicals to safely drill and produce hydrocarbons. Sustainable development challenges in the oil and gas sector encompass flaring and venting, decommissioning oil and gas installations, oil storage tank disposal, drill cuttings management, produced water disposal/treatment, drilling muds and fluids management, greenhouse gas emissions estimation and validation, subsidence, spills, safety, and enhanced profitability (Whitson, 2009).

Each challenge has led to environmental concerns and occasional crises. Major oil companies have made decisions on these challenges, spending billions annually on improving methods, technologies, and engaging with local communities near oil and gas facilities. National and international oil companies have taken measures to address sustainable development challenges under government and public pressure (Whitson, 2009).

Additionally, lobbying occurs between oil company executives and local governments (Schweitzer, 2010). Some oil and gas companies have made significant progress in social corporate responsibility (SCR), supporting the achievement of the SDGs and the 2030 Agenda (UNDP, 2016). Although they don't guarantee a world devoid of environmental crises, these companies have demonstrated substantial efforts to mitigate incidents. Their current achievements, however, suggest they can do more.

Research indicates a growing world population necessitates more affordable and accessible energy (Pérez-Lombard et al., 2008). Price fluctuations fuel fierce competition in the energy market, causing price reductions. Escalating regional, cultural, and security disputes, coupled with climate change, contribute to increased corporate risk and investment costs. Shareholders prioritize economic gain and expect profitability growth. Factors like population growth, intensifying competition, climate change, shareholder expectations, and regional trade patterns (Miron et al., 2010) are long-term drivers that create risks and tensions in the business environment. Oil and gas companies continuously refine their business plans to address these challenges effectively.

Implementation of artificial intelligence by companies and government has led to incorporation of everything small from image recognition to robotics. Businesses and government processes depend on artificial intelligence with technological development and innovation. This made process and style of working very easier, faster, and compatible. An increase in the number of innovations has brought the power along with efficiency of AI into various fields. This includes finance, medicine, marketing, advertising, news, and various other fields (Keramitsoglou et al., 2013). In line with this, industries and companies are undertaking initiatives to undergo various changes in the business process. Moreover, the introduction of technology and its rapid advancement has changed the set of challenges faced by companies in present context. Increasing demand of technology and computer system has led to companies and government to adopt the innovation for betterment and increasing efficiency of the process. In this context, business and government faces certain challenges during its implementation.

Technology Adoption in Oil and Gas

Exploration and production of hydrocarbons from remote and difficult areas, such as beneath the ocean floor, is the primary focus of the upstream oil-and-gas business (O & G). Robotic vehicles, data analytics, and remote monitoring software have all been created and utilised by industry to deal with these hazardous and complicated settings. There have been recent developments in virtual and augmented reality, as well as in the use of large data sets and artificial intelligence. When it comes to technology, the oil and gas business has always been on the cutting edge. Climate change, the need to automate high-risk, error-prone jobs, and the upcoming problems of decommissioning have made business more competitive in recent years (Hassani et al., 2017). O&G must quickly adapt to new ways of operating and interacting with other power producers as many countries, including the United Kingdom, move toward an integrated energy sector (e.g., renewables). Companies must accept technical innovation to remain competitive (Porter, 1985), yet the industry has a reputation for conservatism and a sluggishness to adopt new innovations (Bereznoy, 2019; Daneshy & Bahorich, 2005).

Predictive analytics, transparency, optimization, and value generation are just some of the benefits of AI adoption (McDermott International, 2021).With predictive analytics, equipment and assets can be predicted to be in good working order. Refining and petrochemical planning and schedules that take plant availability into consideration can be informed by equipment degradation or failure that can be predicted 30 days in advance. When presented to industry personnel (planners, schedulers, operators, managers, and plant technicians), it immediately improves the intelligence of planners and schedulers, without the need for translation from people like data scientists, and increases the agility of companies. This is but one possible illustration. Value chain interplay and demand planning are two further examples that can help a plant's management better understand their company's production needs.

The implementation of AI results in increased transparency. Oil and gas companies, and project teams are able to collaborate with up-to-date and accurate information thanks to the fact that data relating to the project may be communicated in real time. In addition to this, the implementation of AI improves overall optimization. Petroleum companies are able to construct digital replicas and perform simulations to maximise throughput in a facility using digital transformation powered by AI, which enables facility optimization. The petroleum companies may also evaluate the impact of energy variations using these simulations.

Another important advantage of implementing AI is the creation of value. The implementation of AI helps petroleum companies produce profit by lowering the risks and uncertainties associated with their projects. In addition, digitalization makes it possible for oil and gas companies to improve the designs of their products, react more quickly to demands from consumers, and interact more effectively with those customers. The industry is already embracing these technologies to digitise its operations, which makes the adoption of new smart technologies an important factor in the overall efficiency and productivity of the sector. Moving downstream into the processing stage, predictive analytics is making a significant difference in boosting equipment uptime. This technique involves installing sensors in rotating and other types of equipment in order to anticipate future problems before they occur. This is beneficial not just to the processing plant, but also to the original equipment manufacturers (OEMs), who receive a sizeable portion of their income from after-sales maintenance contracts. New digital technologies, when coupled with data-driven insights, have the potential to alter operations, thereby increasing both agility and the ability to make strategic decisions. Companies that implement digital technologies are able to reap the benefits of enhanced productivity in their staff, higher efficiencies in their business operations, and increased cost savings in the delivery of their projects. In addition, the application of technology can improve Health, Safety, Security and Environment performance while simultaneously reducing risks.

Because of the considerable operational, financial, and safety risks of failure, the high expense of being the first to accept new technology, and a competitive culture that encourages early adopters to innovate, introducing new technology into the oil and gas industry is a challenging undertaking (Radnejad et al., 2017). It's not uncommon for businesses to consider themselves "second or third generation" consumers of new technologies. As a result of this, the sector's "clock speed," or the rate at which an innovation is adopted and implemented in a corporate context, is extremely slow (For oil and gas, the figure is as high as 16 years; Noke et al., 2008). Small and medium-sized enterprises (SMEs) have also come under fire for being slow and conservative in adopting new technologies (Afolayan & de la Harpe, 2020). It is anticipated that the world that will exist after COVID-19 will continue to struggle with the same problems, including unpredictability and the requirement for making rapid transitions into new ways of operating that make use of technical solutions (Juergensen et al., 2020). A unique aspect of the oil and gas business is that there has been a strong push from within to improve innovation techniques, including a focus on the role of people in the process. Psychological variables, such as lack of ownership, risk aversion, and leadership around technology, and attitudes of unwillingness to change, play a significant influence in slowing technology acceptance in the petroleum business (Oil and Gas Authority, 2018; Wood, 2014).

This gap was addressed by conducting a literature study to identify probable psychological elements that can influence technology adoption decisions in the oil and gas sector (Roberts & Flin, 2020). Five categories of psychological elements were mentioned in the little research that included psychological components. People's personalities, attitudes, social norms, cognitive factors, and organisational characteristics all play a role in risk aversion, according to a study published in the Journal of Personality and Social Psychology (e.g., culture). Most of the time, the studies do not talk about the people who support or oppose new technology. Instead, they focused on organisational features and ways to intervene. Because of that, there does not appear to be a framework in innovation literature, in general, the oil and gas literature specifically, or in relation to similar risky industries, that describes the important psychological aspects that impact technology adoption decisions (Roberts et al., 2021).

Factors Influencing AI Technology Application

Park et al. (2022) selected five variables in their search for a new technology acceptance model that takes into account the social context. These factors are technological, psychological, risk perception, resource, and value aspects. Studies done in the past have concentrated their attention mostly on two of them, namely psychological and technological variables. For instance, Davis (1985) focused on two aspects: perceived usefulness and perceived ease of use. Davis (1985) failed to take into account more objective aspects like resources since those two variables are crucial by-products of the user's subjective psychological judgement (Park et al., 2022). In their research, Venkatesh et al. (2003) proposed UTAUT and paid attention to the factors of anticipation and experience. Independent factors were expanded upon by Venkatesh et al. (2012) with the addition of motivation and price value variables. These factors, like Davis' variables, concentrate on the cognitive and perceptual elements of users. This is one way in which they are comparable. On the other hand, such research failed to take into account additional "fundamental," "objective," and "risky" aspects. In light of that, Park and colleagues (2022) concentrated their research on "basic" value, "objective" resources, and "risk" perception, and value variables in addition to psychological and technological considerations.

First, Park et al. (2022) focused on more underlying value aspects than cognition or perception in psychological factors. Value has been disregarded in prior studies, while value as a fundamental human orientation plays a critical influence in evaluations toward technology. Baazeem (2019) suggested that as users' behaviour is impacted by their religious views, religiosity might influence their judgments in connection to technological difficulties, such as privacy issues. Chao & Yu (2018) found that values such as technological optimism function as a moderator between perceived behavioural control, attitudes, and social influences and behavioural intentions connected to weblog learning. Two personal values (citizens' awareness of time constraints and environmental considerations) were found to be associated with the uptake of new technologies by Belanche et al. (2012). Additionally, Lee (2009) proposed and empirically evaluated a value-based technology acceptance model. They found that three values—social value, emotional value, and functional value—are connected with perceived ease of use or perceived usefulness, which have an impact on behavioural intentions towards the use of mobile media services.

Second, Park et al. (2022) concentrated their attention not just on subjective psychological aspects but also on objective resource factors. Information gap studies have spent a significant amount of time researching the issue of information accessibility in relation to the quantity of economic and social resources. For instance, Martin & Robinson (2007) demonstrated that the likelihood of accessing the internet increased most rapidly for individuals whose families had the highest income levels, whereas the likelihood of accessing the internet increased most slowly for individuals whose families had the lowest income levels. In addition, Abu-Shanab (2011) discovered that education had a substantial influence, both directly and indirectly, on the links between performance expectancy, self-efficacy, perceived trust, and locus of control, as well as behavioural intention to utilise Internet banking. Additionally, Lee (2009) proved that customers' positive or negative experiential elements have considerable impacts on the belief and acceptance of specific technologies.

Third, Park et al. (2022) paid attention to risk perception factors because the traditional TAM approaches technology from the perspective of internal organization technology. Risk perception research approaches technology from the perspective of risk communication at the social level. For example, based on an empirical study of 161 subjects, Im et al. (2008) demonstrated that, in addition to technology type and gender, perceived risk was also a significant variable in influencing users' adoption of technology. Lee (2009) also discussed the role of perceived risk in technology acceptance. The intention to use online banking is adversely affected mainly by the security and privacy risk, as well as financial risk, and is positively affected mainly by perceived benefit, attitude, and perceived usefulness. Similarly, Youn & Lee (2019) highlighted that perceived risks, such as price risks and technological barriers, critically influence technology acceptance. Also, Belanche et al. (2012) said that trust is just as important as perceived ease of use and usefulness when it comes to people using e-government services.

Technological Factor in AI Technological Application

Perceived Usefulness and Perceived Ease of Use

When it comes to research that is related to the acceptability of new technologies, the two most essential criteria are perceived ease of use and perceived utility (Park et al., 2022). Davis (1985) made the suggestion that these two variables be included in TAM, and Venkatesh et al. (2003) included them in UTAUT. It is common practise to investigate both the reported usefulness and the perceived ease of use simultaneously. The following constitutes the definition of each variable: The enhancement of expected performance brought about by the application of technology is what is meant when perceived usefulness is referred to. Davis (1985) defines perceived ease of use as the degree to which the user thinks the technology can be used without requiring a lot of work from them.

These two factors have been the subject of a significant number of investigations in the context of technology acceptance. According to Lee &

Shin's (2020) research, the intention of mothers with infants and toddlers to accept robot-based education improves when they see the utility and simplicity of such education for their children. Kim et al. (2019) showed that the perceived usefulness of an artificial intelligence speaker as well as its ease of use had a beneficial effect on the user's adoption of the technology. According to research carried out by Moslehpour et al. (2018), a larger adoption of an online payment method was associated with better levels of perceived utility as well as simplicity of use. According to the findings of a study conducted by Kim et al. (2019) that looked at the acceptability of information technology by a professional internal auditor, perceived usefulness and ease of use were found to be factors that affected the acceptance of the technology. The acceptability of information technology at its most fundamental level is linked to perceived utility. On the other hand, the acceptability of advanced functions is more closely tied to the perception of how easy they are to use.

Technological Complexity and Relative Advantage

To put it another way, relative advantage refers to how much superior new technologies are judged to be compared to current ones. In Rogers' (2010) Innovation Diffusion Theory, advantages and disadvantages were outlined. Rogers' study aimed to uncover the characteristics that influence innovation diffusion and how it is accepted by the general population. On the basis of the Innovation Diffusion Theory, Moore & Benbasat (1991) stated that a system's acceptability was influenced by factors such as compatibility, ease of use, visibility, image, result demonstrability, and voluntarism. Since then, Rogers (2010) has highlighted the perceived features of relative advantage and complexity, as well as trialability and compatibility, as factors influencing the adoption of new technologies. Researchers have found that relative advantage has an impact on the acceptance of innovation and that its explanatory power has been proved. In the integrated technology acceptance model, Venkatesh et al. (2003) added relative advantage. According to Scott et al. (2008), relative advantage plays a vital role in innovation and can be observed.

Complexity is a measure of how difficult it is to comprehend and make use of new technology. Venkatesh et al. have incorporated it into UTAUT (2003). In addition, it's associated with technology's more compassionate side. It is based on Triandis' (1977) theory of human information systems behaviour that the PC application model was developed (IS). Beliefs drive human behaviour and are shaped by social context, according to theories of human behaviour. In human external contexts, the social element impacts beliefs, and complexity is a factor that affects the usage of information systems in a context of information systems. In human behaviour theory, complexity can be viewed as a social component (I. Park et al., 2022).

Radical innovation

The impact or degree of innovation determines whether a technological advancement is classified as radical or gradual (Ettlie, 1983; Munson & Pelz, 1979). Innovations at the point of emergence of a new technology or technological system that differs from the old technology or system constitute radical innovation. According to Schumpeter & Backhaus (2003), it is a new technology that can lead to "creative destruction" in the economy. Accordingly, R & D operations at the organisational level tend to produce radical innovation.

The risk of market acceptance is high since the development cost is high when the market is underutilised. When we talk about "progressive innovation," we're talking about enhancements or additions to existing technology rather than complete overhauls. There is no immediate ripple effect that causes the initial devastation, but the cumulative effect of incremental innovation is considerable.

There is a lot of talk about AI being a disruptive technology. Technological disruption refers to innovations that have the potential to fundamentally alter a variety of areas of our daily lives, including how we use technology and how markets operate. However, the economic and industrial structure, including the rise of large platform companies and the sharing economy as well as a rise in personalised information and personal lives, have exceeded expectations in regards to artificial intelligence's role in the 3rd industrial revolution. It's obvious that AI's arrival has had a distinct impact compared to past technological developments. As a result, this study assumes that if artificial intelligence is regarded as a radical breakthrough, acceptance anxiety will diminish people's willingness to accept it.

Resource Factor in AI Technological Application

Price value

According to Venkatesh et al. (2012), the price value variable in UTAUT2 is defined as the degree to which it feels more valuable to use the technology in relation to how much it costs to utilise that technology. According to UTAUT2, a model proposed to explain consumer acceptance of new technology, the price value is the most significant difference between the organisational and common customer environments. This is because organisations don't have to pay to use new technology, whereas common customers do almost always have to pay to use it (Venkatesh et al., 2012). Individual consumers may be burdened by the costs of AI-applied products, despite the fact that they are more inventive and advanced than earlier products. When you pay for something that has AI in it, it's likely to have a good effect on the public's perception of it. The impact of price for mobile app uptake has been empirically proven, according to findings by Tai & Ku (2013). In Kong & Choi's (2018) study, the price value is employed to explain the mobile simple money transfers. There was a strong correlation between purchase intention and the product's price worth, per the findings made by Kong & Choi (2018).

Income and Educational Level

Davis et al. (1989) proposed the TAM, which was theoretically developed and used anytime a new technology was introduced. A number of innovative TAM-based models for technology acceptance have been put out by various academics. It has been shown that individual-related and technology-related aspects both influence technology acceptance, according to Schepers & Wetzels (2007), for example. As more and more people use AI-enabled products and services, it is becoming increasingly important to explore the personal characteristics that drive the use of AI. A person's socioeconomic status and educational attainment may play a significant role in determining whether or not he or she is a good candidate for implementing artificial intelligence (AI) (I. Park et al., 2022). Higher-income people have better access to new technologies while the barrier to adoption is higher.

Experience of use

The term "experience" refers to a person's interactive response to the stimulus provided by an actual object (Dewey, 2000). It's not just about driving and utilising a product; it's about an individual's contact with that product (Deaton, 2003). By interacting and providing input, Roto (2006) asserted that it is linked to an entity. The experience of a product that incorporates new technology can help people become more conscious of and comfortable with technology (Agarwal & Prasad, 1997). There must be factors that take into account not only the instrumental but also the personal attributes of the individual. There are two studies that use experience to explain technology acceptance: Venkatesh & Davis (2000) and Venkatesh et al. (2003). Artificial intelligence (AI)-enabled goods will become more commonplace as the number of individuals who have used them and are already familiar with them grows. As a result, everyone who uses an AI-powered product is more likely to warm up to the idea of AI in general.

Facilitating conditions in AI Technological Application

Factors in the environment that facilitate the application of technology are called "facilitating conditions" (Thompson et al., 1991; Venkatesh et al., 2003). Behavioral habits, behavioural objectives, and enabling circumstances are all explored in Triandis (1977). Social variables, as opposed to one's own requirements, serve as enabling conditions. Human behaviour theory was initially introduced into the context of information systems by Thompson et al. (1991) and applied to the model of PC utilisation (MPCU) to explain PC usage. To account for social influences on technology use, Venkatesh and colleagues

(2003) included the facilitation condition as a significant element in their integrated technology acceptance model. It may be difficult for people who are not familiar with new technology to use it. But if they have appropriate contextual support, they are more likely to adopt the technology. For many years, the enabling circumstances for technology acceptance have been studied empirically in great depth (Slade et al., 2015; Song, 2017; Tai & Ku, 2013).

Risk Perception Factor in AI Technological Application

Perceived Risk and Perceived Benefit

Both a technical notion and a subjective notion can be utilised when attempting to make sense of the concept of risk. The first type can be understood in an objective manner by applying a certain approach, whereas the second type acknowledges the existence of a socially created risk. The idea of "perceived risk" is one that was proposed by the subjective constructivist school of thought. This school of thought acknowledges that it is difficult to objectively measure danger (Cox et al., 1967; Short, 1984). The intensity and susceptibility of the damage caused by a risk are taken into consideration when making a subjective assessment of perceived risk (Deaton, 2003; Rayner & Cantor, 1987; Schepers & Wetzels, 2007).

On the other hand, perceived benefit is defined as an individual's sense of effectiveness through material and non-material remuneration for a dangerous object. This can include both monetary and non-monetary benefits. To put it another way, it is the advantage that can be achieved from the action that is taken in response to the risk. Therefore, perceived benefits lead to an increase in risk-taking behaviour (Michalsen, 2003). According to Alhakami & Slovic

(1994) and Fischhoff and colleagues (1978), the relationship between perceived risk and benefit is an inverse one that plays an opposing function for risk. This means that a reduction in one side results in a rise in the other side (Kunreuther et al., 1990; Wiegman & Gutteling, 1995). Previous research (Scott et al., 2008; Starr, 1969) identified perceived risk as a variable that influenced the acceptance of innovative technology, and Park & Koh (2014) as well as Tai & Ku (2013) confirmed that perceived benefit was a variable that increased the intention to actively use information technology.

Image of technology

Because images are linked to emotions in decision-making (Slovic et al., 1991), it is possible to assess how a person feels by assigning a positive or negative value to an image that represents their emotions (A. Lee & Lee, 2005). This method is used in psychological risk studies (Finucane et al., 2003; Slovic et al., 1991). Emotion and image were not included in early studies on technology adoption. However, image or emotional elements were included as the study progressed down to the individual level. As an illustration, the TAM2 had an emotional component called "perceived contentment" (Venkatesh & Davis, 2000). Recent research on the acceptability of technology show that attitudes about technology have a beneficial impact on product use intentions (Kang et al., 2007).

Knowledge

Knowledge can be broken down into two categories: familiarity and expertise, according to Alba & Hutchinson (1987). The primary distinction between the two types of knowledge is whether or not it requires the completion of a job. The state of being able to recognise things based on one's knowledge is known as familiarity, and it does not lead to the completion of tasks. On the other hand, expertise knowledge is a stage in the learning process in which tasks are accomplished through the application of knowledge. This indicates that even if a person is not at the level of professional knowledge, if they have information about technology, then they will enhance their familiarity with it. This is true even if they are not at the level of professional knowledge. Prior knowledge was found to have an effect on the utilisation of mobile phones and wireless Internet, according to Lu et al. (2003). Both Lee & Shin (2020) and Chae (2011) suggested that users' knowledge partially influences the continued acceptance of Internet banking. According to Lee & Shin (2020), smartphone-based mobile banking uptake is influenced by expertise. Internet banking's sustained adoption may be influenced in part by users' expertise, according to Chae (2011). By implication, therefore, if people have a better understanding of AI, it's reasonable to assume that they will be more accepting of it.

Trust

AI systems have been widely adopted in a variety of industries. As a result, the adoption of AI in some areas is hampered by a lack of confidence in the AI system's ability to protect humans (Sheth et al., 2021). Trust in AI systems depends on a variety of factors, including but not limited to the following: fairness, privacy, transparency, and explanation. In order to gain trust in AI-driven choices, it is important to know how they are made and what criteria are taken into consideration. XAI refers to the subfield of AI system explanation.

Data biases, a shortage of data in a particular region of example space, fairness in the collection process, feature importance, and other factors can all be considered when trying to understand an AI system. Human-centered explanations directly linked to decision-making are also essential, comparable to how a domain expert makes judgments based on "domain knowledge," which includes well-established, peer-validated clear guidelines. A human's ability to understand and apply an AI system's outputs (such as classification, recommendations, and forecasts) is essential to creating trust in the AI system. A decision-making process similar to that of an expert is still a work in progress for modern XAI systems.

Another aspect of trust is trust in government – the government's regulatory capabilities. Individuals face an "assumed risk" due to the unknown risk offered by technology. In order for an "assumed risk" to be judged riskier than a well-known risk, necessary data must be missing (Son & Kim, 2014). The public's perception of artificial intelligence appears to be impeded by significant obstacles to technological awareness and adoption. More and more individuals are concerned about the impact of modern technology on their daily lives because of its spread. Hence, people may become anxious when adapting to technology changes. The public relies on trust because of their fear of technology (Lee & Lim, 2005). As a result, public faith in government and the government's position as a risk manager are crucial for technological policies to be accepted. As a result of technical ambiguity or complexity, trust is regarded to be a component that modifies (Paton, 2008). Park (2008) found that trust in the government had a substantial impact on the acceptability of the e-resident card policy. According to Kim et al. (2016), trust has a favourable effect on the acceptance of technology risk.

AI Technology application's Influence on the Petroleum Sector

The oil and gas sector annually provides employment for tens of thousands of people. An artificial intelligence method is created for this purpose, and it is used to examine the application materials of potential employees (Solanki et al., 2022). This will help indicate in the CV which division would be the best fit for the applicant based on the needs of the firm. The HR department will be able to avoid spending money and save time as a result of this. Accounting and spending monitoring in the oil and gas industry are complex, time-consuming, and laborious. The distribution of funds is also highly governed by regulations. All of this is handed over to a trained AI. Accounting staff can focus on other tasks while the trained AI processes the current data and provides more insightful results. To best understand and interpret well-test data, it is recommended to utilize the 9e11 pressure derivative (Allain & Horne, 1990).

Most oil and gas reserves have been discovered and exploited for a very long time, which creates difficulties for the drilling, exploration, reservoir management, and production industries. The petroleum sector, seeing the potential benefits of implementing AI methods like ANNs, has begun to investigate their use. Both the oil and sand industries require machinery, such as truck engines. Maintenance is an enormous expense for businesses. However, AI lessens the financial burden of improving efficiency. Hydrocarbon deposits can be located with the help of competent petrophysicists, geophysicists, and geologists who analyze geological formations for oil and gas corporations. The use of AI could allow for faster data processing, leading to better suggestions on whether to continue exploring, developing, or abandon the project altogether. There is perpetual risk in the oil industry. Both offshore and onshore platforms make it a primary priority. Off the coast, they use hefty machinery, a platform, and helicopters for transporting. Toxic fumes are present on land. Maintaining a secure environment is a daily victory. In the event of a safety concern, data collection is immediately initiated, and the gathered information is analyzed to ascertain the cause and suggest the best course of action for preventing future incidents. In the event of theft, AI can swiftly pinpoint missing components and equipment. Oilfield operation, intervention, and production optimization all face difficulties that can be mitigated by using AI (Akanji & Ofi, 2016).

When it comes to the petroleum business, which has traditionally relied on big warehouses, stocking kinds and levels can be a source of value due to the possibility they offer for strategically predicting demand. These developments have the potential to lessen the need for operating capital and increase satisfaction among customers (Solanki et al., 2022).

Artificial intelligence methods are used to forecast the rock's permeability, porosity, water saturation, and wellbore stability. The Adaptive Neuro-Fuzzy Inference System (ANFIS), an ANN, a support vector machine (SVM), etc., can all be used to make predictions about petrophysical parameters like porosity and permeability. To make an accurate prediction of porosity and permeability using AI, no mathematical equations need to be solved by hand. When it comes to determining and describing reservoir parameters, ANN is one of the quickest and most effective methods. Offshore oil and gas firms employ AI in data science to simplify the mountain of information necessary for oil and gas discovery and production, allowing them to better leverage current infrastructure while also uncovering untapped prospects (Solanki et al., 2022).

Response surface models (RSMs) are a class of non-linear equations and equations that are popular due to their simple mathematical structure and thus straightforward application. The use of AI approaches to bridge the gap between input and output data has reduced developer anxiety. A large number of scholars have also aimed to enhance analytical, numerical, and other procedures in order to better grasp the notion employed in generation. The systems involved are complicated, hence these approaches proved unsuitable for predicting shale hydrocarbon output. Many LSSVM arguments rely on completion parameters, rock-fluid characteristics, and fluid properties gathered from prior investigations, all of which have been shown to be crucial. Artificial intelligence can be used to improve the drilling process. Drilling problems include malfunction, stopped pipe, excessive down-hole vibration, cleaning holes, pressure transients, and regulated pressure drilling are all addressed using artificial intelligence. Reservoir optimization is achieved via analysis of down-hole data and intelligent well-bore drilling (Nunoo, 2018).

In the downstream sector, AI can also be used to forecast fire outbreaks. Fire makes for a reliable worker but a dangerous boss. Because of their large scale of destruction, sudden occurrence, and statistical unpredictability, fires are frequently categorized as extreme events. A wide variety of causes, some of which can be attributed to people and others of which we have no control, contribute to fire outbreaks and other disasters. There are seven main causes of fires in Ghana, and they are as follows: electrical, home, bush, institution, commercial, industrial, and vehicle. The Ghana Fire Service's long-term objective is to bring annual fire death rates down to single digits by the year 2015 (Amoah, 2019). As stated by Amoah (2019), the Fire Service of Ghana needs a reliable estimate of fire occurrences in order to accomplish this goal effectively. There is an issue with modeling extremely rare phenomena that fall outside the range of current data. It is crucial to use a well-founded methodology and model an adequate time series in order to anticipate fire occurrence. Some scholars around the world have done empirical studies of fire, and the Seasonal Autoregressive Integrated Moving Average Model has found use in a number of contexts (SARIMA) (Amoah, 2019). An examination of Dar es Salaam's building fire safety provisions was modeled by (Rubaratuka, 2013). According to the findings, fire is a severe threat to any building, but especially those in Tanzania. As the fires discovered during the investigation showed, not all of the structures had proper fire protection precautions in place. There will probably be a lot of damage. The study also found that including fire protection and preventive strategies into the planning, design, and construction of buildings in Dar es Salaam can dramatically lessen the severity of fire-related losses. Fire safety measures have been inadequately supplied in some of the evaluated structures, and substantial damages are expected to result in the event of fire outbreaks. according to Amoah (2019).

Adewuyi & Kehinde, (2020) evaluated the reaction time of fire stations to a filling station fire outbreak and the safety of healthcare facilities in the downtown region of the city of Ibadan. It is now well established that geographic information systems (GIS) are useful for addressing environmental issues and making informed decisions. It is impossible to emphasize the importance and efficacy of filling/service stations, which have contributed significantly to the economic development of people's lives and the value of their property in countries all over the world. According to this research, not all gas stations in Nigeria meet the requirements set forth by the local government and the Department of Petroleum Resources (DPR).

It can be concluded that the standard regulation was not properly followed in the study area as only 35% of gas stations adhered to the 300-meter local authority standard interval, only 7.2% conformed to the 400-meter Department of Petroleum Resources (DPR) regulation standard, and only 32% had their dispensing pump at least 15 meters from the road. There is little danger of a catastrophic chain reaction between gas stations and hospitals in the event of a fire. More than half of the gas stations in the research region can obtain immediate treatment from the fire station, according to their reaction times in emergencies. That's why it's on to the Local Authority Town Planning Department and the DPR Department to make sure gas stations are appropriately labeled in accordance with the rules they've set. And, the owners of the gas stations that don't follow the rules should be held accountable for their violations. The relevant authority shall conduct inspections of prospective fueling stations before granting approval and building permits to individuals or companies. A contemporary, well-equipped fire service station should be created in the study area and throughout the Ibadan metropolitan region to relieve the current ones, and even more fire service stations should be set up.

Last but not least, all gas stations should be equipped with cutting-edge Tecno Control anti-fire preventative technology.

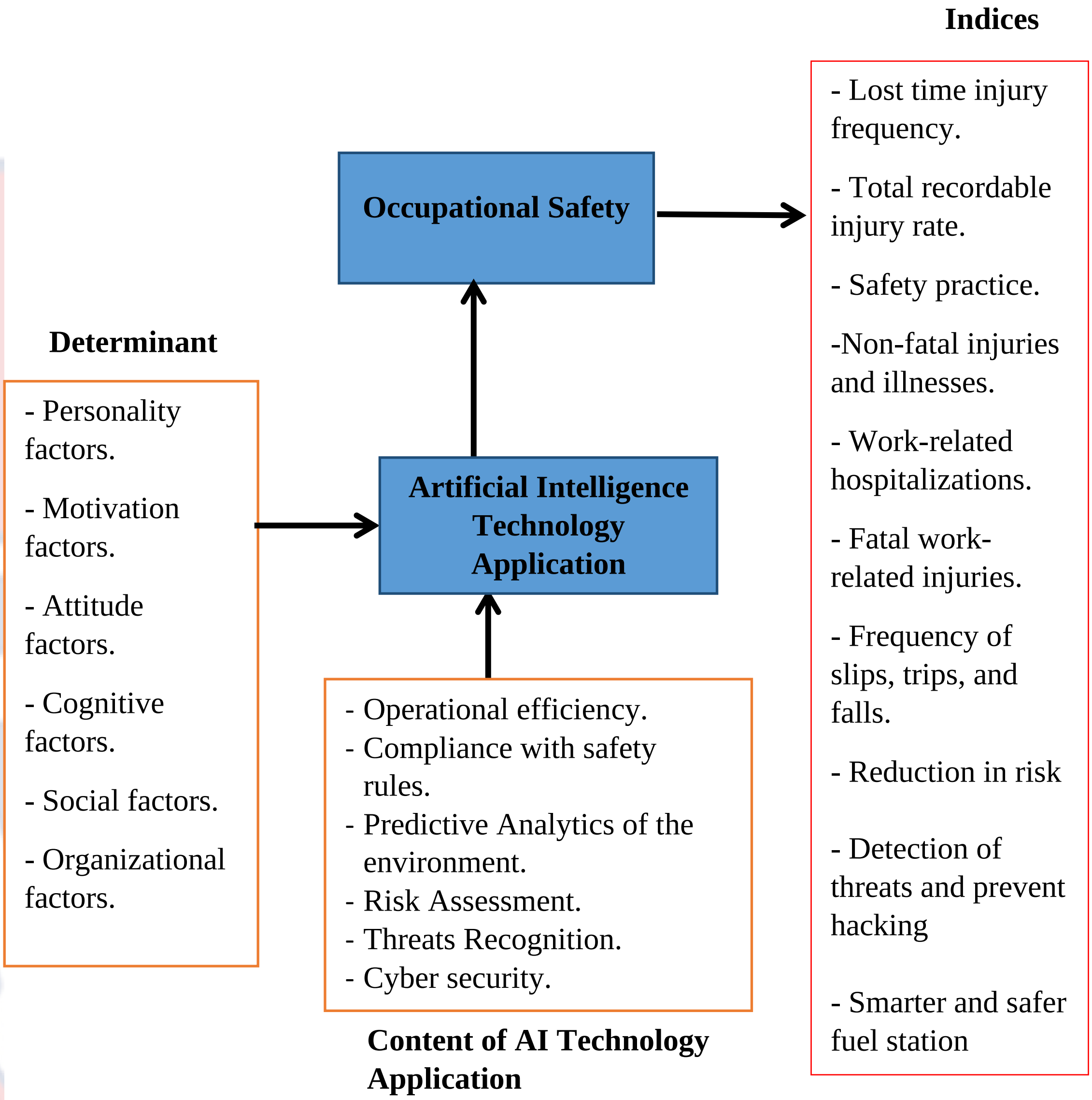
Conceptual Framework

This section looked at integrating the theories into a conceptual framework for the study. It shows the relationship between dependent and independent variables.

Figure 3 below depicts the conceptual framework underpinning the present study. The independent variables are characterized by artificial intelligence technology application and occupational safety acting as the dependent variable. The determinants of artificial intelligence technology application in downstream petroleum industries in the Greater Accra Region, in this study, are hypothesized to be personality factors, motivation factors, attitude factors, cognitive factors, social factors, and organizational factors. The specifics of the conceptual framework are discussed in full detail in subsequent analysis chapters.

The arrows and lines between blocks represent the causal or correlational relationships between these components. For instance, determinants influence the application of AI technology, which then has certain effects, and so on. Similarly, AI technology application influences both occupational safety and its content, which is then measured using various indices. This holistic view provides a comprehensive understanding of how AI applications can be beneficial to occupational safety in the downstream petroleum industries in Greater Accra.

Figure 3: Conceptual framework depicted in a Schema



(Source: Author's own construct)

Artificial Intelligence Technology Application: This building block signifies the use and integration of AI technologies within the Downstream Petroleum Industries in Greater Accra. It is influenced by various determinants such as personality factors, motivation factors, attitude factors, cognitive factors, social factors, and organizational factors.

Determinants: These variables influence the application of AI technology. They include personality factors, motivation factors, attitude factors, cognitive factors, social factors, and organizational factors.

- **Personality Factors**: These include an individual's willingness to adopt new technology (risk-taking propensity), their existing technological proficiency, and adaptability to changes in traditional work processes brought about by AI.
- **Motivation Factors**: These could include incentives for using AI technologies, such as bonuses, recognition, or opportunities for advancement. In addition, the perceived usefulness and ease of use of the AI technology could also affect motivation.
- **Attitude Factors**: The overall attitudes of employees and management towards AI technology. Positive attitudes might be driven by an understanding of the potential benefits of AI, including improved safety and efficiency.
- **Cognitive Factors**: These factors include employees' understanding of AI technologies, their ability to learn how to use new systems, and the cognitive load associated with interacting with the AI technologies.
- **Social Factors**: The influence of peers and societal acceptance of AI technologies could affect the adoption and use of AI in the industry.
- **Organizational Factors**: These are factors such as the organization's readiness to adopt AI, the availability of resources to implement AI technologies, and support from the management for AI adoption.

Occupational Safety: Occupational safety refers to the measures and procedures implemented to ensure the safety and health of employees within the industries. It's linked with AI application and can be quantified using various indices.

Indices: These variables are the measures used to evaluate occupational safety. They include lost time injury frequency, total recordable injury rate, safety practice, non-fatal injuries and illnesses, work-related hospitalizations, fatal work-related injuries, and frequency of slips, trips, and falls.

1. **Lost Time Injury Frequency (LTIF)**: This refers to the frequency of injuries in the workplace that result in an employee being unable to work for a certain period. It's typically calculated as the number of lost time injuries per million hours worked. This metric can demonstrate the severity of injuries and the effectiveness of safety protocols in the industry.

2. **Total Recordable Injury Rate (TRIR)**: This is a comprehensive measure that represents the number of safety incidents that resulted in a recordable injury per 200,000 hours worked. A recordable injury could be any injury that requires medical treatment beyond basic first aid. TRIR includes both lost time injuries and other less severe injuries, providing a broader view of safety performance.

3. **Safety Practice**: This can include a variety of measures that evaluate adherence to established safety protocols and procedures. It could encompass things like safety training completion rates, compliance with personal protective equipment usage, and regular safety audits.

4. **Non-Fatal Injuries and Illnesses**: This measures the number of work-related injuries and illnesses that do not result in death. These can give an indication of overall safety conditions and the types of hazards that employees might be exposed to.

5. **Work-Related Hospitalizations**: This refers to the number of workers who require hospitalization due to work-related injuries or illnesses. This can indicate the seriousness of the incidents that occur in the workplace.

6. **Fatal Work-Related Injuries**: This is the number of deaths that occur due to work-related incidents. Though these incidents are hopefully rare, they are extremely serious and can indicate major safety failings.

7. **Frequency of Slips, Trips, and Falls**: This measures the number of incidents related to slips, trips, and falls - common causes of workplace injuries. This metric can highlight potential issues with the physical work environment or procedural issues.

These indices allow for an evaluation of the overall safety within the petroleum industry in Greater Accra, particularly in relation to the application of artificial intelligence technologies. By assessing these variables, the study can better understand the impact of AI on improving occupational safety in the industry.

Effects of AI: The impact of AI on the industries, which includes reduction in risk, detection of threats and prevention of hacking, smarter and safer fuel station, and precision in decision-making concerning safety. This block is impacted by the application of AI technology.

1. **Reduction in Risk**: AI can greatly reduce risk in the petroleum industry. For example, AI systems can continuously monitor equipment and predict failures, thus preventing accidents before they occur. Similarly, AI can identify patterns and anomalies in safety data, helping to predict and prevent incidents, leading to a safer work environment.

2. **Detection of Threats and Prevention of Hacking**: In the digital age, cybersecurity has become an essential aspect of any industry. AI can be employed to identify potential cyber threats and respond to them more quickly than humans. For instance, machine learning algorithms can learn to identify suspicious activities and raise an alert, and AI systems can help fortify defenses against hacking attempts.

3. **Smarter and Safer Fuel Station**: AI can make fuel stations smarter and safer by automating safety checks, managing fuel levels, predicting maintenance needs, etc. For instance, an AI system could monitor all aspects of a fuel station in real time, from fuel levels to equipment conditions, and trigger alerts or actions as needed.

4. **Precision in Decision-Making Concerning Safety**: AI can enhance decision-making processes by providing accurate, data-driven insights. For instance, AI can analyze large amounts of safety data to identify trends, patterns, and potential issues. These insights can help decision-makers implement more effective safety measures, respond to incidents more effectively, and forecast future risks.

The Effects of AI is influenced by the application of AI technology, which is contingent upon various determinants such as personality factors, motivation factors, attitude factors, cognitive factors, social factors, and organizational factors. The more effectively AI technology is applied, the greater its potential impacts on reducing risk, detecting threats, improving safety, and enhancing decision-making in the petroleum industry.

Contents of AI Technology Application: The details of how AI is applied within the industry, including operational efficiency, compliance with safety rules, predictive analytics of the environment, risk assessment, threats recognition, and cybersecurity. This is linked to the AI technology application block.

1. **Operational Efficiency**: AI can significantly enhance operational efficiency in the petroleum industry. For instance, AI can automate routine tasks, optimize schedules and resource allocation, and streamline various operations. For example, AI systems could predict maintenance needs and optimize maintenance schedules, reducing downtime and improving productivity.

2. **Compliance with Safety Rules**: AI can also play a critical role in ensuring compliance with safety rules. For instance, AI systems can monitor operations and alert management to any deviations from safety protocols. They can also assist in tracking compliance records and identifying areas where more safety training might be needed.

3. **Predictive Analytics of the Environment**: This refers to the use of AI to analyze data from various sources (like sensors, logs, weather data, etc.) to predict potential environmental hazards. These predictions can

enable proactive measures to prevent accidents and improve overall safety.

4. **Risk Assessment**: AI can be used to assess risks more effectively. For example, machine learning algorithms can analyze historical incident data, current operational data, and even external data (like weather data) to identify potential risks and suggest mitigation measures.

5. **Threats Recognition**: AI can identify potential safety threats more quickly and accurately than humans. For instance, AI systems could continually monitor equipment and environmental conditions and raise an alert if they detect any anomalies that could signify a potential safety threat.

6. **Cybersecurity**: In addition to physical safety, AI can also improve cybersecurity. For example, AI systems can monitor network activity, identify suspicious behaviour, and respond quickly to potential cyber threats, thus protecting the industry's digital infrastructure.

The Contents of AI Technology Application block is closely linked to the Artificial Intelligence Technology Application block. The extent and effectiveness of AI technology application can greatly influence how AI is utilized in these areas and consequently affect the overall safety and efficiency in the petroleum industry.

CHAPTER THREE

METHODOLOGY

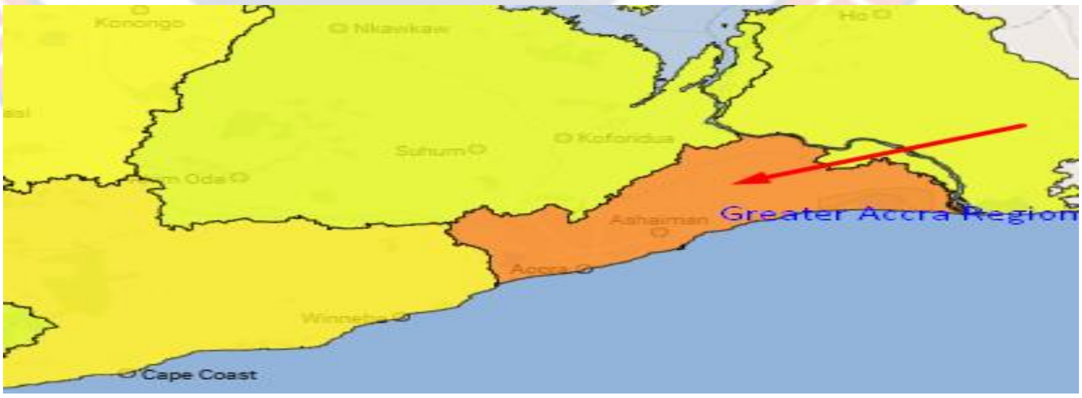
Introduction

This chapter presents the research method that was adopted for the study. It involved the discussion and application of the techniques for the analysis of the data gathered. The remaining portion of the chapter is structured as follows: Section 3.1 discusses the study area; Section 3.2 discusses the research design; Section 3.3 examines the research approach; Section 3.4 presents the research design; Section 3.5 presents data types and sources; Section 3.6 presents the target population; Section 3.7 discusses the choice of sample; Section 3.8 presents data collection; Section 3.9 explores how the data was analysed; Section 3.10 provides details on model specification, while section 3.11 provides the profile of the respondents.

Study Area

The Greater Accra Region of Ghana was chosen as the study area. This is because the region is noted to contain several forms of commercial activities.

Figure 4: Map indicating location of the Greater Accra Region)



Source: Administrative Map of Ghana

The Greater Accra Region is the smallest of Ghana's 16 administrative regions, yet it is the most populous and serves as the country's economic and political hub. It is bordered to the west by the Central Region, north by the Eastern Region, and East by the Volta Region. The Greater Accra Region is home to the capital city, Accra, which is a vibrant urban centre characterized by a mix of modern and traditional architecture, bustling markets, and a diverse population. The region's strategic location along the Gulf of Guinea makes it a key player in the country's trade and industry, particularly in the downstream petroleum sector.

Research Paradigm

The way individuals perceive the world and the principles governing it is an essential aspect of philosophy (Mason, 2014). Philosophy deals with beliefs about the world's functioning and organization, highlighting the importance of comprehending the reality, knowledge, and existence of specific social phenomena, such as AI technology application in occupational safety in the downstream petroleum performance in the Greater Accra Region. People's comprehension of reality is closely connected to their worldview, which has ramifications for research in this domain.

A paradigm embodies the unique perspectives individuals use to understand the world and social phenomena, like the experiences and welfare of informal solid waste collectors in Accra. Long (2007) asserts that a paradigm is a fundamental requirement for perception, as what is observed is influenced by the subject matter, prior visual/conceptual experiences, and the manner of observation (p. 196). According to Guerra et al. (2012), a paradigm is a "methodological and conceptual universe in which the scientist can operate." In other words, a paradigm serves as the interpretive framework through which researchers analyze various aspects of the world, including the social, physical, and biological dimensions of AI technology application in OHS.

Paradigms play a critical role in research, as they significantly affect the research process, particularly regarding understanding AI technology application in occupational safety in the downstream petroleum performance in the Greater Accra Region. Researchers often consider acknowledging, accepting, and admitting research paradigms to be crucial (Guerra et al., 2012), possibly due to their impact on interpreting research results. Research paradigms consist of three elements: methodology, ontology, and epistemology (Guba & Lincoln, 1994). Ontology is concerned with reality, epistemology focuses on the researcher's engagement with reality, and methodology pertains to the techniques used by the researcher to ascertain that reality within the context of AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region.

Four prevalent research paradigms are identified in the literature: positivism, critical theory, constructivism, and realism (Sobh & Perry, 2006; Mc Manus et al., 2017). These paradigms relate to acquiring knowledge and generalizing findings from a specific study, such as investigating AI technology application in occupational safety in the downstream petroleum performance in the Greater Accra Region, to other contexts. Researchers must carefully choose the most suitable paradigm for their study to effectively address the unique aspects of this intricate social phenomenon and ensure the validity and reliability of their findings.

In the context of AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region, the chosen research paradigm significantly influenced the methodologies, interpretations, and recommendations derived from the study. Each of the four prevalent research paradigms—positivism, critical theory, constructivism, and realism—presents distinct advantages and challenges that researchers must consider when conducting their investigation.

A positivist approach, for example, might emphasize the necessity for quantifiable data to analyze AI technology application in occupational safety in downstream petroleum performance. This paradigm would involve gathering and interpreting statistical data to identify patterns, relationships, and trends that could inform the development of effective interventions and policies to enhance OHS in the downstream petroleum sector.

In contrast, a critical theory approach might concentrate on examining the underlying social, economic, and political structures contributing to the challenges encountered by informal solid waste collectors in Accra. This paradigm would entail a qualitative analysis of power dynamics, social inequalities, and institutional barriers affecting AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region.

The constructivist paradigm, conversely, would prioritize the individual experiences and subjective realities of individuals working in the downstream petroleum sector. Researchers using this approach would aim to understand the unique perspectives, motivations, and decision-making processes of these individuals and how they influence AI technology application in OHS in the downstream petroleum sector.

Lastly, a realism-based investigation would attempt to balance the objective and subjective aspects of the research topic by combining quantitative and qualitative methodologies. This approach would provide a comprehensive understanding of AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region, taking into account both the measurable aspects and the individual experiences of those involved.

In summary, selecting an appropriate research paradigm is essential for effectively examining AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region. Each paradigm offers unique insights and methodological approaches that can contribute to a deeper understanding of this complex social phenomenon. By carefully considering the advantages and challenges of each paradigm, researchers can design a rigorous study that generates valuable knowledge, informs policy-making, and ultimately improves the lives of informal solid waste collectors in Accra.

For this study, however, positivism was chosen as the sole research paradigm. The positivism research paradigm derives knowledge about a population from statistical inferences based on observations of a sample. Key principles underpinning the positivism research philosophy include uniformity of the logic of inquiry across all science-based disciplines, the study's primary aim to elucidate and predict, the necessity for the researcher's subject matter to be verifiable through observation or sensory perception, the employment of inductive reasoning solely for refining scientific conjectures, the distinction between science and common sense, the exclusion of common sense from positivism to preserve the objectivity of findings, the reliance on logic rather than human beliefs and interests as the driving force of science, and the importance of problem simplification for enhanced understanding (Easterby-Smith et al., 2008). The positivism paradigm was chosen for its emphasis on empirical data, objective analysis, generalizability, testable hypotheses, and rigorous methodology (Creswell, 2014; Bryman, 2016; Asenahabi, 2019; Huntington-Klein, 2021).

Emphasis on empirical data: Positivism focuses on collecting quantifiable, empirical data that can be systematically measured, analyzed, and verified. Given the nature of the research topic the positivist approach allows for a comprehensive examination of AI technology application in occupational safety by gathering measurable data, such as the number of injuries or accidents among employees in the downstream petroleum sector.

Objective analysis: The positivist paradigm emphasizes the importance of objectivity and seeks to minimize researcher bias. By adopting a positivist approach, the study can ensure that findings are derived from reliable, unbiased data, providing a more accurate representation of the AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region.

Generalizability: Positivism aims to identify universal patterns, relationships, and trends that can be extrapolated to other contexts. By employing the positivist paradigm, the research can generate findings that may be applicable to similar settings or populations, thus contributing to a broader understanding of the occupational health challenges faced by workers in the downstream petroleum sector and informing the development of effective interventions and policies across different regions.

Testable hypotheses: The positivist approach allows for the formulation of testable hypotheses based on existing theories, which can be confirmed or refuted through empirical investigation. This aspect of positivism will enable the research to build upon prior knowledge in the field of OHS and contribute to the development of evidence-based strategies to improve AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region.

Rigorous methodology: Positivist research typically employs rigorous, standardized methodologies, such as surveys, experiments, or statistical analyses, to ensure the reliability and validity of findings. By adopting these methodologies, the research can generate robust, dependable results that can inform decision-making and contribute to the improvement of OHS management in the downstream petroleum sector.

In conclusion, the choice of the positivist research paradigm for this study was driven by its strengths in emphasizing empirical data, objective analysis, generalizability, testable hypotheses, and rigorous methodology. These characteristics allow for a thorough investigation of AI technology application in occupational safety in downstream petroleum performance in the Greater Accra Region. By adhering to the principles of the positivist paradigm, researchers can produce robust, reliable, and generalizable findings that can inform policy development, guide the implementation of effective interventions, and ultimately enhance the occupational health and safety of workers in the downstream petroleum sector.

Research Approach

In this study, the chosen research methodology was a quantitative approach, focusing on the collection and analysis of numerical data. The decision to utilize a quantitative approach aimed to provide a numerical depiction of the application of AI technology in occupational safety within the downstream petroleum sector in the Greater Accra Region. While the quantitative research methodology offers certain advantages, it also presents some limitations.

Advantages of quantitative research include: (1) Standardization and objectivity: By employing standardized measures and instruments, quantitative research ensures consistent and objective data collection, which is particularly valuable when assessing variables such as AI technology application in OHS in the downstream petroleum sector, resulting in reliable and valid findings; (2) Statistical analysis: Quantitative research enables the identification of patterns, trends, and relationships between variables through statistical analysis, allowing for a thorough and systematic examination of complex phenomena, such as the application of AI technology in occupational safety within the downstream petroleum sector (Hirose & Creswell, 2023); (3) Generalizability: Quantitative research often seeks to represent a larger population, enabling generalizations about the application of AI technology in occupational safety within the downstream petroleum sector in the Greater Accra Region based on collected data (Babbie & Mouton, 2010).

However, quantitative research also presents certain drawbacks: (1) Limited insight: Despite allowing for statistical analysis, quantitative research does not offer insights into the subjective experiences of waste collectors, potentially overlooking crucial nuances and complexities related to AI technology application in occupational safety, which might be uncovered through qualitative research (Creswell, 2014); (2) Limited contextual understanding: While quantitative research might provide statistical evidence of AI technology application in occupational safety within the downstream petroleum sector in the Greater Accra Region, it may not account for the cultural, social, or economic factors influencing these practices (Babbie & Mouton, 2019); (3) Bias and validity issues: When measuring sensitive topics, such as well-being and safety performance, quantitative research can be susceptible to bias and validity issues. Respondents might hesitate to provide accurate information due to social desirability bias or fear of consequences, resulting in validity concerns regarding the data (Creswell, 2014).

The quantitative research approach involves collecting and analyzing numerical data using structured and standardized tools, such as surveys, experiments, and statistical analysis. This method applies statistical and mathematical techniques to analyze data and make conclusions about the research problem (Mishra & Alok, 2022). It typically requires a large sample size, and the collected data is often analyzed using statistical software. The objective of a quantitative research approach is to test hypotheses, measure variables, and provide statistical evidence for generalizing findings to the broader population. Examples of research areas employing a quantitative research approach include psychology, sociology, economics, public health, and occupational health and safety.

Data for this study were gathered through a survey questionnaire, distributed to a sample of individuals working in the downstream petroleum sector. The survey aimed to collect information on respondents' demographic characteristics and utilized a structured interview approach with multiple-choice and interval scale questions.

The acquired data was examined using both descriptive and inferential statistics. Descriptive statistics, such as frequencies, percentages, means, and standard deviations, were employed to outline the characteristics of factors influencing AI technology acceptance. Inferential statistics, including correlation analysis and regression analysis, were utilized to investigate the relationships between AI technology acceptance and determinants of AI technology acceptance, as well as the impact of AI technology application on occupational safety.

Research Design

According to Kothari (2004), research design constitutes the blueprint for the collection, measurement, and analysis of data. It is a master plan specifying the methods and procedures for collecting and analyzing the needed information. It ensures that the study is relevant to the problem and uses economical procedures in the collection and analysis of data. Building on the aforementioned, Sileyew (2020) contends that a research design's purpose is to create a fitting structure that steers a study through its various phases, guaranteeing coherence and effectiveness in addressing the research objectives. In other words, a research design functions as the foundational blueprint that directs the entire research process. It delineates the methods and procedures for collecting, analyzing, and interpreting data to answer specific research questions or test hypotheses. A suitable research design ensures that the study's objectives are adequately met. Essentially, a research design acts as a roadmap, providing guidance on the best approach to undertake a research study that achieves the desired outcomes and yields meaningful conclusions. It plays a vital role in ensuring the overall quality, consistency, and validity of the research findings.

The present study employed a cross-sectional study design to guide the direction of the study. That is because it was deemed the most appropriate study design, as it allowed the gathering of information from a wide range of downstream petroleum firms at a single point in time (Bryman, 2016). This study design allowed for the assessment of the current state of AI technology applications and their effect on occupational safety within the downstream petroleum industries in the region. One limitation of cross-sectional design is that since it captures data at a single point in time, cross-sectional study design may not account for changes in AI technology applications or occupational safety over time (Bryman, 2016).

Cross-sectional study design is widely used in social science research for understanding the relationships between variables at a specific point in time (Babbie and Mouton, 2010). This design involves collecting data from a representative sample of the target population, in this case, downstream petroleum industries (refineries, distribution companies, and retail outlets) in the Greater Accra region. The advantage of this design is its ability to provide a snapshot of the situation, allowing researchers to identify potential relationships between the implementation of AI technology and improvements in occupational safety (Groves et al., 2009).

By using a cross-sectional study design, this study provides valuable insights into the current state of AI technology applications in the downstream petroleum industry and their impact on occupational safety. By employing a cross-sectional study design, the study was able to gather information on AI technology applications in occupational safety in the downstream petroleum industry in Greater Accra. The findings derived from this methodology offered valuable insights for industry stakeholders, policymakers, and researchers interested in understanding the role of AI technology in enhancing occupational safety in the petroleum sector.

The cross-sectional study enabled the researcher to identify potential areas for improvement and recommendations made for enhancing the application of AI technology for occupational safety in the region. Additionally, the study design allowed for the identification of the determinants of AI technology application. These insights provided guidance for future research and industry practices by addressing the identified challenges and optimizing AI applications for occupational safety.

Data Types and Sources

The study used both primary and secondary data. Primary data were obtained by administering questionnaires to the study respondents. Secondary data were collected from industry reports, and white papers. The secondary data were used to complement the collected primary data.

Choice of Sample Population of Study

The target population for the study encompassed all oil marketing companies operating in the Greater Accra Region of Ghana. These companies are actively engaged in the sale and distribution of fuel throughout the country.

Sampling Frame

The sampling frame for this study is primarily composed of three institutions: Ghana Oil Company Limited (GOIL), Total Petroleum Ghana Limited, and Power Fuel Distribution Company. Together, these three companies dominate the downstream petroleum sector. They represent three different types of ownership structures: GOIL is government-owned, Total Petroleum Ghana Limited is a multinational corporation, and Power Fuel Distribution is privately owned, overseeing numerous smaller oil marketing companies.

Sampling Size Determination

Yamane (1967) came up with a simple formula for figuring out how big a sample should be. It is as follows:

$$n = \frac{N}{1 + N(e)^2}$$

Where n is the sample size, N is the population size of the sampling frame in the Greater Accra Region, and e is the level of precision.

Using N = 350 (estimates derived from company websites and corporate social media profiles e.g., LinkedIn), e = 0.05

$$n = \frac{350}{1 + 350(0.05)^2}$$

$$n = 186.66$$

The computed sample size for the study was 186.66. Notwithstanding, the preceding arguments, it was thought best to settle on a sample size of 187.

Sampling Technique

Purposive sampling was used to select key respondents from the various companies. Respondents were selected from designated offices that are responsible for the use of technology in their operations as well as key respondents. The researcher also adopted a stratified sampling approach to identify managers, dealers, and customers who have invented or are engaged in operations as well, in order to ascertain a fair representation for the purpose of generating an adequate sample.

Data Collection

Over the course of eight days, from May 3rd to May 10th, 2022, primary data was collected for this study. The selected organisations' upper, intermediate and lower-level employees were given the structured questionnaires.

The questionnaire used by the researcher had both closed-ended and open-ended questions for primary data collection. The closed-ended questions used an interval scale with values ranging from 0 to 10. Basically, primary data was the main source of data for this research. Primary data refers to data collected from the source during the research. Such data is collected directly and fresh from the field for the purpose of research. In view of this, all information gathered through the primary data is accurate and concise.

The questionnaires were distributed in person and online to collect the data. The companies' upper echelons were consulted in order to arrange for convenient times to hand out the surveys in person. Where in-person distribution was not possible, respondents were given access to online versions of the surveys. The data gathering procedure was well-structured and methodical. To get a good cross-section of the company's employees, the employees were divided up the days among the several divisions. After giving participants a full day to fill out the surveys, the filled questionnaires were collected and analysed the results.

There were a few obstacles to overcome during the time period of data gathering. The responders' unpredictability as time went on was the main problem. To counteract this, participants were given a wide window of opportunity within which to fill out the surveys. To avoid misunderstanding of questions, a test run of the survey was performed first, with the results being used to fine-tune the questions for the final version. To avoid possible bias in the responses, respondents were assured that their responses would be kept anonymous and confidential and used only for research. The research data were more trustworthy and valid because of the emphasis on openness and objectivity.

Data Processing

The data from the field were coded and processed, using STATA 15 software. The information was based on the objectives and the conceptual framework of the study.

Observations with missing values for any of the answered questionnaires were excluded from the analysis to maintain the anonymity of respondents. The data collected were then appropriately coded to prepare them for data analysis.

Data Analysis

A data analysis matrix was designed based on the specific objectives of the study.

Data were analyzed using frameworks and techniques depicted in the Data Analysis Matrix (Table 1).

Table 1:Data Analysis Matrix

Specific Objectives	Framework of Analysis	Techniques of Analysis
Describe the State of AI technology application and occupational safety in the downstream petroleum in Greater Accra Region.	Descriptive	Descriptive Statistics
Examine determinants of AI technology	Correlation	Descriptive Statistics

application in downstream petroleum sector		Structural Equation Modelling
Evaluate effects of AI technology application on occupational safety in the downstream petroleum sector within the Greater Accra Region.	Correlation	Descriptive Statistics Regression
Synthesize a model AI technology application system for improved occupational safety.	Synthesis	System improvement, Modelling

To describe the state of AI technology application and occupational safety in the downstream petroleum in Greater Accra Region, the framework of analysis used is descriptive, and the techniques of analysis are descriptive statistics.

To examine determinants of AI technology application, the framework of analysis used is correlation and the techniques of analysis are descriptive statistics and structural equation modelling.

To evaluate effects of AI technology application on occupational safety in the downstream petroleum sector within the Greater Accra Region, the framework of analysis used is correlation, and the technique of analysis is regression analysis.

To synthesize a model AI technology application for improved occupational safety, the framework of analysis used is descriptive statistics, and the techniques of analysis are system improvement and modelling.

Model Specification

Structural Equation Modelling (SEM)

In this study, the researcher is examining the relationship between several factors related to the acceptance and application of AI technology and occupational safety in downstream petroleum industries. The following is the proposed SEM model, based on the variables of research interest.

Here are the latent variables (constructs) and the observed variables (indicators) for this model:

1. **Latent Variables (Constructs):**
    - AI Acceptance and Application
    - Personality Factors
    - Attitude Factors
    - Motivation Factors
    - Cognitive Factors
    - Social Factors
    - Organizational Factors

2. **Observed Variables (Indicators):**
    - AI Acceptance and Application: (This will be the dependent variable in the model. It could be measured by several indicators such as usage frequency, proficiency, etc.)
    - Personality Factors: Risk Aversion, Innovativeness
    - Attitude Factors: Technology Attitudes, Trust

- Motivation Factors: Personal Incentiveness, Fear of Technological Failure
- Cognitive Factors: Risk Perception, Technical Knowledge, Perceptions of Certainty, Previous Experience
- Social Factors: Social Influence, Social Norms
- Organizational Factors: Leadership, Collaboration Culture, Technology Adoption Culture

The model can be specified as follows:

- Each of the observed variables is an indicator of their corresponding latent variable. For example, Risk Aversion and Innovativeness are indicators of the latent variable Personality Factors.
- The latent variables Personality Factors, Attitude Factors, Motivation Factors, Cognitive Factors, Social Factors, and Organizational Factors all predict the latent variable AI Acceptance and Application.

In SEM notation, the model can be described as:

- Personality Factors -> AI Acceptance and Application
- Attitude Factors -> AI Acceptance and Application
- Motivation Factors -> AI Acceptance and Application
- Cognitive Factors -> AI Acceptance and Application
- Social Factors -> AI Acceptance and Application
- Organizational Factors -> AI Acceptance and Application

This model specification was fit using SEM software such as STATA 15, and the resulting estimates provided information about the relationships between the relationships between each construct and its indicators. This gives a comprehensive understanding of the various factors that influence AI acceptance and application in the context of occupational safety in downstream petroleum industries.

Multivariate regression analysis was adopted to show the various relationships between the dependent and independent variables. Regression analysis was done to establish whether independent variables predicted the dependent variable. The R square, t-tests and F-tests and Analysis of Variances (ANOVA) tests were generated by the use of STATA 15 to test the significance of the relationship between the variables under the study and establish the extent to which the predictor variables explained the variation in dependent variable (Brace, Kemp & Snelgar, 2012).

$$
\begin{aligned}
\boldsymbol{AI\ acceptance} &\\
&= C + b_1(Technology\ Attitudes) + b_2(Trust)\\
&+ b_3(Personal\ incentives) + b_4(Fear\ of\ technological\ failure)\\
&+ b_5(Risk\ perception) + b_6(Perception\ of\ certainty)\\
&+ b_7(Memory\ of\ previous\ experience)\\
&+ b_8(Technical\ knowledge) + b_9(Social\ influence)\\
&+ b_{10}(Social\ norms) + b_{11}(Leadership)\\
&+ b_{12}(Collaboration\ culture)\\
&+ b_{13}(Technology\ adoption\ culture) + e_n x_n
\end{aligned}
$$

where **AI acceptance** = the dependent variable (y)

the independent variables (regressors) = Innovativeness, Risk aversion, Technology attitudes, Trust, Personal incentives, Fear of technology failure, Risk perception, Perception of certainty, Memory of previous experience, Technical knowledge, Social influence, social norms, Leadership, Collaboration culture, Technology adoption culture

$\mathbf{b_1, b_2, b_3 ... b_{13}}$ = coefficient of regressors.

C = constant

e_n = error term

Profile of Respondents

This section describes characteristics of the respondents. The discussion covers sex, age, educational level, and years of experience on the job. Table 2 shows the demographics of the participants in the study. 187 respondents were surveyed, with 68.44% of them being males and 31.56% of them being females. This means that the downstream petroleum companies in the Greater Accra Region was dominated by males.

Table 2 provides data on the age distribution of the respondents. The largest age group was between 25 and 35 years, making up 45.45% of the sample. The next most represented age group was between 36 to 45 years old, with 33.16% of respondents. The age groups 46 to 50 and below 25 were comparatively less represented, accounting for 11.23% and 8.02% respectively. Those aged over 50 constituted the smallest group with only 2.14%. This data reveals that the sample is primarily composed of relatively young individuals, which is consistent with literature (Baidoo, 2015; Bambio, 2015) that suggests a more youthful demographic in contemporary workforces, especially in Africa.

An examination of the highest educational qualifications of the respondents showed a diverse range of educational backgrounds. The majority of the respondents held either a Diploma/HND (34.22%) or a Bachelor's degree (33.69%). These were followed by those holding a Master's degree, who constituted 19.79% of the sample. A smaller proportion had Certificates

(9.09%) or a Ph.D. (2.67%), and only a negligible fraction reported having no formal education (0.53%). This distribution might indicate a higher level of education among the respondents, which aligns with literature suggesting increasing educational attainment levels in many sectors of the economy.

Table 2: Demographic Characteristics of Respondents

Demographic Variables		Frequency Frequency	%
Sex			
	Males	128	68.44
	Females	59	31.56
Age			
	Below 25 years	15	8.02
	25 – 35	85	45.45
	36 - 45	62	33.16
	46 - 50	21	11.23
	50 +	4	2.14
Highest Educational Qualification			
	No formal education	1	0.53
	Certificate	17	9.09
	Diploma/HND	64	34.22
	Bachelor's degree	63	33.69
	Masters	37	19.79
	Ph.D.	5	2.67
Years of Experience on the Job			
	1-2 years	26	13.90
	3-5 years	71	37.97
	6-9 years	51	27.27
	10-14 years	30	16.04
	15 years and above	9	4.81
Total Number of Respondents		187	100%

In terms of job experience, a large number of respondents had been in their job for between 3 and 5 years (37.97%). Those with 6 to 9 years of experience constituted 27.27% of the sample, and those with 1 to 2 years of experience represented 13.90%. Individuals with 10 to 14 years of experience were less frequent (16.04%), and the smallest group were those with 15 years and above (4.81%). The relatively short job tenure of most respondents could suggest a dynamic workforce with high turnover, a trend often discussed in labor market research. This could also indicate that the respondents are largely early to mid-career professionals.

CHAPTER FOUR

STATE OF AI TECHNOLOGY APPLICATION AND OCCUPATIONAL SAFETY

Introduction

This chapter analyses the results on the state of AI technology application and occupational safety. The rest of the chapter was structured into eight sections. Section 4.1 presented the areas of AI technology application and occupational safety. Sections 4.2 to section 4.8 were committed to the discourse of the various AI technology application domains. Section 4.2 discussed the results on operational efficiency domain. Section 4.3 examined the safety rules compliance domain. Section 4.4 looked at the predictive analytics of the environment domain. Section 4.5 discussed the risk assessment domain. Section 4.6 discussed threats detection/recognition. Section 4.7 presented the data analysis results on the cybersecurity domain, while section 4.8 looked at the theft and fraud domain.

Areas of AI Technology Application and Occupational Safety

Cronbach's alpha was computed in order to determine the reliability of the instrument that was used. The computed Cronbach's alpha value was determined to be 0.9421, which indicates that the scale that was employed was trustworthy. This is because the computed Cronbach's alpha was larger than 0.70, which is the threshold at which reliability can be considered acceptable (Daud et al., 2018). According to Pallant (2001), a measuring scale is deemed to have a high level of reliability if it has a Cronbach's alpha value that is greater than 0.6.

Figure 5 below compares the areas of AI technology application and occupational safety in the Greater Accra Region’s downstream petroleum sector. In all, seven areas were examined namely theft and fraud, cyber security, threats detection/ recognition, risk assessment, predictive analytics of the environment, compliance with safety rules, and operational efficiency.

Figure 5: A Comparison of the Application of AI in the Greater Accra Region's downstream petroleum sector

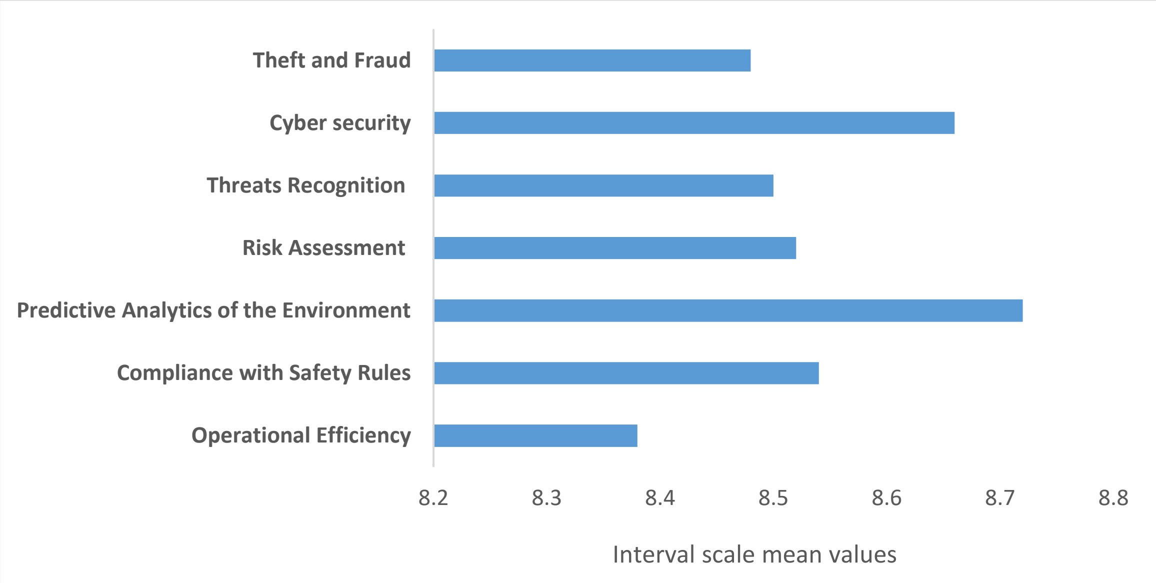


Table 3: Areas of Application of AI Technology

Areas of Application of AI Technology	Median	Skewness	Quartile deviation	Mean	SD
Operational Efficiency				8.38	0.79
Cut down on costs (OE1)	8	0.157	1	8.38	0.80
Prevention of quality failures (OE2)	8	-0.0704	1	8.4	0.80
Time savings (OE3)	8	-0.154	1	8.48	0.78

Compliance with Safety Rules				8.54	0.76
Improve compliance with safety rules (CSR1)	8	-0.133	1	8.4	0.76
Reduce accidents caused by lack of compliance with safety rules (CSR2)	8	-0.036	1	8.34	0.80
Predictive Analytics of the Environment				8.72	0.75
Prevent many occupational health and safety hazards before they happened (PAE1)	8	-0.197	1	8.46	0.78
Save a lot of money that would have otherwise been used to do repairs and damage control (PAE2)	8	-0.074	1	8.4	0.80
Risk Assessment				8.52	0.74
Accurately assess the risk associated with our operations (RA1)	8	-0.021	1	8.56	0.81
Provide insights that inform management of the severity of the risk so that management can take appropriate actions (RA2)	8	-0.083	1	8.48	0.77
Threats Recognition				8.5	0.78
Recognize threats (TR1).	8	-0.134	1	8.34	0.80
Implement security sensors to track and decipher information on potential fires outbreaks (TR2).	8	-0.070	1	8.54	0.76
Neutralize identified threats such as putting on water sprinklers when sensors detect smoke (TR3).	8	-0.134	1	8.46	0.78
Categorize identified threats in order of severity (TR4).	8	-0.104	1	8.34	0.80
Cyber security				8.66	0.79
Make internal network difficult for bad actors to hack or penetrate (CS1)	8	-0.182	1	8.28	0.88
Improve cyber security (CS2).	8	-0.114	1	8.5	0.81

Theft and Fraud				8.48	0.77
Reduce the occurrence of theft and fraud at the workplace (TF1)	8	-0.048	1	8.4	0.76
Increase accountability (TF2)	8	-0.024	1	8.44	0.78
Increase transparency (TF3)	8	-0.011	1	8.66	0.83

The results in Figure 5 show that predictive analytics of the environment recorded the highest score of 8.72 on the 10-point interval scale. This was followed by cyber security with a score of 8.66, and compliance with safety rules in third place recording a score of 8.54. However, the difference between the mean scores of predictive analytics of the environment variable and cyber security variable, was found to be only 0.06 (i.e., 8.72 – 8.66 = 0.06).

To determine whether that difference (0.03) was statistically significant or not, a paired t-test was conducted on the 10-point interval scale scores. The results showed that the difference between the scores for predictive analytics of the environment and cyber security was not statistically significant (t = 0.6098; p = 0.5427). However, the difference between the scores for predictive analytics of the environment and compliance with safety rules was found to be statistically significant (t = 2.3368; p = 0.0205). Table 3 provides a detailed analysis of areas of application of AI technology.

Per the results in Table 3 and Figure 5, operational efficiency recorded the lowest score of 8.38 on the 10-point interval scale, followed by Theft and fraud (8.58). Operational efficiency, and theft and fraud, thus, seem to be the least important areas of consideration when downstream oil companies are deploying AI technology in occupational safety practices. It is worth noting that none of the standard deviations obtained for the constructs and their associated subconstructs, as shown in Table 3, was above one.

A paired t-test showed that the difference between predictive analytics of the environment and compliance with safety rules was statistically significant (p-value = 0.0205, t= 2.3368). The preceding suggests that downstream petroleum companies' attitude towards the deployment of AI for predictive analytics of the environment, and cyber security is markedly different from that exhibited towards compliance safety. Since operational efficiency got the lowest average interval scale score, it appears to be the area where downstream petroleum companies in Ghana's Greater Accra Region use AI technology the least, when it comes to ensuring occupational safety practices.

In the subsequent sections of this chapter, each of the areas of AI technology application under investigation is delved deeper into. First, the current state of using AI technology to improve operational efficiency is broken down and discussed in the light of literature.

Operational Efficiency

Three dimensions of the domain, operational efficiency, were examined. These dimensions were cutting down on costs, prevention of quality failures, and time savings.

Table 4: Application of AI Technology in Operational Efficiency

Operational Efficiency	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
Cut down on costs (OE1)	1.6 (3)	5.35 (10)	6.95 (13)	44.92 (84)	41.18 (77)
Prevention of quality failures (OE2)	0 (0)	5.88 (11)	5.88 (11)	50.80 (95)	37.43 (70)
Time savings (OE3)	0 (0)	4.81 (9)	6.95 (13)	47.59 (89)	40.64 (76)

NB: Values in parathesis represent numbers of respondents.

Cut Down on Costs (OE1)

Concerning cutting down on costs, approximately 41.18% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement "My firm uses AI to cut down on costs (OE1);" while 44.92% moderately agreed (scored between 6-8 on a 0-10 scale), forming the majority. Around 6.95% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to reduce operational costs or not. However, 5.35% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement, and 1.6% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale).

Cutting down costs is not a far-fetched notion. Every company in any conceivable industry would want to cut costs to lower costs of operations. The downstream oil and gas sector is no exception. A combined 86.1% of the respondents either had a high level of agreement (scored between 8-10 on a 0-

10 interval scale) or moderately agreed (scored between 6-8 on a 0-10 interval scale) that AI should cut down on costs (OE1). According to a 2017 Markets & Markets report, there is pressure on oil and gas companies to cut costs.

In a poll conducted in 2015 by Cisco, leaders in the oil and gas industry responded that their primary focus is on maximising the potential of the resources they already possess. The majority of those who participated in the survey identified "operational efficiency of existing projects" and "maintenance of assets and infrastructure" as the top two areas that will benefit most from additional investment in the coming two years (Moriarty et al., 2015). This survey was in 2015, and seven years down the line, it can be observed that many ‘big-time’ petroleum firms are making investments in artificial intelligence technologies. According to a 2017 Markets & Markets report, the value of AI in the oil and gas industry could reach a staggering $2.85 billion by 2022 – with an astounding compound annual growth rate (CAGR) of 13%. This would be a monumental increase from the current value of AI, which was estimated to be around $600 million in 2017. Big data technologies, digitization of the oil and gas industry, investments in AI-related start-ups, and increasing pressure to cut production costs are all things that have led to this rise.

More and more organizations are incorporating AI into a wide range of applications as the technology becomes more inexpensive. As a result of AI's ability to automate labor-intensive activities, it reduces labour costs while also boosting quality (Appen, 2022).

Prevention of Quality Failures (OE2)

Concerning prevention of quality failures, 37.43% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the notion that AI does prevent quality failures (OE2)." This figure was lower than that reported for those who had a high level of agreement with the statement, "My firm uses AI to cut down on costs (OE1)." The observation seems to suggest that downstream petroleum firms prioritize operational efficiency over quality failure prevention, although the meanvalue for preventing quality failures (8.40) is marginally higher than that for cutting down on costs (8.38). However, 50.80% of survey respondents moderately agreed (scored between 6-8 on a 0-10 interval scale) with the statement, "My firm uses AI to prevent quality failures (OE2)," thus making the majority. 5.88% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure whether their firm was using AI to prevent quality failures or not. However, 5.88% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement, "My firm uses AI to prevent quality failures (OE2)." No one had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement.

The issue of quality failures is an important one any oil and gas enterprise. In downstream petroleum sector, quality failures may border on such things as faulty pumps, corrosion of tankers, leakages, and faulty instrumentation. These quality failures can lead to accidents and disasters. As a result of several mishaps and tragedies, the petroleum sector has been linked to a wide range of safety and environmental issues (Ambituuni et al., 2014). Including downstream, this is particularly relevant to the entire industry.

One instance of an oil and gas disaster due to a quality failure that readily comes to mind is the June 3 disaster of 2015 at Circle, a suburb of Accra. When the GOIL station, located near the Kwame Nkrumah Interchange, in the city's downtown region (Baiocchi, 2015),, exploded, it was crowded with people, automobiles, and buses, all anxious to leave for their various destinations after several days of flooding in the city (Karimi & Lett, 2015). However, it is widely thought that the explosion was caused by a leak in the station's gasoline tanks. As soon as the electricity was restored, a "pop" was heard and the fire started, according to one of the survivors. At least 96 persons who had taken refuge in the station were killed in the blaze. As a result of the flooding, water had mingled with the fuel. When the explosion of the tanks occurred, the mingled water facilitated the spread of the fire to surrounding buildings and killed more people. Rescue operations were hampered by the on-going downpours and floodwaters.

Time savings (OE3)

About 40.64% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement "My firm uses AI to save time (OE3);" while 47.59% moderately agreed (scored between 6-8 on a 0-10 scale) with the statement, thus making the majority. 6.95% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 scale), unsure if their firm was using AI to save time or not. However, 4.81% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 scale) with the statement, and none of the survey respondents had a high level of disagreement (scored between 0-2 on a 0-10 scale) with the statement. The time-saving potential of artificial intelligence technology is vast. During the planning stages of a gasoline filling station, artificial intelligence (AI) technology can be used to survey a potential construction site and gather sufficient information to develop 3D maps, drawings, and construction plans (Debney, 2018).

One day is now all that is needed to complete a task that, in the past, would have taken several weeks (Debney, 2018). This enables businesses to save not only time but also money that would have been spent on labour. The use of artificial intelligence allows for more efficient planning and task distribution among personnel. For instance, workers can input information into a data system such as sick days, vacancies, and unexpected departures, and the system can adjust the project accordingly. The AI will recognise that the responsibility for completing the assignment must be transferred to another employee, and it will make the necessary arrangements on its own initiative.

Safety Rules Compliance

Two dimensions of the domain, safety rules compliance, were examined. These dimensions were improving compliance with safety rules, and reduction of accidents caused by lack of compliance with safety rules.

Table 5: Application of AI Technology in Safety Rules Compliance

Compliance with Safety Rules	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
Improve compliance with safety rules (CSR1)	0 (0)	4.28 (8)	7.49 (14)	51.34 (96)	36.90 (69)
Reduce accidents caused by lack of compliance with safety rules (CSR2)	0 (0)	5.35 (10)	9.09 (17)	48.66 (91)	36.90 (69)

NB: Values in parathesis represent numbers of respondents.

Improving Compliance with Safety Rules

Approximately 36.90% of respondents had a high level of agreement (scored 8-10 on a 0-10 interval scale) with the statement "My firm uses AI to improve compliance with safety rules (CSR1)," while 51.34% moderately agreed (scored 6-8 on a 0-10 interval scale), making up the majority. About 7.49% expressed an uncertain stance (scored 4-6 on a 0-10 interval scale), unsure whether their firm was using AI to improve compliance with safety rules or not. However, 4.28% moderately disagreed (scored 2-4 on a 0-10 interval scale) with the statement, and none expressed a high level of disagreement (scored 0-2 on a 0-10 interval scale).

When it comes to compliance with safety rules, downstream petroleum firms seem more focused on improving compliance than reducing accidents caused by lack of compliance. This is evidenced by 51.34% of survey respondents indicating a high level of agreement (scored 8-10 on a 0-10 scale) with the statement "My firm uses AI to improve compliance with safety rules (CSR1)" compared to the 48.66% for the statement "My firm uses AI to reduce accidents caused by lack of compliance with safety rules (CSR2)." Furthermore, a smaller percentage of respondents expressed uncertainty (CSR1: 7.49%; CSR2: 9.09%) regarding the statement "My firm uses AI to improve compliance with safety rules (CSR1)," along with a lower percentage of respondents disagreeing with CSR1 (4.28%) compared to CSR2 (5.35%).

The apparent strong concern for improving compliance with safety rules may have a lot to do with reducing accidents caused by lack of compliance with safety rules. The downstream petroleum firms do realize that the “cure” for reducing accidents due to lack of compliance with safety rules is to improve compliance with safety rules. Hence, the finding that seem to suggest that downstream petroleum firms are more concerned with improving compliance with safety rules than reducing accidents caused by the lack of compliance with safety rules. Achaw & Boateng, (2012) observed that there are, in fact, specific safety concerns that are intrinsic to the operations of the oil, gas, and other energy-related industries. Thus, it was only natural that oil and gas firms be concerned with compliance with safety rules. These hazards, according to Achaw & Boateng (2012), if they are not regulated or managed in an appropriate manner, have the potential to cause damage to human life, property, and the environment.

Although there are a few local regulations in Ghana that deal with certain aspects of occupational health and safety in the country's industry, Achaw & Boateng (2012) found that the country does not have a comprehensive national policy on occupational health and safety to direct the activities of the industrial sector. As a direct consequence of this, each of the businesses that researchers looked into created their own set of operational safety requirements. This, to a large extent, explains the preoccupation downstream petroleum firms have with compliance safety rules and the use of AI technology to enforce it. From the data collected, it appears that in Ghana it is only the multinationals that are using AI technology in their day-to-day operations. Some multinational companies like Shell are "walking the AI talk" as evident in the scenario below.

Imagine a scenario in which a guy is waiting for his car to finish filling up at a Shell gas station in Singapore, and he decides to light up a cigarette while he is there. He does not realise that by doing so, he runs the risk of his car catching fire or exploding. It is now possible to utilise algorithms powered by artificial intelligence to distinguish this behaviour from the myriad of other activities taking place at the filling station, such as drivers cleaning the windshields of their vehicles and passengers purchasing food. This is made possible by virtue of a device inside the station that is running Microsoft Azure IoT Edge and an onsite video camera that records the footage of incidents for data processing. The Microsoft Azure IoT Edge installed onsite at the filling station enables local processing of data without relying on the cloud and allows for basic machine learning techniques to exclude irrelevant information (Langston, 2018). This serves as the first line of defence at the "intelligent edge." With the help of AI, other high-risk situations can be found as well, like reckless driving, theft, and improper fuelling, among others.

Images with possible "red flags" are immediately uploaded to the cloud service provided by Microsoft, where they may be used to build increasingly advanced deep learning AI models. These are able to determine that the man is smoking and immediately raise an alarm on an onsite dashboard. This gives the station management the opportunity to take preventative measures and turn off the pump before any damage is caused. This pilot project, which is now being implemented at two gas stations in Thailand and Singapore, is just one example of how Shell is integrating artificial intelligence (AI), cloud computing, and Internet of Things (IoT) technologies across all aspects of its energy business (Langston, 2018). Shell has developed cutting-edge technologies that are making operations safer, boosting efficiency, saving money, and assisting employees in communicating and sharing solutions across the global company. These technologies can be found everywhere from oil and natural gas fields to gas pumps and electric charging stations.

Shell has decided to fuel its new enterprise-wide artificial intelligence platform with the help of C3 IoT and Microsoft Azure in order to speed up the digital transformation of its operations on a worldwide scale. It has plans to implement the Shell AI Platform in a diverse range of applications, such as determining when hundreds of thousands of pieces of equipment in offshore production hubs, refineries, or wells require maintenance before problems arise and ensuring that parts and inventory can reach remote locations quickly. Yuri Sebregts, Shell's executive vice president for technology and chief technology officer, stated that "the new possibilities in working with data over the last few years are unlocking amazing opportunities in all aspects of what we do in the company" (Langston, 2018).

For instance, Shell is now able to predict in many instances 24 or 48 hours in advance when a compressor is at risk of failing, which is something that was not feasible to accomplish in the past despite the fact that there is a lot of instrumentation on these enormous and sophisticated equipment. They have shown this on a few tens of compressors, and they believe that applying it to tens of thousands of units all around the world will be of tremendous assistance. The C3 IoT (Internet of Things) and Microsoft makes it possible for businesses to effortlessly ingest and visualise real-time data from all aspects of their business operations. Shell intends, at some point in the not-too-distant future, to use the platform to tackle further difficulties including machine learning, computer vision, and natural language processing. This is just one of the ways that Shell and Microsoft are working together to help digitally transform a company like Shell, which employs 85,000 people in 70 different countries, manages critical energy infrastructure all over the world, and operates 44,000 retail gas station and convenience store locations all over the world (Langston, 2018).

Reducing Accidents Caused by Lack of Compliance with Safety Rules

About 36.90 % of respondents had high level of agreement with the statement, "My firm uses AI to reduce accidents caused by lack of compliance with safety rules (CSR2)." That figure was identical to that obtained for the statement, "My firm uses AI to improve compliance with safety rules (CSR1)." 48.66% agreed with CSR2, thus making the majority. 9.09% of respondents were neutral, being unsure of whether their firm was using AI to reduce accidents caused by lack of compliance with safety rules or not. However, 5.35% of respondents disagreed with the above statement, and no respondent strongly disagreed with the statement, “My firm uses AI to reduce accidents caused by lack of compliance with safety rules.”

The oil and gas business is one of the most dangerous and demanding industries in terms of the level of physical security required. Employees at energy sites are subjected to a variety of safety risks on a daily basis, including but not limited to the following: hazardous processes, excessive operating temperatures, dangerous weather conditions, and the ongoing possibility of fires and explosions (Scylla, 2021). As a result, businesses are required to comply with a wide variety of stringent regulatory compliance requirements to reduce accidents by maintaining acceptable levels of safety and security and to safeguard people, property, and assets. If requisite safety protocols are not followed, there is a risk of significant accidents and ensuing injuries, as well as potential financial fines for the organisation. To reduce the probability of accidents at a downstream petroleum site, oil and gas operation sites can benefit from the use of AI-powered computer vision technologies that can assist security personnel in real-time site inspections and monitoring. Safety precautions, such as wearing the proper protective gear, keeping a safe distance from the machinery, and staying in specified safety areas, are monitored by AI algorithms integrated in cameras. In the event of even the tiniest deviations from compliance, the management is notified immediately. A variant of the above AI technology is what Shell is piloting in Singapore.

Predictive Analytics of the Environment

Two dimensions of the domain, predictive analytics of the environment, were examined. These dimensions were prevention of occupational health and safety hazards before they happened, and predictive preventive maintenance.

Table 6: Application of AI Technology in Predictive Analytics Environment

Predictive Analytics of the Environment	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
Prevent many occupational health and safety hazards before they happened (PAE1)	0 (0)	4.28 (6)	8.56 (16)	47.06 (88)	40.11 (75)
Save a lot of money that would have otherwise been used to do repairs and damage control (PAE2)	0 (0)	4.28 (8)	10.70 (20)	45.99 (86)	39.03 (73)

NB: Values in parathesis represent numbers of respondents.

Preventing Occupational Health and Safety Hazards before they happened.
About 40.11% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement "AI helps my firm to prevent many occupational health and safety hazards before they happened"; while 47.06% moderately agreed (scored between 6-8 on a 0-10 scale) with the statement. This means that a total of 87.17% of survey respondents either had a high level of agreement or moderately agreed with the statement that AI helps their firms prevent many occupational health and safety hazards before they occurred – a

strong indication of the high priority downstream petroleum firms in the Greater Accra Region place on occupational health and safety. This is not surprising considering the June 3rd Flood and Fire disaster that occurred in 2015.(Baiocchi, 2015; Karimi & Lett, 2015). 8.56% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to prevent many occupational health and safety hazards before they happened. However, 4.28% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement, and none of the respondents had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement.

The results of the study as seen in Figure 5 showed that the commonest area of AI application in the Greater Accra Region's downstream petroleum sector tended to be predictive analytics of the environment, as evinced by it obtaining the highest mean value of 8.72. The preceding result meant that the ability to predict what could happen in the operating environment (predictive analytics of the environment) under certain hazardous conditions matters most to downstream petroleum companies than any other thing, as far as the scope of the present study is concerned. That is because downstream petroleum businesses appear to be most keen on preventing any occupational health and safety hazards before they happen and saving a lot of money that would have otherwise been used to do repairs and damage control.

Saving a lot of money that would have otherwise been used to do repairs and damage control

About 39.03% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "The predictive power of AI is used to help my firm save a lot of money that would have otherwise been used to do repairs and damage control (PAE2);" while, 45.99% moderately agreed (scored between 6-8 on a 0-10 interval scale) with the statement. This implies that a total of 85.02% of survey respondents either had a high level of agreement or moderately agreed with the statement that the predictive power of AI is used to help their firm save money on repairs and damage control – a strong indication of the high priority downstream petroleum firms in the Greater Accra Region place on predictive preventive maintenance. However, concerning predictive analytics of the environment, oil and gas firms in the downstream segment of the industry seem to prize the application of predictive analytics in occupational health and safety more when compared to predictive preventive maintenance that leads to cost savings. This is evidenced by the fact that 87.17% of survey respondents either had a high level of agreement or moderately agreed with the statement that AI helps their firms prevent many occupational health and safety hazards before they happened, compared to the 85.02% reported for the statement, "the predictive power of AI is used to help my firm save a lot of money that would have otherwise been used to do repairs and damage control." About 8.56% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to prevent many occupational health and safety hazards before they happened. However, 4.28% of respondents had a moderate level of disagreement (scored between 2-4 on a

0-10 scale) with the statement, and none of the respondents had a high level of disagreement (scored between 0-2 on a 0-10 scale) with the statement.

The upstream, middle, and downstream operations of the oil and gas industry all use machinery that is at least 15 years old (Vaz, 2022). As a result, they require routine maintenance and inspection in order to remain functional. However, this type of reactive maintenance does not offer any guarantees against unplanned downtime (Vaz, 2022). This is where the predictive power of AI comes in. Predictive maintenance in the oil and gas industry can be achieved via Internet of Things (IoT)-enabled technology, such as sensor data, and predictive analytics. As a result of this, maintenance expenses are reduced, and unanticipated equipment breakdowns are avoided.

Every year, the typical oil and gas company experiences at least 27 days of unexpected downtime, which results in a loss of revenue of $38 million (Vaz, 2022). Even if the system is out for only 3.65 days, the resulting losses could reach up to $5 million. Because of this, predictive maintenance is quite significant. Innovative technologies for predictive maintenance make use of artificial intelligence, machine learning, and advanced analytics to identify possible problems and notify the appropriate technicians in order to avert the possibility of equipment failure and associated safety hazards. According to a report by McKinsey as cited in Vaz (2022), an offshore oil and gas business implemented a predictive maintenance solution, which led to a reduction in downtime of twenty percent and an increase in yearly production of more than five hundred thousand barrels of oil.

One use case of the predictive power of AI in the predictive maintenance of petroleum filling stations is the monitoring of tank pressure. Monitoring the tank pressure is crucial for the protection of workers, the maintenance of the uncompromised integrity of the tank's contents, and the reduction of emissions necessary to remain in compliance with ever more stringent environmental requirements (Vaz, 2022). In addition, the fluctuations in the liquid level and temperature make it essential to do constant pressure checks on the storage tank. Real-time monitoring using predictive maintenance solutions and IoT tank sensors for ullage, pressure, temperature, or discharging rate can tackle these challenges and manage tank pressure changes effectively. As a result, oil and gas companies can ensure rapid response to performance fluctuations, higher emissions, potential oxidation, or imminent equipment failure.

A paired t-test showed that the difference between the meanvalues for predictive analytics of the environment and compliance with safety rules was statistically significant, as evinced by a p-value of 0.0205, which is below 0.05. The preceding suggests that downstream petroleum companies' attitude towards the deployment of AI for predictive analytics of the environment, and cyber security is markedly different from that exhibited towards compliance safety. Since operational efficiency got the lowest average Interval scale score, it appears to be the area where downstream petroleum companies in Ghana's Greater Accra Region use AI technology the least, when it comes to ensuring occupational safety practices.

Risk Assessment

Two dimensions of the variable, risk assessment, were examined. These dimensions were accurate assessment of risk, and provision of risk insights.

Table 7: Application of AI Technology in Risk Assessment

Risk Assessment	Frequency Distribution of Responses, % (n)				
	0-2	**2-4**	**4-6**	**6-8**	**8-10**
Accurately assess the risk associated with our operations (RA1)	0 (0)	4.81 (9)	8.02 (15)	41.71 (78)	45.45 (85)
Provide insights that inform management of the severity of the risk so that management can take appropriate actions (RA2)	0 (0)	3.74 (7)	9.63 (18)	45.99 (86)	40.64 (76)

NB: Values in parathesis represent numbers of respondents.

Accurate Assessment of Risk

Concerning accurate assessment of risk, about 45.45% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the notion that AI is used to accurately assess the risk associated with firm operations (RA1)." This figure was higher than that obtained for the statement, "Our AI is used to provide insights that inform management of the severity of the risk so that management can take appropriate actions (RA2)." 41.71% moderately agreed (scored between 6-8 on a 0-10 interval scale) with RA1. 8.02% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to accurately assess the risk associated with their company operations. However, 4.81% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement (i.e., RA1). No respondent had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that artificial intelligence is used to accurately assess the risk associated with company operations. Risk is an inherent part of the oil and gas business.

When dealing with and assessing unstructured data, which is the kind of information that does not easily fit into structured rows and columns, the application of artificial intelligence as a risk management tool can be of great assistance (Hans, 2016). Cognitive technologies such as natural language processing (NLP), a subcomponent of AI, use sophisticated algorithms to do text analysis in order to get insights and determine sentiment from unstructured data. Examples of unstructured data sources in the oil and gas sector are weekly staff reports, technical reports, supervisors' reports, audit reports, and internal memos. These reports when subjected to artificial intelligence technology could lead to the unearthing of valuable insights on risks, that may otherwise not be apparent to humans. According to Hans (2016), the implementation of cognitive analytics can position firms at the forefront of their industries, given that research conducted by the International Data Group in 2015 estimated that approximately 90 percent of the data collected today is unstructured. When managers of downstream petroleum companies use cognitive technology to predict and manage risk in a proactive way, they not only gain a competitive edge, but they can also use risk to boost the performance of their businesses.

Provision of Insights that inform management of the severity of the risk

Regarding provision of insights that inform management of the severity of the risk, About 40.64% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the notion that AI is used to provide insights that inform management of the severity of the risk so that management can take appropriate actions (RA2). This figure was lower than that obtained for the statement, "Our AI is used to accurately assess the risk associated with our operations (RA1)." 45.99% moderately agreed (scored between 6-8 on a 0-10 interval scale) with RA2. 9.63% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to provide insights that inform management of the severity of the risk so that management can take appropriate actions. However, 3.74% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement (i.e., RA2). No respondent had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that their firm uses artificial intelligence to provide insights that inform management of the severity of the risk so that management can take appropriate actions. In highly competitive environments, these AI-powered insights can make all the difference. It is possible, using artificial intelligence technologies, to gain insights as to why one petroleum filling station is consistently underperforming when compared to others operating under the same brand. Royce (2019) of Google calls it the “disruption of insight,” alluding to the capability of AI-powered insights to totally disrupt an industry. According to Google, AI is currently being implemented in sixty percent of the world's enterprises because of the powerful insights AI technology provides (Sheth, 2018).

Threats Detection/Recognition

Two dimensions of the variable, risk assessment, were examined. These dimensions were accurate assessment of risk, and provision of risk insights.

Table 8: Application of AI Technology in Risk Detection/Recognition

Threats Detection/Recognition	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
Recognize threats (TR1).	0 (0)	5.35 (10)	7.49 (14)	49.20 (92)	37.97 (71)
Implement security sensors to track and decipher information on potential fires outbreaks (TR2).	0.53 (1)	5.35 (10)	10.16 (19)	48.13 (90)	35.83 (67)
Neutralize identified threats such as putting on water sprinklers when sensors detect smoke (TR3).	0 (0)	5.35 (10)	10.70 (20)	50.27 (94)	33.69 (63)
Categorize identified threats in order of severity (TR4).	0 (0)	5.35 (10)	10.16 (19)	46.52 (87)	37.97 (71)

NB: Values in parathesis represent numbers of respondents.

Recognition of Threats (TR1)

Concerning recognition of threats, 37.97 % of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "Our AI is used to recognize threats (TR1)." That figure was higher than that for statement TR2, which is, *Implement security sensors to track and decipher information on potential fires outbreaks* (35.83%) and TR3, which is, *Neutralize identified threats such as putting on water sprinklers when sensors detect smoke* (33.69%) but equal to that for TR4 (i.e., *Categorize identified threats in order of severity*), suggesting that occupational safety threats such as lighting a cigarette at a filling station can be catastrophic. The use of AI can isolate these behaviors and alert sent to the responsible party such as the manager of the filling station for the threat to be immediately removed. Using certain artificial intelligence-based technologies such as sensors real time data can be picked up about the condition of petroleum storage tanks at filling stations. And if there is leakage, AI technologies can be used to detect such a threat for immediate action to be taken.

Moreover, about 49.20% of respondents moderately agreed (scored between 6-8 on a 0-10 scale) with the statement "Our AI is used to recognize threats (TR1)," further emphasizing the importance of threat detection or recognition to downstream petroleum firms. 7.49% expressed an uncertain stance (scoring between 4-6 on the 0-10 interval scale), unsure if their firm was using AI for threat detection or not. However, 5.35% had a moderate level of disagreement (scored between 2-4 on the 0-10 interval scale) with the statement (TR1). No respondent had a high level of disagreement (scored between 0-2 on the 0-10 interval scale) with the statement that artificial intelligence is used to recognize threats.

Implementation of security sensors to track and decipher information on potential fires outbreaks (TR2)

About 35.83% of respondents had a high level of agreement (scored between 8-10 on the 0-10 interval scale) with the statement, "My firm uses AI to implement security sensors to track and decipher information on potential fire outbreaks (TR2)," while 48.13% moderately agreed (scored between 6-8 on the 0-10 interval scale) with TR2. 10.16% expressed an uncertain stance (scored between 4-6 on the 0-10 interval scale), unsure if their firm was using AI to implement security sensors to track and decipher information on potential fire outbreaks. However, 5.35% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with statement TR2. No respondent had a high level of disagreement (that is, scored between 0-2 on the 0-10 interval scale) with the statement that artificial intelligence is used to implement security sensors to track and decipher information on potential fire outbreaks.

Through their applications in virtually every industry, sensor technologies have made people's lives easier in many aspects of their daily routines (Javaid et al., 2021). Sensors are devices that detect changes in the source or environment and collect signals in order to develop a reaction that is appropriate for the detected change. It is possible to make use of a wide variety of sources, such as light, temperature, motions, pressure, and so on and so forth. Innovative sensor technologies are used in a wide variety of applications in lifestyle, healthcare, fitness, manufacturing, as well as the downstream petroleum sector. Some examples of these uses include when connected to a network, sensors not only provide important information but also share that information with other connected devices and administrative systems. Therefore, sensors are essential to the efficient operation of a lot of different businesses. In the downstream petroleum sector, as indicated earlier above, AI-powered sensors can be used to monitor the environmental conditions at the petroleum filling station so that if such environmental variables as temperature and pressure exceed acceptable threshold levels, an alert can immediately be sent to the manager of the facility for the necessary support actions to be taken, while the AI takes corrective actions. If there is leakage, AI technologies can be used to detect such a threat for immediate action to be taken. One core advantage of an AI technology system is its ability to process large volumes of structured and unstructured data, but most especially unstructured data, at lightning speeds for quick insights. Time to insights is an important metric worth considering when considering the use of any AI technology, as a delayed insight has the potential to become useless, especially when the occupational safety issue it is supposed to prevent has already happened (Royce, 2019).

Neutralization of Identified Threats (TR3)

Artificial intelligence has a role to play in the neutralization of identified threats. About 33.69% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "Our AI is used to neutralize identified threats such as putting on water sprinklers when sensors detect smoke (TR3)," while 50.27% moderately agreed (scored between 6-8 on a 0-10 scale) with TR3. This finding implies that a significant majority (83.96%) of respondents in the survey either moderately agreed or had a high level of agreement with the notion that AI technology plays a crucial role in their firm's response to identified threats. It highlights the growing importance of AI in addressing various risks and challenges faced by firms within the downstream petroleum sector. 10.70% expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to neutralize identified threats like activating water sprinklers when sensors detect smoke. However, 5.35% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement (i.e., TR3). No respondent had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that artificial intelligence is used to neutralize identified threats such as putting on water sprinklers when sensors detect smoke.

Categorization of Identified Threats in order of Severity (TR4)

Not all identified threats fall within the same order of severity. About 37.97% of respondents had a high level of agreement (scored between 8-10 on the 0-10 interval scale) with the statement, "Our AI is used to categorize identified threats in order of severity (TR4)," while 46.52% moderately agreed (scored between 6-8 on the 0-10 interval scale) with TR4. This suggests that 84.49% of respondents had either moderate or high levels of agreement with the notion that their firms use AI technology to categorize identified threats in order of severity. The severity of the threat determines what type of action will be taken. For instance, a fire outbreak event will be categorized at a higher level of severity than an occupational safety hazard of a worker not wearing personal protective equipment, as the impact of a fire outbreak in an oil and gas facility is far more devastating and immediate. About 10.16% expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), unsure if their firm was using AI to categorize identified threats in order of severity. However, 5.35% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement (i.e., TR4). No respondent had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that artificial intelligence technology was being used to identify threats in order of severity.

Cyber Security

Two dimensions of the variable, cyber security, were examined. These dimensions were making internal network difficult for bad actors to hack or penetrate and improving cyber security.

Table 9: Application of AI Technology in Cyber Security

Cyber Security	Frequency Distribution of Responses, % (n)				
	0-2	2-4	3-6	6-8	8-10
Make internal network difficult for bad actors to hack or penetrate (CS1)	1.07 (2)	4.81 (9)	11.76 (22)	43.85 (82)	38.50 (72)
Improve cyber security (CS2)	0 (0)	4.81 (9)	8.56 (16)	43.85 (82)	42.78 (80)

NB: Values in parathesis represent numbers of respondents.

Making internal network difficult for bad actors to hack or penetrate (CS1)

Approximately 38.50% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "AI technology is used to make my company's internal network difficult for bad actors to hack or penetrate (CS1)," while 43.85% moderate level of agreement with CS1 (scored between 6-8 on a 0-10 interval scale), suggesting that 82.35% of respondents either had moderate or high level of agreement with the notion that AI technology is used to make their company's internal network difficult for bad actors to hack or penetrate. 11.76% of respondents expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale), being unsure of whether their firm was using AI to make their company's internal network difficult for bad actors to hack or penetrate. However, 5.35% of respondents had moderate level of disagreement with the above statement (i.e., CS1) (scored between 2-4 on a 0-10 interval scale). No respondent had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that artificial intelligence technology was being used to make their company's internal network difficult for bad actors to hack or penetrate.

Improve Cyber Security (CS2)

Approximately 42.78% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "My firm deploys AI technology to improve the company's cyber security (CS2)," while 43.85% had moderate level of agreement with CS2 (scored between 6-8 on a 0-10 scale), suggesting that 86.63% of respondents had either moderate or high level of agreement with the notion that AI technology is used to improve their firm's cyber security. Based on this data, downstream petroleum firms seem to be more focused on improving cyber security than making their internal network difficult for bad actors to hack or penetrate, since a higher percentage of survey respondents (86.63%) moderately agree or had strong level of agreement with the notion that AI technology is used to improve their firm's cyber security compared to the 82.35% percentage frequency for CS1. This could be because the digital environment is facing ever-evolving hacking targets and methodologies (Flowers, 2020). Over the past five years, the incidence of cybercrime has risen by 67%, resulting in a 72% increase in the cost incurred by each organization. According to the 2019 Accenture's Cost of Cybercrime study, conducted across 16 industries and 11 countries, both threats and impacts are increasing. Some people even consider these crimes as "acts of war." 11.76% of respondents were neutral (scored between 4-6 on a 0-10 interval scale), being unsure of whether their firm was using AI to make their company's internal network difficult for bad actors to hack or penetrate. However, 5.35% of respondents had a moderate level of disagreement with the above statement (i.e., CS1) (scored between 2-4 on a 0-10 interval scale). No respondent had a strong level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement that artificial intelligence technology was being used to make their company's internal network difficult for bad actors to hack or penetrate.

Furthermore, per the results of the study in Table 3, the second commonest area considered for the deployment of AI was observed to be cyber security (8.66). The results of a paired t-test showed that the difference between the mean values for predictive analytics of the environment and cyber security was not statistically significant ($t = 0.6098$; $p = 0.5427$), suggesting that downstream petroleum companies' attitude towards the deployment of AI for predictive analytics of the environment is not markedly different from that exhibited towards cyber security. In other words, downstream oil firms view cyber security, and predictive analytics of the environment as equally important, when it comes to deploying AI.

Theft and Fraud

Two dimensions of the domain, safety rules compliance, were examined. These dimensions were reduction in the occurrence of theft and fraud at the workplace, increase in accountability, and increase in transparency.

Table 10: Application of AI Technology in Theft and Fraud

Theft and Fraud	Frequency Distribution of Responses, % (n)				
	0-2	**2-4**	**4-6**	**6-8**	**8-10**
Reduce the occurrence of theft and fraud at the workplace (TF1)	0 (0)	4.28 (8)	7.49 (14)	51.87 (97)	36.36 (68)
Increase accountability (TF2)	0 (0)	4.28 (8)	8.56 (16)	48.13 (90)	39.04 (73)
Increase transparency (TF3)	0 (0)	4.81 (9)	9.09 (17)	34.76 (65)	51.34 (96)

NB: Values in parathesis represent numbers of respondents

Reducing the Occurrence of Theft and Fraud (TF1)

Approximately 36.36% of respondents expressed a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "My firm uses AI to reduce the occurrence of theft and fraud at the workplace (TF1);" meanwhile, 51.87% expressed a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). This indicates that a considerable 88.23% of survey respondents expressed either a moderate or high level of agreement with the notion that AI was employed in their firm to mitigate theft and fraud. From this observation, it can be inferred that theft and fraud might be prevalent challenges in the downstream petroleum sector, given the number of study participants responding affirmatively to statement TF1. This perhaps explains why companies, including oil and gas firms, are turning to artificial intelligence to detect and prevent everything from mundane theft to that committed by their own employees (Quest et al., 2018). Companies can identify potential areas of criminal activity, such as fraud, money laundering, and terrorist financing, as well as more mundane crimes, such as employee theft, cyber fraud, and fake invoices, through the use of AI, which assists public agencies in more effectively and efficiently prosecuting these offences (Quest et al., 2018). In a paper, Vaithianathasamy (2019) makes the case that it is essential for businesses to always keep in mind that thieves and fraudsters are entrepreneurs; this is the first and most important rule for limiting risk and managing theft and fraud. It's a common misconception that hackers are lone wolves that wear hoodies (Vaithianathasamy, 2019). According to Vaithianathasamy (2019), a significant number of them are very sophisticated fraud operations that make use of the most cutting-edge technologies available, including artificial intelligence (AI). Against the above backdrop, AI technology usage in the operations of an oil and gas firm may no longer be an option.

About 7.49% of respondents expressed a neutral stance (scored between 4-6 on a 0-10 interval scale), being unsure of whether their firm was using AI to reduce the occurrence of fraud or not. However, 4.28% of respondents expressed moderate level of disagreement with the above statement (scored between 2-4 on a 0-10 interval scale), and none expressed a high level of disagreement with the statement (scored between 0-2 on a 0-10 interval scale).

Increasing Accountability and Transparency (TF2)

Approximately 39.04% of respondents expressed a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "My firm uses AI to increase accountability (TF2)," while 48.13% expressed moderate level of agreement with TF2 (scored between 6-8 on a 0-10 interval scale), suggesting that 87.17% of respondents expressed either a moderate or high level of agreement with the notion that AI technology is used to increase accountability. However, regarding transparency, more of the survey respondents (51.34%) had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "My firm uses AI to increase transparency (TF3)." The preceding appears to suggest that when it comes to the downstream petroleum sector, transparency seems to be more of an issue than accountability, although transparency and accountability are closely related themes, as evinced by the Pearson correlation coefficient of 0.7786, which was found to be statistically significant ($p < 0.05$).

Olujobi (2021) argues that Nigeria's downstream petroleum sector has been characterised by corruption and a lack of openness and accountability, according to reports on fuel subsidies. In another instance, after discovery of oil in large commercial quantities in Ghana and in a bid to avoid the curse of resources, Obeng-Odoom (2015) observed that transparency being a primary focus, led to the proliferation of many transparency-centred institutions, and think tanks, that are focused on transparency. The Ghana Extractive Industries Transparency Initiative (GHEITI) is one such example, although it predates the discovery of oil in large commercial quantities. One interesting thing about this organization is the coinage of its name – transparency features prominently further lending credence to assertions that transparency may be more of an issue than accountability, though both are closely linked.

Approximately, 8.56% of respondents expressed a neutral stance (scored between 4-5.9 on a 0-10 interval scale), being unsure of whether their firm was using AI to increase accountability, compared to 4.81% for transparency (scored between 4-6 on a 0-10 interval scale). However, 4.28% of respondents had a moderate level of disagreement with the statement TF2 (scored between 2-4 on a 0-10 interval scale), while 4.81 had a moderate level of disagreement with statement TF1 (scored between 2-4 on a 0-10 interval scale). However, no respondent had a high level of disagreement with the statement that artificial intelligence technology was being used to increase accountability or transparency.

CHAPTER FIVE

DETERMINANTS OF AI TECHNOLOGY APPLICATION

Introduction

This chapter tries to answer the second research question, " What are the determinants of AI Technology application in occupational safety practices within the Greater Accra Region's downstream petroleum industry?" In addressing the preceding research question, fifteen (15) different factors, known from literature to be key determinants of technology acceptance as proxy for AI Technology application, were subjected to structural equation modelling (Roberts et al., 2021). The fifteen (15) factors acted as the independent variable. AI acceptance and application acted as the dependent variable and was proxied by the responses to the question, "Does your firm apply artificial intelligence technology in its operations?" The findings from this analysis will be useful in designing interventions to promote the widespread use of cutting-edge technologies in Oil and Gas (O&G) and other high-hazard fields. The rest of the chapter is structured as follows: Section 5.1 presents a priori expectations on the personality factors (section 5.1.1.1) , attitude factors (section 5.1.2), motivation factors (section 5.1.3), cognitive factors (section 5.1.4), and organizational factors (section 5.1.6). Section 5.2 presents the data analysis. Section 5.2 was further subdivided into descriptive statistics (section 5.2.1), inferential statistics (section 5.2.2), evaluation of results (section 5.2.3), and theoretical implications of findings on determinants of AI acceptance (section 5.2.4).

A Priori Expectations

Artificial Intelligence Technology Application (AITA) will be determined by personality factors, Attitude Factors, Motivation Factors, Cognitive Factors, Social factors and Organisational Factors.

$$AITA - f(Pfi, Afi, Mfi, Cfi, Sfi, Ofi)$$

Where Pfi represents Personality factors

$Afi\ reresents\ Atitude\ factors$

$Mfi\ represents\ Movtivation\ factors$

$Cfi\ represents\ Cognitive\ factors$

$Sfi\ represents\ Social\ factors$

$Ofi\ represents\ organisational\ factors$

Personality Factors

Personality (Category): a person's unique set of traits, interests, motivations, values, and perceptions of oneself and one's abilities and emotions, as well as the ways in which these influence how they deal with life (American Psychological Association Dictionary). Innovativeness and risk aversion both play a role in technology uptake.

Innovativeness

The ability to think outside the box is a key component of being innovative (Aldahdouh et al., 2019; Hurt et al., 1977). Additionally, this includes an eagerness to try out new technologies (both personally and professionally). This might be anything from a desire to continue with what has worked in the past to an openness to trying something new. When it comes to the definition of "innovativeness," researchers can not agree on what it means (Hauser et al., 2006). They have come up with everything from a willingness to learn about and adopt new products (Goldsmith & Hofacker, 1991) to a willingness to take risks and a capacity to deal with uncertainty (Agarwal & Prasad, 1997) to an openness to change (Bartels & Reinders, 2011; Hurt et al., 1977). The phrase "innovativeness" is more commonly used in the oil and gas industry than "openness to change" when discussing the adoption of new technologies.

Introducing new technology into the oil and gas industry is a difficult task because of the significant operational, financial, and safety risks of failure; the high expense of being the first to embrace; and, a competitive culture that encourages early adopters to innovate (Radnejad et al., 2017). It is not uncommon for businesses to consider themselves "second or third generation" consumers of new technologies. As a result of this, the sector's "clock speed," or the rate at which an innovation is adopted and implemented in a corporate context, is extremely slow (estimated as high as 16 years for oil and gas; Noke et al., 2008). Small and medium-sized enterprises (SMEs) have also come under fire for being slow and conservative in adopting new technologies (Afolayan & de la Harpe, 2020). The post-COVID-19 world is expected to encounter similar issues, with uncertainty and the necessity for rapid transitions into new methods of functioning using technical solutions" (Juergensen et al., 2020). A unique aspect of the oil and gas business is that there has been a strong push from within to improve innovation techniques, including a focus on the role of people in the process (Juergensen et al., 2020).

Personality traits, such as innovativeness in one's professional life, known as an "exploration" trait within O&G (Perrons et al., 2018), impact adoption intentions from the perspective of decision makers (Tabak & Barr, 1999). Additionally, they appear to have strong ties to concepts like domain-specific inventiveness (Goldsmith & Hofacker, 1991) and technological inventiveness (Thakur et al., 2016). It may be instructive to study O&G technology adoption from an innovativeness standpoint, as has been done for procurement (Steenstra et al., 2020).

Per the above, it is, thus, expected that innovativeness will have a significant positive influence on AI acceptance and application.

Risk Aversion

The propensity, when deciding between different options, to avoid those that involve a risk of loss, even if said risk is relatively low. This includes a person's inclination to take risks, which is an important factor in determining the chance of adopting a high-risk technology. In their empirical research, Roberts and colleagues (2021) discovered that risk aversion was sufficiently distinct from innovativeness to warrant being a separate component. This distinction allowed them to draw the conclusion that risk aversion should be considered its own as a factor. This is reflected in the broader business literature (for example, Sauner-Leroy, 2004), and within the oil and gas industry, it is acknowledged that this is related to safety management (Roberts et al., 2021).

In accordance with the findings of the research on risk (Deery, 1999; Ji et al., 2011), risk aversion (tolerance) was classified as a personality characteristic, whereas risk perception was understood to be a cognitive element. Psychological variables, such as risk aversion, lack of ownership and leadership around technology, and attitudes of unwillingness to change, play a significant influence in slowing technology adoption in the oil and gas business (Oil and Gas Authority, 2018; Wood, 2014). Risk aversion is a factor in technology adoption in the oil and gas industry on both an individual and a sector level (Oyovwevto, 2014). These risk aversion obstacles may be amplified for game-changing breakthroughs (Radnejad & Vredenburg, 2019) in light of the recent flood of disruptive technology into the oil and gas sector (Venables, 2018).

Based on the above, it is expected that risk aversion will have a significant negative influence on AI technology acceptance by reducing adoption.

Attitude Factors

Attitudes (Category): This refers to a person's internalized judgments of other people, things, events, or ideas that can have an effect on their conduct. Affective, conative, and cognitive attitudes are three components of an attitude (Fishbein & Ajzen, 2005).

Technology Attitudes

This refers to the evaluations that an individual makes about novel technical products including the people, objects, events, and ideas associated with their adoption (Edison & Geissler, 2003). People's perceptions of how a new technology would affect their lives will be included in this. Technology attitudes were found to play a significant role in the decision-making process (Edison & Geissler, 2003). One of the most important factors in determining a company's performance was to cultivate a positive attitude toward technology and innovation. This was often juxtaposed with a deep-seated doubt that the technology would work, often because similar technology was viewed as having failed earlier. "Not Invented Here" syndrome, where people, teams or corporations don't want to explore new ideas or technologies from external firms or locations because of the belief that they may be of lesser quality, is an example of a negative attitude towards technology.

Positive attitudes toward technology can only be fostered by active participation and a sense of ownership on the part of the user. Roberts & Flin (2020) observed that involving end-users at the earliest stages of product development can help build confidence and enthusiasm for the AI technology, while also giving people a chance to voice concerns about any possible dangers they may encounter such as worries about being laid off.

It is expected that positive technology attitudes will exhibit a significant positive influence on AI technology acceptance.

Trust

This is an individual's belief in the abilities, reliability, and truthfulness of others (or objects) (Demolombe, 2004). Trust in this adoption context is a belief in the technology and all of the players involved (e.g., developers, managers participating in the adoption of new technology, leadership) (Ratnasingam, 2005). The importance of trust increases when there is a high degree of risk or uncertainty involved (e.g., an unknown company or technology). AI technology adoption requires strong relationships between developers, potential customers, managers, and end users built on mutual respect and trust at every step of the decision-making and adoption process.

It is expected that trust will have a significant and positive influence on AI technology acceptance.

Motivation Factors

Motivation (Category): The driving force that promotes us to act, whether we are conscious of it or not. In Herath (2010), motivation was defined as an individual's underlying requirements, such as a person's emotions.

Personal Incentives

Perceived rewards or punishments (to be avoided) operate as motivators for certain activities, according to this theory. Personal motivations for embracing new technology include the desire to increase job performance, compensation or promotion, or to prevent redundancy (Gagné & Deci, 2005). They influence behaviour, attitudes, and risk perceptions. Motivation can be classified as either extrinsic (e.g., tangible rewards, such as a bonus) or intrinsic (e.g., pleasure). Decisions on technology are said to be heavily influenced by personal incentives, whether they are favourable or bad. Some of these motives were clearly stated, such as how a good introduction might be identified (Roberts et al., 2021). Perceived risk of job loss predicted public acceptance of AI in a study evaluating the influence of country and individual characteristics on public acceptance of artificial intelligence and robotics technologies (Vu & Lim, 2022).

Personal incentives will exert a significant and negative effect on AI technology acceptance.

Fear of Technology Failure

Concerns and reasons for introducing new technology, as well as the possibility that it will fail, are discussed here. Taking a risk is often accompanied by apprehensions about failing (Atkinson, 1957), but in this situation, the decision-maker is more concerned with the operational effects than the personal ramifications. They may include worries about the safety ramifications of a technological failure or the impact on operational performance that a technology failure may have on (e.g., cost or lost production time).

It is expected that the fear of technology failure will have a significant negative influence on AI technology acceptance.

Cognitive Factors

Cognitive Factors (Category): Attention, perception, memory, language use, and problem-solving are some of the mental processes that drive knowledge and comprehension of the environment. The adoption of new technology is influenced by a variety of cognitive processes, including how people perceive danger and judge uncertainty, as well as their memory and decision-making processes.

Risk Perception

Risk perception can be defined as the subjective assessment by a person of the degree of risk associated with a specific threat; it involves gathering information and rendering a judgement on the level of risk as well as the potential loss that could be experienced in a given situation. A person's perception of risk is distinct from their tolerance for risk, yet both may be affected by it (Slovic, 1987; Slovic et al., 1991). A person's perception of risk is influenced by previous experiences, attitudes, motivations, expertise, and culture, and this perception is not always a true reflection of the actual risk. It is important to note that the dangers of adopting a new technology can be both personal and organisational (e.g., loss of reputation, job security, or financial benefits) if it fails.

It is expected that risk perception will have a significant influence on AI technology adoption.

Perception of Certainty

The degree of confidence that an individual has regarding the forecasting of events and conditions in the present or the future (e.g., decisions or actions). It is a measure of how confident one is in several aspects of the technology, including how it operates, who created it, how it will be distributed, and whether or not it will be successful (Johnson & Slovic, 1995). The more certain an individual is about a new technology like AI, the more likely they are to adopt that new technology.

It is expected that perception of certainty will have a significant positive influence on AI technology adoption.

Memory of Previous Experience

It is these memories of positive and negative encounters with technology and new ways of working (Agarwal & Prasad, 1999) that will have an impact on how people perceive risk and make decisions going forward. Technologies decisions can be skewed by prior unpleasant encounters with new technology. In a study by Ozturk & Hancer (2015), it is reported that there were substantial variations in users' intentions to make use of RFID technology based on previous experiences.

It is expected that a previous positive experience of an old technology will have a significant and positive influence on the adoption of a new technology like AI.

Technical Knowledge

In this context, it refers to the process of an individual recalling his or her domain-specific information, which has a direct impact on performance (Agarwal & Prasad, 1999). Being familiar or aware of something is known as knowledge, and it is a measure of how much one understands about it. Risk perception and decision-making are based on a foundation of technical knowledge and hands-on experience. This was thought to be closely linked to how people view risk and how much uncertainty they have.

To be able to effectively assess the dangers and advancements of technology, it is necessary to invest large resources in maintaining key skills. While it may be possible to keep up with technology advancements in and outside the sector, it can be challenging to do so. Accurate assessment of risk was hampered by a lack of knowledge in those areas. Education and expertise about new technology are becoming increasingly important to operators and suppliers alike, decreasing risk perceptions and ambiguity.

It is expected that technical knowledge will exert a significant and positive influence on AI technology adoption.

Social Factors

Social Factors (Category): When people think about, analyse, and evaluate their own and others' conduct, they are engaging in what is known as social cognition (American Psychological Association Dictionary). Included in this is the influence of role models and group affiliations (e.g., status and hierarchies).

Social Influence

Any alteration in a person's thoughts, feelings, or actions brought on by other individuals is referred to here (American Psychological Association Dictionary). Any one of these scenarios could be the case. Personal and professional network members, role models, opinion leaders, and social hierarchies were found to have an impact on attitudes, behaviors, and intentions to adopt new technology. Technology decisions can also be influenced by the opinions of people in the same social group (e.g., if others are starting to use this technology, a decision-maker may be more open to the possibility of introducing it). To illustrate how the social environment affects technology decisions, consider product champions (individuals who are well-known in their industry, have a large network, and are able to effectively communicate the product's value proposition and potential impact to others in their sector) (Markham & Aiman-Smith, 2001).

Personal and professional networks and role models, as well as social hierarchies, have been demonstrated to influence attitudes, behaviors, and intentions to adopt new technology. These social links can be used as leverage to influence people's attitudes toward technology. Despite the importance of product champions, Roberts et al. (2021) discovered that a well-connected and well-respected individual has the potential power to derail a project. Meanwhile, Upadhyay et al. (2021) observed that social influence exerts a positive impact on AI acceptance.

It is expected that social influence will have a significant positive influence on AI technology adoption.

Subjective/ Social Norms

Perceptions that an individual has about whether or not people relevant to that individual believe that the individual should or should not undertake a particular activity (e.g., coworkers and supervisors) (Ajzen, 1991). A person's desire to preserve a positive image in a reference group can impact their acceptance of new technologies. An individual's social status might be enhanced or lowered depending on how the new technology is viewed by others (Moore & Benbasat, 1991). As an illustration, imagine not being allowed to express your concerns about a new technology because the individual is expected to agree with the company's innovation manager.

It is expected that social norms will have a significant influence on AI technology adoption.

Organizational Factors

Organizational Factors (Category): At the organizational level, these are the psychological elements. In the context of business, industry and services, an organization is an organized entity (e.g., composed of numerous components that work together to accomplish a specific task).

Leadership

An investigation into how people in all levels of management (e.g., line managers, senior supervisors, managing directors and chief officers) think and act in order to impact the culture and behaviour of their organisations (Northouse, 2018). This encompasses traits of leadership related to creativity and a clear vision of the future of the organisation, including how technology fits into that goal (e.g. Hameed et al., 2012).

Attitudes, motivations, and objectives, as well as a long-term perspective on technological advancement, are all factors that influence how a business and its employees adopt new technologies. The way a company adapts to new technologies can be greatly influenced by the leadership qualities of its top executives (e.g., background, attitudes, personality traits, risk perceptions, and expertise). Priorities set by leaders and their companies will have a significant impact on the incentives and rewards offered to employees.

It is expected that leadership will have a significant influence on AI technology adoption.

Collaboration Culture

In order to achieve a common purpose, people both inside and outside the business must work together (Dodgson, 2018). Norms, methods, and leadership surrounding collaboration are all part of this. Embracing a culture of collaboration means being willing to share your expertise and knowledge with others (both internally, for example, between departments and externally, for example, with other companies). The culture of collaboration and the desire to be transparent about new technology will influence and interact with the culture of technology adoption.

It is expected that collaboration culture will have a significant influence on AI technology adoption.

Technology Adoption Culture

The specifics of an organization's culture can be found in its treatment of technology and innovation (Frambach & Schillewaert, 2002; Kratzer et al., 2017). Social norms, standard practises and risk-taking methods, processes (including procurement), incentives, organisational willingness to change, and access to resources are all included in this. These include the norms, priorities, and style of working with new technologies but also the safety culture (and how this produces a fear of failure/or a culture of failure—how does the organisation behave and respond to potential and real failure), organisational priorities and wider values.

How technology is viewed as part of an organization's priorities, strategy, and core business fall within the bounds of technology adoption culture. When it comes to innovation, this was also tied to the organisation's willingness to take risks, how it handles failure and uncertainty (e.g., blaming or learning cultures), and how it allocates its resources.

It is expected that collaboration culture will have a significant influence on AI technology adoption.

Presentation and Interpretation of Results

Descriptive Statistics

Cronbach's alpha was computed to determine the reliability of the instrument that was used to gather primary data to answer the second research question that was stated in section 5.0. This was done to answer the question that was presented there. Because the computed value of Cronbach's alpha was found to be 0.9480, it may be deduced that the scale that was used was reliable. The reason for this is that the computed value of Cronbach's alpha was more than 0.60, which is the threshold beyond which reliability is deemed acceptable (Daud et al., 2018). If a measuring scale has a Cronbach's alpha value that is larger than 0.6, then it is considered to have a high level of reliability, as stated by Pallant (2001).

Central Tendency

Figure 6 compares the determinants of AI technology acceptance. The results in Figure 6 show that innovativeness recorded the highest mean value of

8.54±0.75. This was followed by technology attitudes with a mean value of 8.50±0.73, trust (8.50±0.65), leadership (8.50±0.75), and technical knowledge (8.48±0.70). The fear of technology failure recorded the lowest mean value of 8.32±0.78. The preceding, therefore, presupposes that petroleum downstream firms seeking to adopt AI technology in their firms would do well to first consider innovativeness, followed by the rest.

Using paired t-tests, further analyses were conducted to determine whether the differences among the variables, technology attitudes, trust, leadership, and technical knowledge were statistically significant. The p-values obtained for the conducted paired t-tests were as follows: technology attitudes vs. trust (p = 1.000); technology attitudes vs. leadership (p = 1.000); technology attitudes vs. technical knowledge (p = 0.5427).

Figure 6: Comparison of the Determinants of AI Technology Acceptance

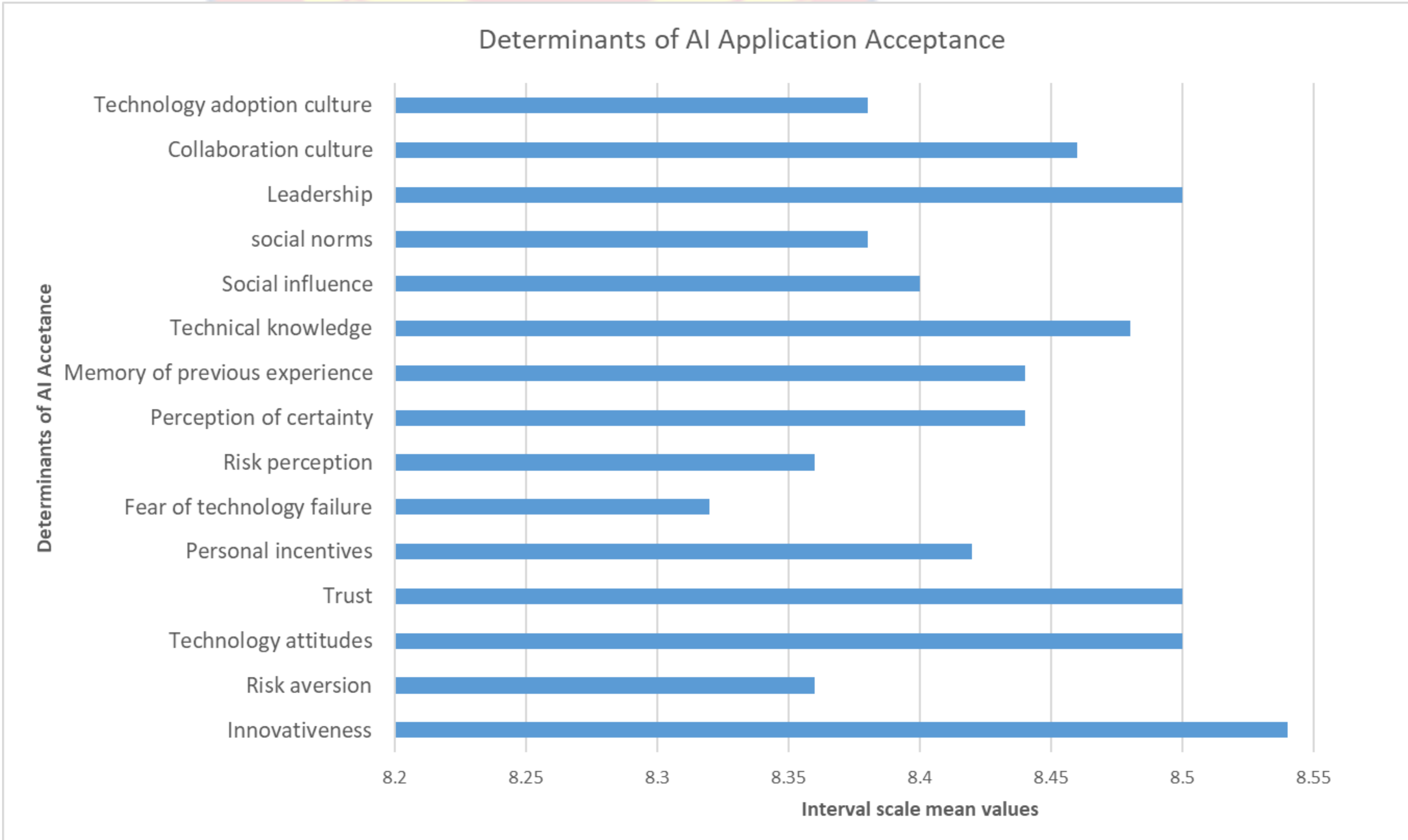


Table 11 Detailed Analysis of Determinants of AI Technology Acceptance

Determinants of AI Acceptance	mean value	SD
Personality Factors		
Innovativeness (PF1)	8.54	0.75
Risk aversion (PF2)	8.36	0.73
Attitude Factors		
Technology attitudes (AF1)	8.5	0.65
Trust (AF2)	8.5	0.75
Motivation Factors		
Personal incentives (MF1)	8.42	0.70
Fear of technology failure (MF2)	8.32	0.72
Cognitive Factors		
Risk perception (CF1)	8.36	0.80
Perception of certainty (CF2)	8.44	0.75
Memory of previous experience (CF3)	8.44	0.69
Technical knowledge (CF4)	8.48	0.68
Social Factors		
Social influence (SF1)	8.4	0.70
social norms (SF2)	8.38	0.76
Organizational Factors		
Leadership (OF1)	8.5	0.76
Collaboration culture (OF2)	8.46	0.71
Technology adoption culture (OF3)	8.38	0.78

Source: Survey data (2022)

Since the p-values obtained for the paired t-tests were greater than 0.05, it was, thus, concluded that the differences among the variables, technology attitudes, trust, leadership, and technical knowledge was not statistically significant. It is, therefore, safe to conclude that the mean values for these variables were the same. Table 4 provides a detailed analysis of areas of application of AI technology.

It is important to notice that none of the standard deviations that were found for the constructs, which are displayed in Table 4, were greater than 1. The standard deviation is a measurement that indicates how spread out a set of numbers is. It determines the degree to which all the people who participated in the study gave similar responses to a particular question or statement. Since none of the standard deviations were found to be more than 1, it is safe to state that the respondents reached a high level of consensus regarding the factors that determine the level of acceptance of AI technology.

Table 12: Frequency Distribution of Responses on Determinants of AI technology Application

AI technology Acceptance Determinants	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
Innovativeness	0	3.74 (7)	6.95 (13)	47.59 (89)	41.71 (78)
Risk aversion	3.21 (6)	9.63 (18)	0	53.48 (100)	33.69 (63)
Technology attitudes	0	1.07 (2)	8.56 (16)	54.55 (102)	35.83 (67)
Trust	0	3.74 (7)	7.49 (14)	48.66 (91)	40.11 (75)
Personal incentives	0	3.21 (6)	6.42 (12)	56.15 (105)	34.22 (64)
Fear of technology failure	0	3.21 (6)	9.09 (17)	56.15 (105)	31.55 (59)

Risk perception	0.53 (1)	5.35 (10)	5.35 (10)	53.48 (100)	35.29 (66)
Perception of certainty	0	2.14 (4)	8.56 (16)	54.55 (102)	34.76 (65)
Memory of previous experience	0	1.60 (3)	9.09 (17)	53.48 (100)	35.83 (67)
Technical knowledge	0	3.21 (6)	9.63 (18)	48.66 (91)	38.50 (72)
Social influence	0	2.67 (5)	8.56 (16)	54.55 (102)	34.22 (64)
Social norms	0	4.28 (8)	8.02 (15)	52.41 (98)	35.29 (66)
Leadership	0	3.74 (7)	8.02 (15)	47.59 (89)	40.64 (76)
Collaboration culture	0	1.60 (3)	11.23 (21)	49.73 (93)	37.43 (70)
Technology adoption culture	0	5.35(10)	6.95 (13)	51.34 (96)	36.36 (68)

NB: Values in parathesis represent numbers of respondents.

Innovativeness

Approximately 41.71% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I do not mind trying new things such as AI (PF1)" while, 47.59% had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale), thus making the majority. 6.95% of respondents expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). However, 3.74% of respondents disagreed with the above statement (scored between 2-4 on a 0-10 interval scale).

In the petroleum industry, trying new things is not something that is taken lightly because of the huge risks associated with the industry. One mistake, and people die. As a result, executives in the petroleum industry, and the downstream sector in general, would prefer to stick with what works rather than try new things, especially when those new things are not generated in-house. The finding that 41.71 percent of respondents had strong level of agreement with the statement, "I do not mind trying new things such as AI" seems to suggest that employees working within the petroleum downstream sector may have a personality of innovativeness. But whether that personality trait translates into acceptance of AI technology is another matter. There is also the issue of organisational factors that may not be favourable towards employee innovativeness, and so even if an employee has the desire to try out new things to help the company, the organisational culture may not encourage it and, thus, stifle it. However, with the spate of technological breakthroughs, employees in the downstream sector, notwithstanding, seem to be becoming more audacious considering that 88.78% either had moderate or high level of agreement with the statement, "I do not mind trying new things."

Risk Aversion

About 33.69 % of respondents had high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I am not risk averse to AI usage in company operations." That figure was lower than that reported for those who had strong level of agreement with the statement, "I do not mind trying new things such as AI." Using the results of a paired t-test (t= 2.3124; p = 0.0218), the preceding assertion is further buttressed by the fact that the meanvalue (as seen in Table 11) for innovativeness (8.54) was found to be significantly higher than that for risk aversion (8.36), as evinced by a p-value of 0.0218 ($t = 2.3124$), which is less than 0.05. The foregoing observations seem to suggest that employees of downstream petroleum firms may be considerably more innovative than risk averse. This implies that they appear significantly more willing to try new things than being risk averse to AI usage in company operations. This presupposes that employees of downstream petroleum firms are open to accepting AI technology introductions.

However, 53.48% of survey respondents had moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement, "I am not risk averse to AI usage in company operations," thus making the majority. None of the respondents were neutral. However, 9.63% of respondents disagreed (scored between 2-4 on a 0-10 interval scale) with the statement, "I am not risk averse to AI usage in company operations." About 3.21% of respondents had high level of disagreement (scored between 0-1 on a 0-10 interval scale) with that statement.

Technology Attitudes

About 35.83% of respondents had high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I am enthusiastic and open about AI usage," while 54.55% had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale), thus making the majority. About 8.56% of respondents expressed a neutral stance (scored between 4-6 on a 0-10 interval scale), even though technology, including AI, has heavily influenced modern society (Gupta, 2021). The use of technology in today's society has resulted in significant shifts in the majority of societal practices. As time goes on, more and more people are getting reliant on various forms of technology. The rise of technology has made communication, travelling, conducting business, acquiring knowledge, and enjoying entertainment all the much simpler. Technology advancement is commonplace at the present time, and the intersection of society and technology is drawing ever closer (Gupta, 2021). However, 1.07% of respondents had moderate level of disagreement with the above statement (scored between 2-4 on a 0-10 interval scale), and none of the survey respondents had high level of disagreement with the statement (scored between 0-1 on a 0-10 interval scale). That meant that only 9.63% of respondents were not particularly "enthusiastic and open about AI usage.". This suggests that a massive 90.37% of respondents were “enthusiastic and open about AI usage.” This represents a significant shift since players in the petroleum sector are known to traditionally resist changes in technology. But that tendency is changing.

In today's competitive market, many analysts believe that technological advancements are the single most important aspect of gaining an edge. It is also a crucial factor for companies that rely heavily on technology to succeed, such as the petroleum industry. The petroleum industry is one of the world's most important, technologically advanced, and technology-reliant businesses. An investigation by Ebneyamini and Bandarian (2018) highlights the significance of technological developments in the oil industry worldwide. Players, they say, need to keep tabs on technological developments and factor them into their business models if they want to stay afloat and maintain an edge in the market. The authors argued that new technologies had changed the petroleum and natural gas industries irrevocably. The ability to develop one's own technologies or gain access to the most cutting-edge ones at just the right time appears to be the most important factor in a company's survival, especially when it comes to expanding the company's market share, revenue, and leadership position beyond the foundations upon which the business model is built. This crucial piece has the ability to fortify the oil and gas industry's other power pillars.

Trust

About 40.11% of respondents had high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I have trust in the usefulness of AI," whereas 48.66% moderately agreed with the statement (scored between 6-8 on a 0-10 interval scale). Respondents appeared rather more trusting of AI than enthusiastic about it, since a greater proportion of respondents had high level of agreement with the statement, "I have trust in the usefulness of AI," when compared to a similar response to the statement, "I am enthusiastic and open about AI usage," which recorded a proportion of 35.83%. However, 3.74% of the respondents had a moderate level of disagreement with the statement (scored between 2-4 on a 0-10 interval scale), "I have trust in the usefulness of AI," whereas 7.49% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale), suggesting the possibility that the downstream sector is becoming increasingly open to AI use in its operation, hence the minimal resistance represented by the low proportions of respondents disagreeing with the statement, "I have trust in the usefulness of AI."

Aside the petroleum sector, an ever-growing number of areas, from medicine to politics to law enforcement to predictive maintenance, rely on AI and ML to help with human decision-making (Susto et al., 2015). That perhaps explains why there appears to be minimal resistance, as suggested above, to a new technology like AI in a sector like the downstream petroleum industry that values stability. Many ML-trained algorithms now outperform human experts in their respective fields, and this trend is expected to continue (Szegedy et al., 2017). Given the recent advances in what is being called "cognitive automation," however, the importance of human decision makers is sometimes underestimated (Ribeiro et al., 2016). Recent events have shown that many people do not like being dependent on AI and would rather trust human professionals, even though the latter are more likely to be incorrect; this is despite the fact that AI is becoming increasingly advanced (Polonski, 2018). Despite this seeming discord, understanding human users' trust in AI-based decision support systems is crucial if these technologies are to be used for the good of humanity (Schmidt et al., 2020). There are three main considerations that make this an option.

To begin, according to Venkatesh et al. (2016), trust is essential for the widespread adoption of any new technology, and artificial intelligence is not an exception to this rule (Siau & Wang, 2018). People have a right to be suspicious about committing critical decisions to an AI assistant, especially when the aid makes judgements without presenting a transparent explanation for preferring one option over a group of options (Polonski, 2018). Second, even when professionals have gained the ability to rely on AI-based decision support systems, they still need to have faith in those systems in order for them to adhere to the system's forecasts, classifications, and recommendations (Schmidt et al., 2020). When it comes to deciding how to react to the output generated by AI, humans will still have the last say in many situations. Understanding the processes that influence human trust in AI is critical for avoiding the potential repercussions and side-effects of 1) incorrectly rejected and 2) baseless trust. These issues are equally as important to address as problems relating to the deployment of AI systems. Understanding the processes that influence human trust in AI is critical. Since humans are increasingly dependent on AI to inform, originate, and defend their judgments, it is essential to evaluate when, how, why, and in what circumstances people tend to place an excessive amount of trust in these systems.

Personal Incentives

About 34.2% of respondents had high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I don't feel I am going to be out of a job if I adopt the AI system," while 56.15% had moderate level of agreement with that statement (scored between 6-8 on a 0-10 interval scale). This meant that 90.35% of respondents did not feel their jobs were under threat because of AI adoption. It, therefore, stands to reason that such individuals would have no problem accepting AI. Notwithstanding, 9.65% of respondents did not share those same sentiments, as 6.42% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale) and

3.21% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement above.

Fear of Technological Failure

About 31.55% of respondents had a strong level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I am willing to explore new technologies without fear of technology failure," which is comparatively lower than the percentage frequency reported for the statement, "I don't feel I am going to be out of a job if I adopt the AI system." The preceding suggests that personal incentives may be a stronger motivational factor for AI acceptance than fear of technological failure. However, 56.15% of respondents had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement, "I am willing to explore new technologies without fear of technology failure." This reported proportion was the same as those who expressed a moderate level of agreement with the statement on personal incentives. About 9.09% expressed neutral stance (scored between 4-6 on a 0-10 interval scale) in their fear of technological failure, although 3.21% moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement.

Risk Perception

Approximately 35.29% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I consider AI technology usage an acceptable risk," while 53.48% had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale), thus making the majority. About 5.35% of respondents expressed a neutral stance in their risk perception of AI usage (scored between 4-6 on a 0-10 interval scale), although another 5.35% of respondents had moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the above statement. Only 1 person representing 0.53% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with the statement. Of the four cognitive factors, risk perception recorded the lowest mean value of 8.36±0.8

Although, a high percentage of respondents indicated that they considered AI technology usage an acceptable risk, it was not clear whether respondents fully appreciate the wide range of risks associated with AI usage. It has been stated by Perry & Uuk (2019) that there are two types of dangers connected with AI systems: governance (which involve matters of state, economy, governance, and morality) and technical safety. Two potential dangers that artificial intelligence (AI) could bring to civilization have been highlighted by the Future of Life Institute (Crockett et al., 2020). Many groups throughout the world, including the (IEEE, 2019) and the (EU, 2019), have raised concerns about the potential dangers posed by totally Independent AIs that are programmed to harm and kill people. In the second, where the interests of humans and machines are at odds, an AI system may end up helping society, but only by using "a destructive way for achieving its purpose.

There are five potential sources of artificial intelligence risks that have been identified by Cheatham et al. (2019): data difficulties, technology troubles, misbehaving models, security snags, and data bias. "Data difficulties," refers to issues touching on proper data usage, such as meeting the requirements of the

General Data Protection Regulation (GDPR) and other relevant authorities. "Technology troubles" occurs when an AI system falls short of expectations, such as by missing a critical anomaly. Concerned with potential threats to the data and, by extension, the data model, "Security Snags" focuses on AI-driven cybersecurity. The term "misbehaving models" is used to describe those that are based on inaccurate or incomplete information. Finally, there are dangers inherent with human-machine AI system interactions, such as the human interpreter being unable to make sense of the results because of poor training. Embedded prejudice in corporate or industrial cultures, personal and unconscious bias, and data bias all contribute to one of AI's major dangers: inaccurate results. When choosing training data for AI systems, it's important to keep bias in mind and work to eliminate it. Human-labelled data used for training purposes may have biases. It is important to keep an eye on dynamic environments where training, validation, and testing are performed and where models are constantly learning and improving to make sure that they don't develop a hidden bias over time.

Perception of Certainty

Approximately 34.8% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I like to go along with what I know works," while 54.55% had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). The preceding suggests that 89.31% of respondents would like to be sure that the AI technology to be adopted really works before they accept it. These individuals thrive on certainty.

However, 2.14% of the respondents did not feel that way, and 8.56% essentially 'sat on the fence,' being unsure of their position in this matter.

Memory of Previous Experience

Approximately 35.8% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I think about the changes I will have to make in the implementation of AI technology at my workplace," while 53.48% had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). This meant that 89.31% of respondents think about the changes they will have to make in the implementation of AI technology at their workplace. About 9.09% of respondents expressed a neutral stance in their memory of previous experience, although 1.60% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the above statement. Of the four cognitive factors, risk perception recorded the lowest mean value of 8.36±1.

Technical Knowledge

About 38.5% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "I understand where technology fits in the process of running a platform," while 48.66% had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). The better the technical knowledge of respondents, the more likely they are to accept AI. Of the four cognitive factors, technical knowledge scored the highest mean value of 8.48, suggesting that respondents may have a high level of technical knowledge. About 9.63% of respondents expressed a neutral stance. However, 3.21% of respondents expressed moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the above statement.

Social Influence

Approximately 34.2% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "Social influences within my network play a key role in my acceptance of new technology," while 54.55% had moderate level of agreement with that statement (scored between 6-8 on a 0-10 interval scale). This implies that 88.77% of respondents appear to be greatly influenced by their social network when it comes to their acceptance of new technology. It, therefore, stands to reason that, such individuals would have no problem accepting AI if their social networks either approve it or are familiar with AI applications. Notwithstanding, 11.23% of respondents did not share those same sentiments, as 8.56% were expressed a neutral stance (scored between 4-6 on a 0-10 interval scale), whereas the remaining 2.67% had moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement above.

Social Norms

Approximately 35.29% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "At the workplace, I am expected to behave in a certain way," while 52.41% had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). About 8.02% of respondents expressed a neutral stance, although 4.28% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the above statement.

Leadership

About 40.6% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "Firm leadership is able to get every member of the firm onboard any new initiative," while 47.59% had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). Of the three organizational factors considered in the study, leadership was the one organizational factor that had most respondents (40.64%) expressing a high level of agreement (scored between 8-10 on a 0-10 interval scale). About 8.02% of respondents were unsure about the above statement, while 3.74% of respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the above statement.

Collaboration Culture

About 37.43% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, “As a firm, we look to other industries to see what they’re doing and how we can translate their experience.” Meanwhile, about 49.73% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement, whereas 11.23% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). About 1.60% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with the statement.

Technology Adoption Culture

Approximately 36.36% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "New technology like AI has really been part of the core strategy of the company, and everybody lives and breathes this," while 51.34% had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). Of the three organizational factors considered in the study, technology adoption culture was the one organizational factor concerning which most of the respondents expressed a moderate level of agreement (51.34%). About 6.95% of respondents expressed a neutral stance (scored between 4-6 on a 0-10 interval scale) about the above statement, while 5.35% of respondents had a moderate level of disagreement with the statement (scored between 2-4 on a 0-10 interval scale)

5.2.2 Inferential Statistics

This section seeks to investigate the determinants of AI technology application using Structural Equation Modelling (SEM). To conduct the SEM, a path diagram was first constructed with arrows leading from the independent variables and pointing to the dependent variable. Figure 7 provides a screenshot of the constructed SEM path diagram. Figure 8 presents the SEM path diagram showing the coefficients associated with each pathway.

Figure 7: Screenshot of the SEM path diagram

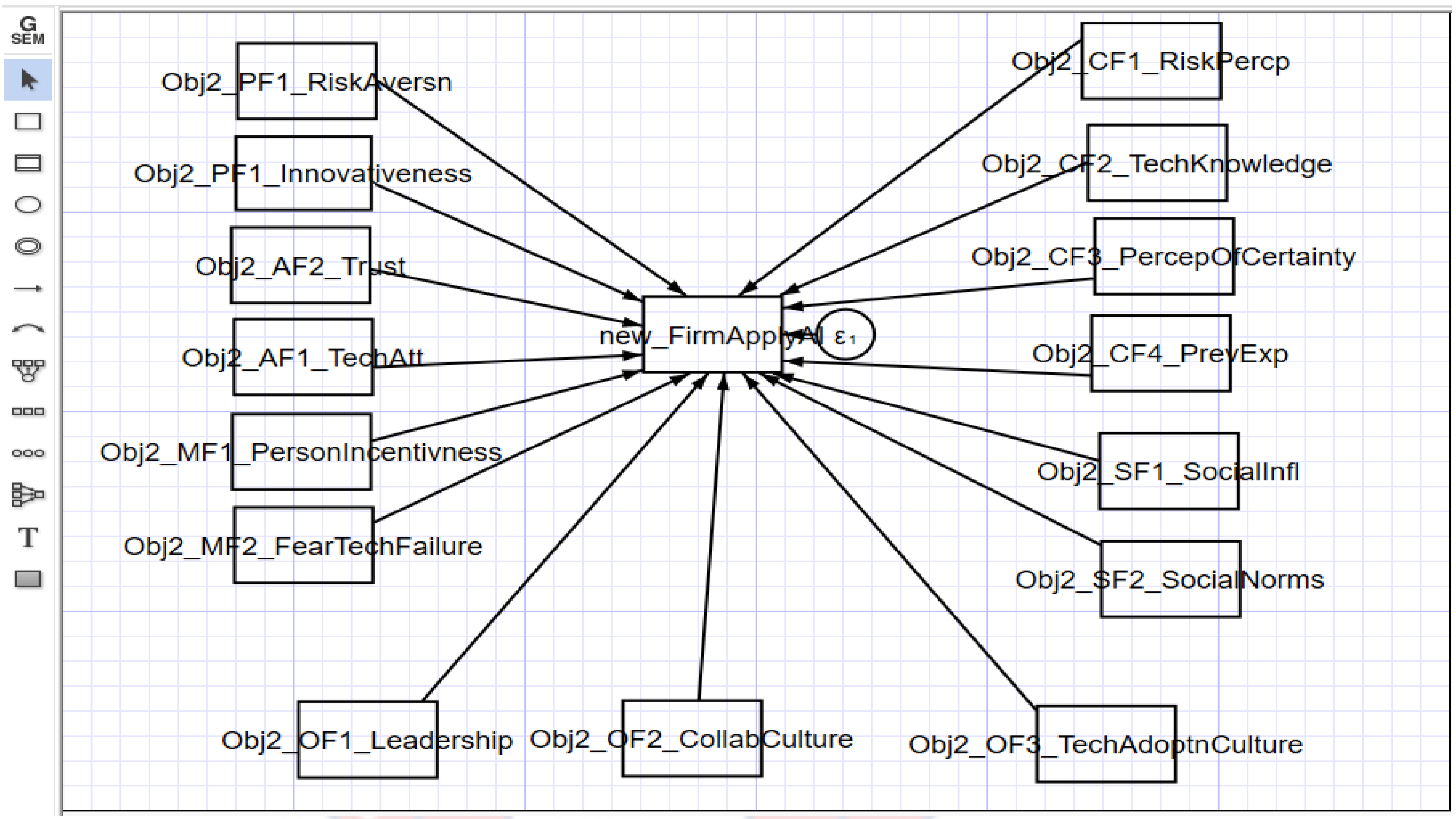


Figure 8: SEM Path Diagram showing the coefficients associated with each pathway

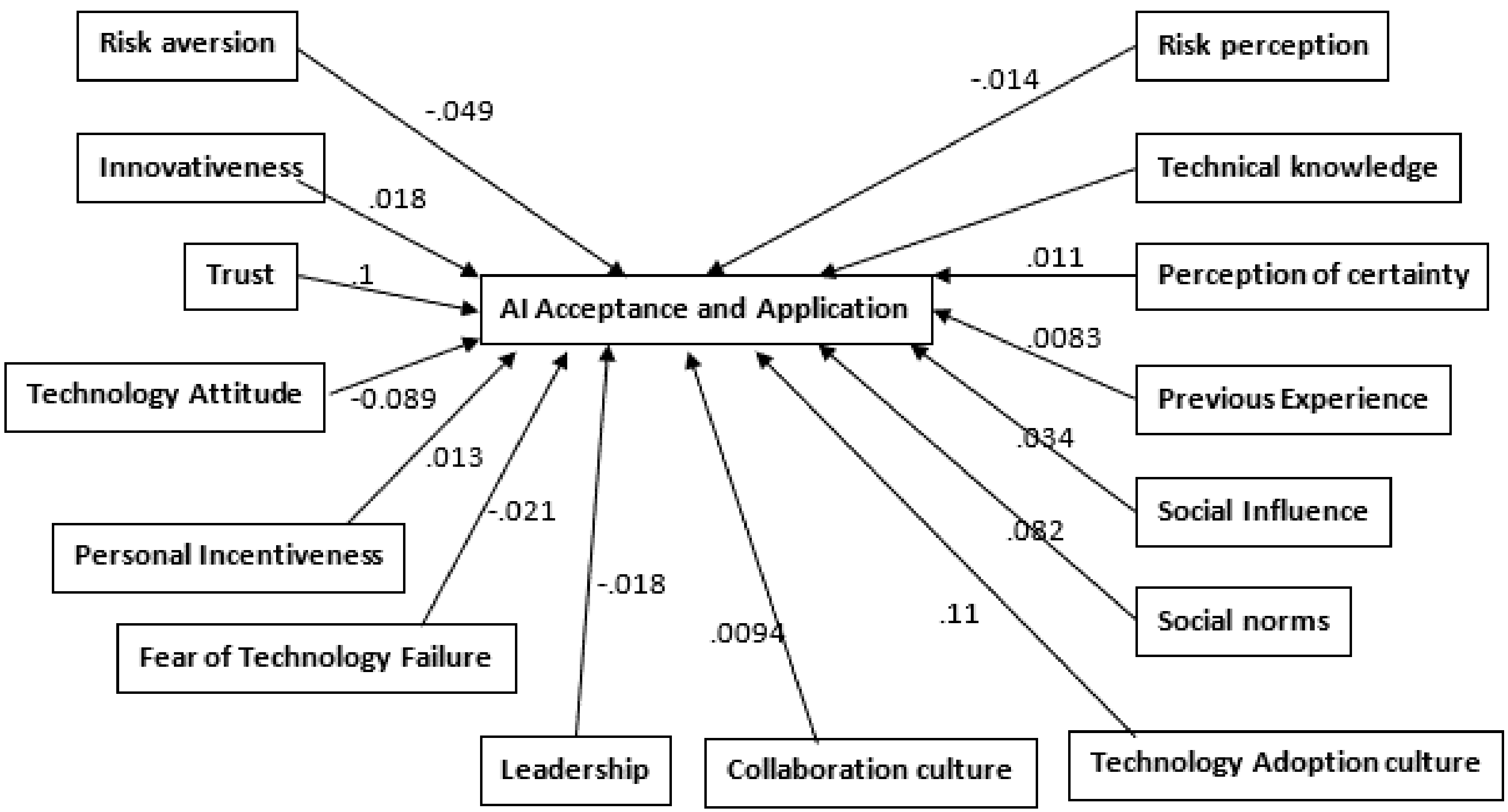


Table 13: SEM Results on the Determinants of AI Acceptance and Application

	Observed Information Matrix (OIM)					
Structural Equations	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
AI Acceptance and Application						
Personality Factors						
Risk Aversion	0.01811	0.028574	0.63	0.526	-0.03789	0.074114
Innovativeness	0.048958	0.032951	-1.49	0.137	-0.11354	0.015625
Attitude Factors						
Technology Attitudes	**0.088707**	**0.033472**	**-2.65**	**0.008***	**-0.15431**	**-0.0231**
Trust	**0.103046**	**0.032714**	**3.15**	**0.002***	**0.038928**	**0.167165**
Motivation factors						
Personal Incentiveness	0.013143	0.0285	0.46	0.645	-0.04272	0.069002
Fear of Technological failure	0.020587	0.033145	-0.62	0.535	-0.08555	0.044375
Cognitive Factors						
Risk perception	0.014036	0.028987	-0.48	0.628	-0.07085	0.042778
Technical knowledge	0.011405	0.032482	0.35	0.726	-0.05226	0.075068
Perceptions of certainty	0.013776	0.030878	0.45	0.655	-0.04674	0.074295
Previous experience	0.008266	0.030741	0.27	0.788	-0.05199	0.068516
Social Factors						
Social influence	0.034121	0.034256	1	0.319	-0.03302	0.101261
Social norms	**0.082282**	**0.030549**	**2.69**	**0.007***	**0.022408**	**0.142156**
Organizational Factors						
Leadership	0.01776	0.030437	-0.58	0.56	-0.07742	0.041895
Collaboration culture	0.009373	0.032257	0.29	0.771	-0.05385	0.072596
Technology adoption culture	**0.106705**	**0.027562**	**3.87**	**0***	**0.052683**	**0.160726**
_cons	1.045309	0.11584	9.02	0	0.818267	1.27235

Table 13 presents SEM results on the determinants of AI acceptance and application. The results of the SEM analysis showed that of the 15 AI acceptance factors investigated, only four were found to significantly influence AI acceptance and application. These four were technology attitudes (coeff. = 0.088707; p = 0.008), trust (coeff. = 0.103046; p = 0.002), social norms (coeff. = 0.082282; p = 0.007), and technology adoption culture (coeff. = 0.106705; p = 0).

Since technology attitudes, and trust fall under the attitude factors; social norms under social factors; and technology adoption culture under organizational factors, this suggests that attitude factors, social factors and organizational factors may well be significant determinants of AI acceptance and application in downstream petroleum sector. This, thus, presupposes that cognitive factor, per the findings of this study, had no influence on AI acceptance.

To ensure that the above findings are robust, multiple linear regression analysis was also performed on the same independent variables used in the structural equation modelling above. The results obtained are reported in Appendix 1. The reported results are no different from those reported by the SEM output. The results of the multiple regression analysis showed that technology attitudes ($p = 0.012$), trust ($p = 0.003$), social norms ($p = 0.011$), and technology adoption culture ($p = 0.000$) are significant determinants of AI acceptance (Appendix 1); thus, confirming the SEM results.

Beta coefficients were also computed. In multiple regression analysis, the beta coefficient determines the size of influence of an independent variable over a dependent variable, thus enabling an investigator to determine which of the statistically significant independent variable under investigation has the biggest influence on the dependent variable. From the results of the multiple regression analysis reported in Appendix 1, beta coefficients for technology attitudes, trust, social norms and technology adoption culture were respectively found to be -0.2269, 0.3039, 0.2441, and 0.3282. The preceding means that technology adoption culture has the biggest significant influence on AI acceptance since it recorded the largest beta coefficient of 0.3282. This was followed by trust (beta = 0.3039), and social norms (beta = 0.2441), with technology attitudes having the smallest significant influence on AI acceptance.

Evaluation of Results

In this section, the results are evaluated against a priori expectation and the key significant findings against existing literature.

Table 14: Evaluation of SEM Findings on Determinant of AI Acceptance against A Priori Expectations

Determinants of AI Acceptance.	A Priori Expectation	Results/Findings	Status
Innovativeness	Significant and positive influence on AI acceptance.	Innovativeness had a positive influence on AI acceptance, but the influence was not statistically significant (Coeff = 0.048958; p = 0.137).	Results partially contradicts a priori expectation.

Risk Aversion	Significant negative influence on AI acceptance.	Risk aversion had a positive influence on AI acceptance and this influence was not significant (Coeff = 0.01811; p = 0.526).	Results contradict a priori expectation.
Technology Attitudes	Significant positive influence on AI acceptance.	Technology attitudes had a positive influence on AI acceptance, and this influence was found to be significant (Coeff = 0.088707; p = 0.008).	Results confirm a priori expectation.
Trust	Significant and positive influence on AI technology acceptance.	Trust had a positive influence on AI acceptance, and this influence was found to be significant (Coeff = 0.103046; p = 0.002).	Results confirm a priori expectation.
Personal Incentives	Significant and negative effect on AI acceptance.	Personal incentiveness had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.013143; p = 0.645).	Results contradict a priori expectation.
Fear of Technological Failure	Significant and negative influence on AI acceptance.	Fear of technological failure had a	Results contradict a

		positive influence on AI acceptance, and this influence was not significant (Coeff = 0.020587; p = 0535).	priori expectation.
Risk Perception	Significant influence on AI technology acceptance.	Risk perception had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.014036; p = 0.628).	Results contradict a priori expectation.
Perception of Certainty	Significant and positive influence on AI technology acceptance.	Perception of certainty had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.013776; p = 0.655).	Results partially contradict a priori expectation.
Memory of previous experience	Significant and positive influence on AI acceptance.	Memory of previous experience had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.008266; p = 0.788).	Results partially contradict a priori expectation.
Technical knowledge	Significant and positive influence on AI acceptance.	Technical knowledge had a positive influence on AI acceptance, and this influence	Results partially contradict a priori expectation.

		was not significant (Coeff = 0.011405; p = 0.726).	
Social Influence	Significant and positive influence on AI technology acceptance.	Social influence had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.034121; p = 0.319).	Results partially contradict a priori expectation.
Social Norms	Significant influence on AI technology acceptance.	Social norms had a positive influence on AI acceptance, and this influence was significant (Coeff = 0.082282; p = 0.007).	Results confirm a priori expectation.
Leadership	Significant influence on AI technology acceptance.	Leadership had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.01776; p = 0.56).	Results partially contradict a priori expectation.
Collaboration culture	Significant influence on AI technology acceptance.	Collaboration culture had a positive influence on AI acceptance, and this influence was not significant (Coeff = 0.009373; p = 0.771).	Results partially contradict a priori expectation.

Technology Culture	Adoption	Significant influence on AI technology acceptance.	Collaboration culture had a positive influence on AI acceptance, and this influence was significant (Coeff = 0.106705; p = 0.000).	Results confirm contradict a priori expectation.

Technology Attitudes

The acceptance of any technology depends on the development and cultivation of a positive technology mindset in which innovation is regarded as valuable to the team, department, company, or industry (Roberts et al., 2021). The results of the present study showed that technology attitudes exert a significant and positive influence on AI technology acceptance. The preceding seem to be supported by findings made by Edison & Geissler (2003) and Roberts et al. (2021). People's perspectives on technology were analyzed by Edison & Geissler (2003), who looked at what factors might influence people's openness to new technologies. Technology attitudes was found to be one. Edison & Geissler (2003) further observed that people with positive technology attitudes tend to be optimists and are typically younger, have more complex cognitive processes, and are likely to be open to new experiences and ideas.

In a study that they conducted, Roberts et al. (2021) wanted to investigate the significance of having a solid grasp of the psychological elements that lie behind the technology adoption process. The corporate decision makers, who are the "gatekeepers" to the introduction of new technology by their respective corporations, were the primary subject of that study. It has been said that the oil and gas business is notoriously slow to embrace new innovations in technology. A collection of six categories covering 15 psychological elements that influence the organizational decision-maker was established through a thematic analysis of an interview study with 37 innovative technology stakeholders from the petroleum sector. Attitudes were one of the categories, and this subcategory encompassed technology attitudes. In a related study, Forrester Research observed that technology attitudes was a key determinant influencing the acceptance of a broad array of digital technologies like mobile phones and computers (Modahl, 1999), and AI technologies are no exception in that regard.

Trust

The results of the present study showed that trust exerts a significant and positive influence on AI technology acceptance. This finding appears to be supported by Liu & Tao (2022) and Siau et al. (2004). Liu & Tao (2022) reported trust to be a factor that directly impacted the acceptance of AI-powered technologies, while Siau et al. (2004) found trust to be a key determinant for the acceptance of digital technologies like AI.

Trust is a belief in both the technology and the stakeholders (Ratnasingam, 2005). Trust is vital when uncertainty or risk is present. An instance of uncertainty or risk is the introduction of a new technology like AI. Trust is crucial for technology adoption among all stakeholders, including developers, potential clients, managers, and end-users. People tend to be wary of new things, whether it makes their lives simpler or not (Roberts et al., 2021). This makes trust crucial in that regard since trust can enable stakeholders overlook their wariness and embrace AI.

A person's choices may be influenced by how much they trust others or an organization. One's ability to gain others' trust is the primary factor in being accepted A person's choices may be influenced by how much they trust others or an organization. One's ability to gain others' trust is the primary factor in being accepted (Wanner et al., 2022). Human-social connections (Hengstler et al., 2016; McKnight et al., 1998), seller-buyer ties (Gefen, 2000; Siau & Shen, 2003), and relationships within a virtual team all rely heavily on mutual trust (Hengstler et al., 2016; McKnight et al., 1998). How much trust people have in technology is another defining characteristic of their interactions with it (Li et al., 2008; Siau et al., 2004). It is generally agreed that trust consists of one or more of the following components: (1) a set of shared convictions about another person's underlying good character, reliability, competence, and predictability (trusting beliefs); (2) an intention to rely on that person in the face of uncertainty (trusting intention); or (3) both of these components working together (Siau & Wang, 2018). The trustee in a human-technology or human-machine interaction may not even be a human being, but rather the technology or the firm that developed it. Moreover, trust in the system and trust in the service provider will have reciprocal effects (Siau & Wang, 2018). Thus, the preceding idea assumes that employees of a downstream petroleum firm may not trust an AI technology in and of itself but may do so because they trust the organization and, by extension, the organization's decision to embrace the AI technology.

Mutual trust evolves with time. According to the available data, trust is something that must be earned over time through consistent, reciprocal relationships (Gefen, 2000). Sometimes, though, a trustor does not need direct knowledge of the trustee—or any form of experience with the trustee—to decide whether to trust him, such as with an object or a relationship. When two people meet for the first time, for instance, that initial impression might have a lasting impact on the level of trust between them. There, trust will be established according to a person's character or an organization's signals (Siau & Wang, 2018). Initial trust refers to this type of trust in a new technology and is crucial in driving its widespread acceptance (Li et al., 2008). Careful consideration must be given to both the first stages of trust formation and ongoing trust growth (Siau & Shen, 2003). Both the establishment of trust and its ongoing cultivation are crucial in the context of AI (Siau & Wang, 2018). Mutual trust evolves with time. According to the available data, trust is something that must be earned over time through consistent, reciprocal relationships (Gefen, 2000). Sometimes, though, a trustor does not need direct knowledge of the trustee—or any form of experience with the trustee—to decide whether to trust him, such as with an object or a relationship. Careful consideration must be given to both the first stages of trust formation and ongoing trust growth (Siau & Shen, 2003). Both the establishment of trust and its ongoing cultivation are crucial in the context of AI (Siau & Wang, 2018).

Social Norms

The results of the present study showed that social norms exert a significant and positive influence on AI technology acceptance. This finding agrees with Sohn & Kwon (2020), who found that subjective norms has the second largest influence on AI acceptance. This seems to suggest that AI is a socially interesting technology with little in the way of actual user experience, so potential users are still influenced by the opinions of others when deciding whether to adopt AI technology. This view is shared by Sohn & Kwon (2020) in his study on AI-based intelligent products. It is, thus, safe to say that while artificial intelligence technology is being developed rapidly in tandem with a wide range of products, it is still in the early phases of social acceptance, and the influence of others still plays a vital part in creating trust in the technology (Li et al., 2008). That perhaps explains why Del Giudice et al. (2022) in their paper suggested that social norms have a significant impact on whether AI is accepted or rejected.

Technology Adoption Culture

The results of the present study showed that technology adoption culture has a significant and positive influence on AI technology acceptance. This finding is supported by (Roberts & Flin, 2020) who conceptualised technology adoption culture as a core factor predicting acceptance of new technologies like AI. This finding suggests that downstream petroleum firms that do not have an organizational culture that is open to new and emerging technologies, may most likely not be willing to accept AI technologies into their operations.

Theoretical Implications of Findings on Determinants of AI Acceptance

This study has important theoretical implications for future studies on the acceptance of AI technologies. First, this study presents information on factors influencing AI acceptance in the downstream petroleum sector using the individual as the primary unit of analysis. Moreover, the study adopted psychological constructs from (Roberts et al., 2021) Psychological Technology Adoption Framework. Of the 15 constructs or factors investigated, four of them namely technology attitudes, trust, social norms, and technology adoption culture, were observed to be significant determinants of AI acceptance in the downstream petroleum sector. These findings are supported by Roberts et al.'s (2021) Psychological Technology Adoption Framework. Furthermore, the findings seem to suggest that acceptance of new technologies is influenced by psychological factors and appears to occur at the individual level. This means that downstream firms will do well to analyse AI acceptance at the individual and psychological level. This further implies that even when considering organizational factors like the technology adoption culture, which was observed to be a statistically significant determinant of AI acceptance, it will be wise to find out how well the various individuals, especially those with direct oversight of the AI technology application, have been influenced by the organization's technology adoption culture. Ignorance of such considerations could spell doom for the AI technology project. But not only that, but the technology attitudes of the individual is also another significant factor to consider. Despite the preceding, such a person's social network can become another sticking point. This is so because social norms were also found to be a statistically significant determinant of AI acceptance, meaning that when it comes to AI technology acceptance, individuals' decision to accept or reject may be heavily influenced by the views and values of the members of their social network.

Per the above, the "say so" or views of individuals when deploying AI technologies in downstream petroleum firms really matter. This is where the agency theory and stakeholder theory come into play. With agency theory, a principal may pass a policy, but if the agent suffers from conflicts of interest, the desired outcome may not be realized. A case in point is the possibility of an AI technology making the job of the agent redundant after him/her deploying the AI technology. In such instances, the agents could do all in their power to defeat the success of the AI deployment. Trust is cardinal in that regard. This makes trust a key psychological factor that interfaces with the agency theory. Trust is paramount when dealing with stakeholders like employees. Perhaps, that explains why trust was found to be one of the significant determinants of AI acceptance.

Per the results of the study, cognitive factors and motivation factors appear to be insignificant in influencing AI adoption, considering none of the constructs under these factors was found to exert a statistically significant influence on AI acceptance (Table 6). Fear of technological failure and fear of incentives (both motivation factors) had no significant bearing on AI acceptance, and neither risk perception nor technical knowledge (cognitive factors) had any effect on AI acceptance.

CHAPTER SIX

EFFECTS OF AI TECHNOLOGY APPLICATION ON OCCUPATIONAL SAFETY IN DOWNSTREAM PETROLEUM INDUSTRIES

Introduction

This chapter seeks to determine the effects of AI Technology application on occupational safety practices in the downstream petroleum sector within the Greater Accra Region. It addresses the third research question, "What are the effects of AI application on occupational safety practices in the downstream petroleum sector within the Greater Accra Region?" The study identified four effects of AI application namely reduction of risk, recognition of threats and prevention of hacking, smarter and safer fuel station, and precision in decision. The result on each effect is presented and discussed. The remaining portion of the chapter is structured as follows: Section 6.1 discusses the results on reduction of risk.; Section 6.2 analysed the data on recognition of threats and prevention of hacking; Section 6.3 discusses the results on smarter and safer fuel station;, Section 6.4 analysed the data on precision in decision; and finally Section 6.5 compared the effects of AI technology application.

Reduction of Risk

The petroleum sector, and for that matter, the downstream petroleum sector, is inextricably linked with risks. As such, any opportunity to reduce these risks is a welcome one.

Table 115: Frequency Distribution of Responses on Reduction of Risk as an effect of AI Technology Application

Reduction of Risk	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
AI as part of the built system of the fuel station has helped to alert staff of impending dangers such as fire outbreaks (RR1).	4.81 (9)	2.14 (4)	12.83 (24)	31.55 (59)	48.66 (91)
AI has helped to predict fire outbreak in fuel stations (RR2).	4.81 (9)	1.07 (2)	12.30 (23)	34.76 (65)	47.06 (88)
AI system has helped automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks (RR3).	5.35 (10)	1.07 (2)	11.76 (22)	37.97 (71)	43.85 (82)
AI system has reduced the number of risks between staff and the discharge of fuel from transport to the fuel stations (RR4).	4.81 (9)	1.60 (3)	11.23 (21)	32.62 (61)	49.73 (93)

AI systems have produced an operation free of risk for effective business transaction between different companies in the downstream petroleum industry (RR5).	4.28 (8)	1.60 (3)	9.63 (18)	39.57 (57)	44.92 (84)

NB: Values in parathesis represent numbers of respondents

Descriptive Statistics

From results shown in Table 15 above. about 48.66% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI as part of the built system of the fuel station has helped to alert staff of impending dangers such as fire outbreaks (RR1)." This majority response indicates the vital role artificial intelligence plays in alerting staff in downstream petroleum firms about impending disasters, such as fire outbreaks. This notion is further supported by the 31.55% of respondents who expressed moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). About 12.83% expressed a neutral stance (scored 4-6 on a 0-10 interval scale) concerning statement RR1, unsure whether AI helps alert staff of impending dangers such as fire outbreaks. However, 6.95% had either moderate or high levels of disagreement with statement RR1. These levels of disagreements could be the result of some workers' negative attitudes towards risk management. Osabutey et al. (2013) in a paper found that some oil and gas workers have a bad attitude towards risk management, even though the industry in which they operate is a risky one.

Approximately 47.06% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has helped to predict fire outbreak in fuel stations (RR2)." This majority response indicates the important role artificial intelligence plays in predicting fire outbreaks in fuel stations. This notion is further supported by the 34.76% of respondents who expressed a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale). About 12.30% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale) concerning statement RR2, unsure whether AI has helped to predict fire outbreaks in fuel stations. However, 4.81% of respondents had a high level of agreement with the statement (scored between 0-2 on a 0-10 interval scale), and 1.07% had moderate level of disagreement with the statement (scored between 2-4 on a 0-10 interval scale) that AI has helped to predict fire outbreaks in fuel stations. But then, these dissenters are in the minority. This particular effect is of utmost importance, considering the findings made by Amoah (2019).

Amoah (2019) found that the frequency of fire outbreaks is expected to keep growing with the passage of time. Per the results of that study, the persistent rise in the pattern of the number of fire outbreaks poses a significant risk to the nation's economy. This risk might be significantly exacerbated if it continues. The outcomes of the fire forecasting efforts will be helpful in providing an estimate of the number of fire incidents, which can then be utilized in the process of planning fire activities in that region. Based on the findings of the study, it was recommended that those responsible for fire management and prevention in Ghana make use of the formulated Seasonal Auto Regressive Integrated Moving Average (SARIMA) model for the goal of forecasting, mitigating, and providing insurance against fire outbreaks.

Fire makes for a poor master because of its destructive nature. It is common practice to label a fire as an extreme event because of its relative rarity, enormous damage, and unexpectedness from a statistical perspective. Both fire outbreaks and natural disasters can be traced back to a wide variety of causes, some of which are attributable to humans while others are outside of our sphere of influence. Electrical, domestic, bush, institutional, commercial, industrial, and vehicle fire outbreaks are the primary causes of fires in Ghana (Amoah, 2019). These are the seven main categories that are used to classify the primary causes of fire outbreaks in Ghana. The mission of the Ghana Fire Service is to seek a reduction in the number of fire outbreaks on a systematic and annual basis, and they aspire to attain a single-digit fatality rate from fires by the year 2015 (Amoah, 2019). Fire outbreaks in fuel stations is one example of commercial fire outbreaks. The use of AI to predict fire outbreak in fuel stations is sure to mitigate the occurrence of such commercial fire outbreaks, thereby contributing towards efforts to attain a single-digit fatality rate (Amoah, 2019).

Adewuyi & Kehinde (2020) evaluated the responsiveness of fire stations to an outbreak of fires at filling stations in the urban core area of the Ibadan metropolitan area. It has been demonstrated that Geographic Information Systems (GIS) are useful tools and technologies that may effectively solve geographic problems and function as decision support systems in the resolution of environmental issues. It is impossible to overstate the significance of filling and service stations' contributions to the socioeconomic development of human life and property, as well as their management's role in making such contributions successful. The study found that only 35% of filling stations followed the 300m local authority standard distance, 7.2% conformed to the 400m by the Department of Petroleum Resources (DPR) regulatory norm, and 32% had their dispensing pump at least 15m from the road. Evidence like this suggests that not all Nigerian filling stations meet the requirements set forth by the country's local government and its Department of Petroleum Resources (DPR). The outcome of the test to determine how quickly a fire station would respond to an emergency at a filling station revealed that more than half of the filling stations (60.8% of them) in the area under investigation can receive prompt treatment. As a result, the Local Authority Town Planning and the DPR Department shall make certain that filling stations have accurate citations for them to comply with the regulation requirement that has been set by them. But then, what happens to the remaining 39.1% of filling stations that are unable to receive prompt treatment from fire stations; that is where AI technology application's ability to predict fire outbreak in fuel stations comes in.

Adewuyi & Kehinde (2020), thus, recommended that some of the filling stations that do not adhere to the regulation standard ought to be subjected to an investigation, and the owners of any filling stations that are found to be in violation of the regulation standard ought to be penalised. In the event that there are other individuals who are interested in entering the business of filling stations, the relevant authority shall conduct an inspection prior to granting approval and beginning construction of such filling stations. The study site, as well as the entirety of the Ibadan metropolitan area, must have adequate provisions made for a contemporary and well-equipped fire service station to provide relief to the stations that are already in place, and even more fire service stations need to be created (Adewuyi & Kehinde, 2020). In conclusion, it is imperative that all fuel filling stations install cutting-edge anti-fire preventive control systems, in their filling stations.

In the table 15 shown above, about 43.85% had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, “AI system has helped automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks (RR3).” The preceding response formed the majority, indicating how vital artificial intelligence is in enabling automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks. This notion is further buttressed by 37.97% of the respondents who had a moderate level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement that “AI system has helped automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks.” About 11.76% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale) concerning statement RR3, not being sure whether AI does help in automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks. However, 6.42% expressed moderate or high levels of disagreements with statement RR3.

Approximately 43.85% of respondents had a strong level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI system has reduced the number of risks between staff and the discharge of fuel from transport to the fuel stations (RR4)." This majority response indicates the significant role artificial intelligence plays in reducing risks between staff and the discharge of fuel from transport to the fuel stations. This notion is further supported by the 32.62% of respondents who had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale).

About 11.23% expressed a neutral stance (scored 4-6 on a 0-10 interval scale) concerning statement RR4, not being sure whether AI has reduced the number of risks between staff and the discharge of fuel from transport to the fuel stations. However, 6.21% of respondents expressed moderate (scored between 2-4 on a 0-10 interval scale) or high levels of disagreement (scored between 0-2 on a 0-10 interval scale) with statement RR4.

Approximately 44.92% of respondents had high levels of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI systems have produced an operation free of risk for effective business transaction between different companies in the downstream petroleum industry (RR5)." This majority response indicates the crucial role artificial intelligence plays in creating risk-free operations for effective business transactions between various companies in the downstream petroleum industry. This idea is further supported by the 39.57% of respondents who had moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale).

About 5.88% of respondents expressed a neutral stance (scored 4-6 on a 0-10 interval scale) concerning statement RR5, not being sure whether AI has produced an operation free of risk for effective business transactions between different companies in the downstream petroleum industry. However, 5.88% of respondents had either moderate or high levels agreement of disagreement with statement RR5.

Inferential Statistics

Table 16 provides the results of analysis of variance for responses of study participants to various statements on reduction of risk as an effect of AI technology application.

Table 16: Results of Analysis of Variance for Responses of Study Participants to Various Statements on Reduction of Risk as an Effect of AI Technology Application

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Statements on Redn in Risk	0.143125	3	0.047708	0.007993	0.998943	3.862548
Responses to statements	5309.976	3	1769.992	296.5541	2.59E-09	3.862548
Error	53.71678	9	5.968531			
Total	5363.836	15				

Statement as a source of variation registered an F value of 0.007993, which is lower than the F critical value of 3.862548 (Table 16). Moreover, the p-value obtained for statements on reduction in risk was 0.998943, which is greater than 0.05. These results implied that the various statements on reduction in risk as an effect of AI technology application were not significantly different since p-value was greater than 0.05. This implied that the various statements on reduction in risk were similar to one another.

Responses as a source of variation obtained an F value of 1769.99992 at a p-value of 2.5×10^{-9}, which is less than 0.05. That suggests frequency distribution of the responses provided was significantly different from one another (since the p-value was less than 0.05) across the various statements on Reduction in Risk as an effect of AI technology application. This meant that respondents viewed the risk reduction effect of AI technology application differently. Therefore, it is safe to conclude that the responses given to the various statements on reduction in risk as an effect of AI technology application were not similar.

Recognition of Threats and Prevention of Hacking

Table 17 presents the frequency distribution of responses concerning the recognition of threats and prevention of hacking as an effect of AI technology application.

Table 17: Frequency Distribution of Responses on the Recognition of threats and Prevention of hacking as an effect of AI Technology Application

Recognition of Threats and Prevention of Hacking	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
AI has prevented criminals from hacking into the operation system of the fuel station (RTPH 1).	4.28 (8)	1.07 (2)	10.70 (20)	35.29 (66)	48.66 (91)

AI has assisted in detecting early fire outbreaks in the fuel stations (RTPH 2).	4.28 (8)	0.53 (1)	11.76 (22)	37.97 (71)	45.45 (85)
AI has helped the prevention of fire outbreak in and around the fuel stations (RTPH 3).	4.28 (8)	1.07 (2)	11.76 (22)	34.22 (64)	48.66 (91)
AI has assisted in the discharge of fuel from the depot to the fuel station (RTPH 4).	5.88 (11)	0.53 (1)	7.49 (14)	39.57 (74)	46.52 (87)
AI has assisted in managing the transaction between clients and the staff of the fuel stations (RTPH 5).	4.81 (9)	1.60 (3)	12.83 (24)	35.29 (66)	45.45 (85)
AI has enhanced quick transfer and transmission of data from one fuel station to the other for faster intervention (RTPH 6).	5.35 (10)	1.60 (3)	11.76 (22)	35.29 (66)	45.99 (86)

NB: Values in parathesis represent numbers of respondents

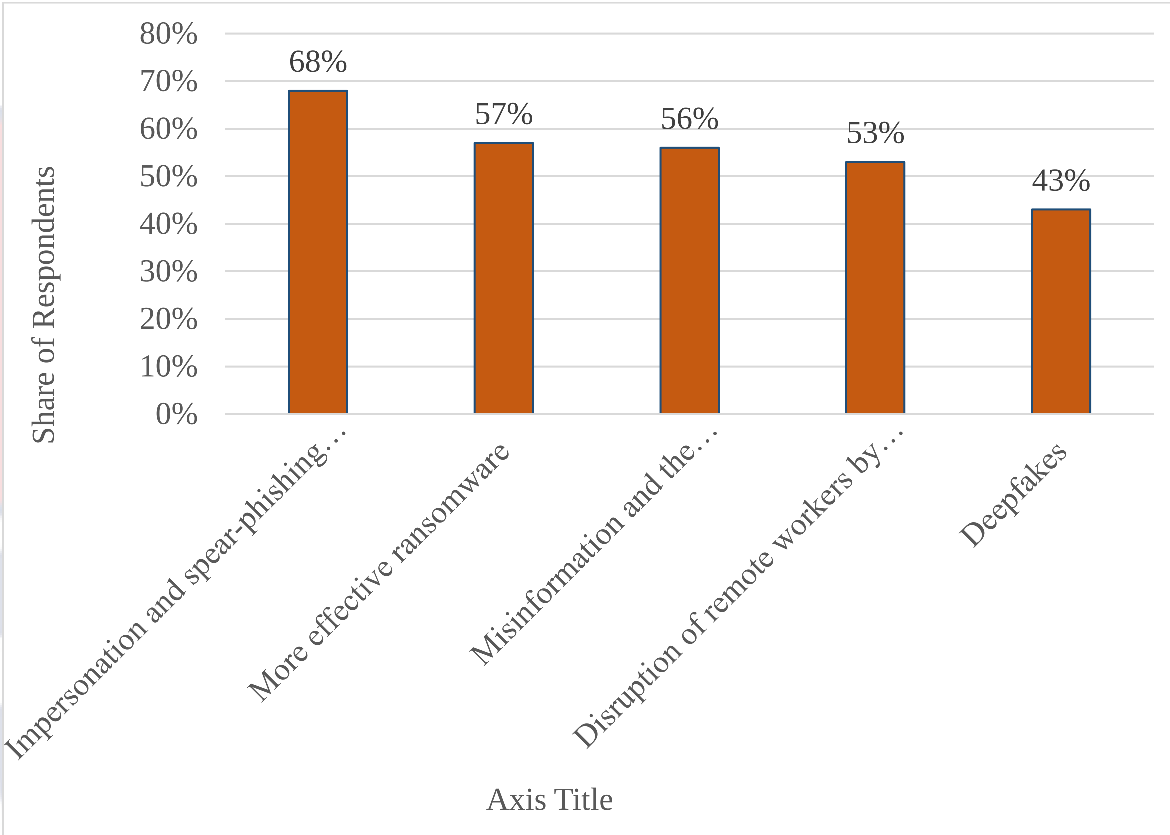
Descriptive Statistics

From Table 17 above, about 48.66% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has prevented criminals from hacking into the operation system of the fuel station (RTPH 1)." This majority response highlights the crucial role artificial intelligence plays in preventing criminals from hacking into the operation system of fuel stations. This idea is further supported by the 35.29% of respondents who had a moderate level of agreement with the statement (scored between 6-8 on a 0-10 interval scale).

About 10.70% of respondents expressed a neutral stance (scored 4-6 on a 0-10 interval scale) concerning statement RTPH 1, not being sure whether AI prevents criminals from hacking into the operation system of the fuel station. However, 4.28% of respondents had a high level of disagreement and a moderate level of disagreement with statement RTPH 1.

However, attacks on computer systems can take a variety of forms, and hackers and scammers are skilled in all of them (Daengsi et al., 2022). The majority of these assaults use a particular piece of software that entirely takes control of the system of the user (Chatchalermpun & Daengsi, 2021), in this case that of the downstream petroleum firm. According to Cisco (2023), the definition of phishing is the process of delivering fraudulent messages that appear to emanate from a credible source; it is typically done through email. Phishing attacks have as their primary objective the acquisition of sensitive information such as login credentials and credit card details (Back & Guerette, 2021). It is also possible that the attacks will involve planting malware on consumers' computers and then demanding a ransom in exchange for eradicating the infection. An effective phishing attack could consist of luring a user into clicking a link to a website from within an email (Miller et al., 2020). This would be an excellent illustration of a phishing assault. The user would then willingly supply the attacker's website with their login details because they mistakenly believed that they were accessing a website that they normally use and trusted. Email, spear phishing, voice phishing, and social media phishing are some of the most popular types of phishing attempts (Ansari et al., 2022).

Figure 9: Potential scenarios of AI-enabled cyberattacks worldwide as of 2021



(Source: Statista)

Phishing is one of the most prevalent forms of attack utilized by cybercriminals and con artists. Phishing was implicated in 36% of all data breaches, according to research that was conducted by Verizon not too long ago (Aljeaid et al., 2020). Over the past few years, there has also been a growth in the practice of phishing (Alamri et al., 2022). The rise in the number of people using the internet has resulted in an increase in the number of persons who are susceptible to assault. Therefore, the practice of phishing presents an ongoing risk to the community in the modern day. The growth of AI technology has also contributed to an increase in phishing scams. The use of methods such as artificial intelligence and machine learning by attackers to manage their operations has considerably increased in recent years (Miller et al., 2020; Purkait, 2015). Phishing attackers have made particular use of advanced technology in artificial intelligence (Purkait, 2015). The graph shown in figure 9 above demonstrates that a rising number of phishing assaults are making use of AI to achieve their goal.

According to Statista, there were around 245,771 phishing assaults documented in the month of January 2021 (Thormundsson, 2022). Therefore, phishing is a significant concern all over the world in the modern era. Attackers are gaining access to additional strategies and tips for controlling their assaults (Thormundsson, 2022). The data that was just presented demonstrates the critical need of formulating strategies that strengthen defenses against assaults (Purkait, 2015). Artificial intelligence-based cyber security is one of these ways. It has been demonstrated through study that AI-based cyber security can achieve considerable outcomes in the field of cyber security (Ansari et al., 2022). Research into the application of AI to cyber security suggests that improving users' awareness would be an effective way to promote security for the vast majority of individual users.

From Table 17 above, approximately 45.45% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, “AI has assisted in detecting early fire outbreaks in the fuel stations (RTPH 2).” The majority view highlights the importance of AI in early fire detection at fuel stations. Additionally, 37.97% had moderate level of agreement (scored between 6-8 on a 0-

10 interval scale), while 11.67% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 4.28% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale), and 0.53% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with RTPH 2.

Approximately 48.7% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, “AI has helped the prevention of fire outbreak in and around the fuel stations (RTPH 3).” This majority view demonstrates AI's significant contribution to reducing fire risk around fuel stations. Furthermore, 34.22% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 11.67% expressed neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 4.28% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale), and 1.07% of the respondents had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with RTPH 3.

About 46.52% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, “AI has assisted in the discharge of fuel from the depot to the fuel station (RTPH 4).” This majority view highlights the importance of AI in assisting fuel transfer from depots to stations. Additionally, 39.57% had a moderate level of agreement (scored between 6-8 on a 0-10 scale), while 7.49% expressed a neutral stance (scored between 4-6 on a 0-10 scale). In contrast, 5.88% had a high level of disagreement (scored between 0-2 on a 0-10 scale), and 0.53% of respondents had moderate level of agreement with RTPH 4.

About 45.45% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "AI has assisted in managing the transaction between clients and the staff of the fuel stations (RTPH 5)." This majority view emphasizes AI's importance in managing transactions between clients and fuel station staff. Furthermore, 35.29% of respondents had moderate level of agreement (scored between 6-8 on a 0-10 scale), while 12.83% expressed a neutral stance (scored between 4-6 on a 0-10 scale). In contrast, 4.81% had a high level of disagreement (scored between 0-2 on a 0-10 scale), and 1.60% of respondents expressed moderate level of disagreement with RTPH 5.

Approximately 45.99% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "AI has enhanced quick transfer and transmission of data from one fuel station to the other for faster intervention (RTPH 6)." This majority view highlights AI's importance in enhancing data transfer and transmission between fuel stations for faster intervention. Additionally, 35.29% of respondents had a moderate level of agreement (scored between 6-8 on a 0-10 scale), while 11.76% expressed a neutral stance (scored between 4-6 on a 0-10 scale). These results collectively suggest that AI plays a vital role in various aspects of fuel station operations, including early fire outbreak detection, fire prevention, fuel discharge, transaction management, and data transfer for faster intervention.

In a risky line of business, like oil and gas, the ability to intervene quickly before an incident gets out of hand is most essential. The use of AI to speed up data transfer and transmission from one fuel station to the other is an advantage that should not be taken lightly.

Inferential Statistics

Table 18 provides the results of the analysis of variance for the responses of study participants to various statements on the recognition of threats and prevention of hacking as an effect of AI technology application.

Table 18: Results of Analysis of Variance for Responses of Study Participants to Various Statements on Recognition of threats and Prevention of hacking (RTPH) as an Effect of AI Technology Application

ANOVA

Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Statement on RTPH	0.48392	4	0.12098	0.032411	0.997685	3.259167
Responses to statements	6747.42	3	2249.14	602.5531	2.41E-13	3.490295
Error	44.7922	12	3.732683			
Total	6792.696	19				

Statements as a source of variation registered an F value of 0.032411, which is lower than the F critical value of 3.259167 (Table 8). Moreover, the p-value obtained for statements on recognition of threats and prevention of hacking was 0.997685, which is greater than 0.05. These results implied that the various statements on recognition of threats and prevention of hacking as an effect of AI technology application were not significantly different since p-value was greater than 0.05. This implied that the various statements on recognition of threats and prevention of hacking were similar.

Responses as a source of variation obtained an F value of 602.5531 at a p-value of 2.41×10^{-13}, which is less than 0.05. That suggests frequency distribution of the responses provided was significantly different from one another (since the p-value was less than 0.05) across the various statements on recognition of threats and prevention of hacking as an effect of AI technology application. This meant that respondents viewed the recognition of threats and prevention of hacking effect of AI technology application differently. Therefore, it is safe to conclude that the responses given to the various statements on recognition of threats and prevention of hacking as an effect of AI technology application were not similar.

Smarter and Safer Fuel Station

Table 19 presents the frequency distribution of responses concerning smarter and safer fuel Station as an effect of AI technology application.

Table 19 presents the frequency distribution of responses concerning smarter and safer fuel Station as an effect of AI technology application.

Smarter and Safer Fuel Station	Frequency Distribution of Responses, % (n)				
	0-2	**2-4**	**4-6**	**6-8**	**8-10**
AI has assisted fuel station to transact business with clients through their machines without human involvement (SSFS 1).	5.88 (11)	0.53 (1)	6.95 (13)	33.69 (63)	52.94 (99)
AI has reduced the risk of fire outbreaks at the fuel station through no involvement of human beings in the transaction line (SSFS 2).	5.88 (11)	1.07 (2)	8.56 (16)	41.18 (77)	43.32 (81)
AI has supported management to introduce smart cards for their clients (SSFS 3).	4.81 (9)	1.07 (2)	8.02 (15)	35.83 (67)	50.27 (94)
AI has assisted in risk free fuel station for safer environment to do business (SSFS 4)	3.74 (7)	0	9.09 (17)	36.36 (68)	50.80 (95)

AI has assisted in non-human interaction in the purchases of fuel by clients at the fuel stations (SSFS 5)	9.63 (18)	0	10.70 (20)	37.97 (71)	41.71 (78)

NB: Values in parathesis represent numbers of respondents

Descriptive Statistics

The results in Table 19 above shows that, about 52.94% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has assisted fuel stations to transact business with clients through their machines without human involvement (SSFS 1)." This majority view highlights the importance of AI in assisting fuel stations to transact business without human involvement. Additionally, 33.69% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 6.95% remained neutral (scored between 4-6 on a 0-10 scale). In contrast, 5.88% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale), and 0.53% had a moderate level of disagreement (scored between 2-4 on a 0-10 scale) with SSFS 1.

About 43.32% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has reduced the risk of fire outbreaks at the fuel station through no involvement of human beings in the transaction line (SSFS 2)." This majority view highlights the importance of AI in reducing fire risks at fuel stations by eliminating human involvement in the transaction line. Additionally, 41.18% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 8.56% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 5.88% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale), and 1.07% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with SSFS 2.

Approximately 50.27% of respondents (table 19) had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has supported management to introduce smart cards for their clients (SSFS 3)." This majority view shows the importance of AI in supporting management to introduce smart cards for clients. Furthermore, 35.83% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 8.02% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 4.81% had a high level of disagreement (scored between 0-2 on a 0-10 interval scale), and 1.07% had a moderate level of disagreement (scored between 2-4 on a 0-10 interval scale) with SSFS 3.

Approximately 50.80% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI has assisted in free risk fuel station for a safer environment to do business (SSFS 4)." This majority view highlights AI's importance in creating risk-free fuel stations for a safer business environment. Additionally, 36.36% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 9.09% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 3.74% had a high level of disagreement (scored between 0-2 on a 0-10 scale with SSFS 4.

Approximately 41.71% of respondents had a high level of agreement (scored between 8-10 on a 0-10 scale) with the statement, "AI has assisted in non-human interaction in the purchases of fuel by clients at the fuel stations (SSFS 5)." This majority view emphasizes the importance of AI in facilitating non-human interactions for fuel purchases at fuel stations. Additionally, 37.97% had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale), while 10.70% expressed a neutral stance (scored between 4-6 on a 0-10 interval scale). In contrast, 9.63% of respondents had a high level of disagreement (scored between 0-2 on a 0-10 interval scale) with SSFS 5. These results collectively suggest that AI plays a crucial role in various aspects of fuel station operations, including fire risk reduction, the introduction of smart cards, creating risk-free environments, and facilitating non-human interactions for fuel purchases.

Inferential Statistics

Table 20 provides the results of the analysis of variance for the responses of study participants to various statements on smarter and safer fuel station as an effect of AI technology application.

Table 20: Results of Analysis of Variance for Responses of Study Participants to Various Statements on Smarter and Safer Fuel Station (SFSS) as an Effect of AI Technology Application

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Statements on SSFS	4.899819	3	1.633273	0.176204	0.909835	3.862548
Responses to Statements	5882.44	3	1960.813	211.5409	1.16E-08	3.862548
Error	83.42276	9	9.269195			
Total	5970.763	15				

Statements as a source of variation registered an F value of 0.176204, which is lower than the F critical value of 3.862548. Moreover, the p-value obtained for statements on smarter and safer fuel station was 0.909835, which is greater than 0.05. These results implied that the various statements on smarter and safer fuel station as an effect of AI technology application were not significantly different since p-value was greater than 0.05. This implied that the various statements on smarter and safer fuel stations were similar.

Responses as a source of variation obtained an F value of 211.5409 at a p-value of $1.16x10^{-08}$, which is less than 0.05. That suggests frequency distribution of the responses provided was significantly different from one another (since the p-value was less than 0.05) across the various statements on smarter and safer fuel station as an effect of AI technology application. This meant that respondents viewed smarter and safer fuel station effect of AI technology application differently. Therefore, it is safe to conclude that the responses given to the various statements on smarter and safer fuel stations as an effect of AI technology application were not similar.

Precision in Decision

Table 21 presents the frequency distribution of responses concerning precision in decision as an effect of AI technology application.

Table 21: Frequency Distribution of Responses on Precision in Decision as an effect of AI Technology Application

Precision in Decision	Frequency Distribution of Responses, % (n)				
	0-2	2-4	4-6	6-8	8-10
AI support quick and precise decision (PD 1)	4.28 (8)	1.60 (3)	3.74 (7)	36.36 (68)	54.01 (101)
AI support management with the needed information at the right time to achieve the goals of the organization (PD 2)	4.28 (8)	0.53 (1)	6.95 (13)	35.29 (66)	52.94 (99)
AI gives smart and calculable data for detailed analysis (PD 3)	4.28 (8)	1.60 (3)	6.95 (13)	32.09 (60)	55.08 (103)
AI detect errors in data very fast for quicker resolution of faults (PD 4)	4.28 (8)	1.07 (2)	6.95 (13)	40.64 (76)	47.06 (88)
AI gives quicker alert and inform staff on operational risks (PD 5)	4.81 (9)	0	11.23 (21)	34.76 (65)	49.20 (92)
AI transmit data and other valuable information to technical staff for an	4.81 (9)	1.60 (3)	13.90 (26)	33.69 (63)	45.99 (86)

informed operational planning (PD 6)					
AI quickly integrate all unit's data for proper easy monitoring and evaluation (PD 7)	4.81 (9)	2.14 (4)	5.35 (10)	33.16 (62)	54.55 (102)

Descriptive Statistics

The results in Table 21 above, shows that about 54.01% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI supports quick and precise decision-making (PD 1)." This majority view emphasizes the role of AI in enabling quick and precise decisions. Additionally, 36.36% of respondents had a moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI supports quick and precise decision-making (Lee et al., 2013). Such AI capability could be life-saving in times of emergencies. About 3.74 % expressed a neutral stance concerning statement PD 1, not being sure whether AI support quick and precise decision. However, 4.28% of respondents had a strong level of disagreement (scored between 0-2 on a 0-10 interval scale), while 1.60% had moderate level of disagreement with PD 1.

Approximately 52.94% of respondents had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI supports management with the needed information at the right time to achieve the goals of the organization (PD 2)." This view is further supported by 35.29% of respondents had moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI supports management with the needed information at the right time to achieve the goals of the organization." One of the beauties of AI is its ability to rummage through rims of digital data, structured and unstructured alike, obtained from various sources (Zysman & Nitzberg, 2020). These sources could be human actions (such as the lighting of a cigarette or fire at the filling stations), and sensors (temperature, position, and images). Zysman & Nitzberg (2020) wrote that after being trained on enormous amounts of data, an AI is able to make predictions and choose appropriate actions. However, about 6.95 % expressed a neutral stance concerning statement PD 2, not being sure whether AI supports management with the needed information at the right time to achieve the goals of the organization. However, 4.28% had high levels of disagreement (scored between 0-2 on a 0-10 interval scale), while 0.53% had moderate levels of disagreement with PD 2.

About 55.08% of respondents showed a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI gives smart and calculable data for detailed analysis (PD 3)." This response constituted the majority, indicating that AI provides smart and calculable data for detailed analysis. This notion is further supported by 32.09% of respondents who had moderate level of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI gives smart and calculable data for detailed analysis." About 6.95% expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale) regarding statement PD 3, unsure whether AI provides smart and calculable data for detailed analysis. However, 4.28% expressed a high level of disagreement (scored between 0-2 on a

0-10 interval scale), while 1.60% expressed moderate levels of disagreement (scored between 2-4 on a 0-10 interval scale) with PD 3.

About 47.06% of respondents showed a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI detects errors in data very fast for quicker resolution of faults (PD 4)." This response constituted the majority, indicating that AI detects errors in data quickly for faster fault resolution. This notion is further supported by 40.64% of respondents who had moderate levels of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI detects errors in data very fast for quicker resolution of faults." About 6.95% expressed an uncertain stance (scored between 4-6 on a 0-10 interval scale) regarding statement PD 4, unsure whether AI can detect errors in data quickly for faster fault resolution. However, 4.28% expressed a high level of disagreement (scored between 0-2 on a 0-10 interval scale), while 1.07% had moderate levels of disagreement (scored between 2-4 on a 0-10 interval scale) with PD 4.

The majority of respondents, approximately 49.20%, had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement "AI gives quicker alerts and informs staff on operational risks (PD 5)." Most of the respondents expressed high levels of agreement, suggesting that AI provides quicker alerts and informs staff on operational risks. This idea is given additional support by the fact that 34.76% of respondents had moderate levels of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI gives quicker alerts and informs staff on operational risks." About 11.23% of respondents had a neutral stance (scored between 4-6 on a 0-10 interval scale) about the statement PD 5, as they were uncertain whether AI provides quicker alerts and informs staff on operational risks. On the other hand, 4.81% of respondents had high levels of disagreement (scored between 0-2 on a 0-10 interval scale) with PD 5.

The majority of respondents, approximately 45.99%, had a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement "AI transmits data and other valuable information to technical staff for informed operational planning (PD 6)." The preceding suggests most of the respondents held the view that AI transmits data and other valuable information to technical staff for informed operational planning. This idea is given additional support by the fact that 33.69% of respondents had moderate levels of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI transmits data and other valuable information to technical staff for informed operational planning." About 13.90% of respondents had a neutral stance (scored between 4-6 on a 0-10 interval scale) about the statement PD 6, as they were uncertain whether AI transmits data and other valuable information to technical staff for informed operational planning. On the other hand, 4.81% of respondents had high levels of disagreement (scored between 0-2 on a 0-10 interval scale) with PD 6, while 1.60% had moderate levels of agreement (scored between 2-4 on a 0-10 interval scale) with the statement.

About 54.55% of respondents showed a high level of agreement (scored between 8-10 on a 0-10 interval scale) with the statement, "AI quickly integrates all unit's data for proper easy monitoring and evaluation (PD 7)." The preceding response constituted the majority of responses to statement PD 7, indicating that AI quickly integrates all unit's data for proper easy monitoring and evaluation. This notion is further supported by 33.16% of respondents who expressed moderate levels of agreement (scored between 6-8 on a 0-10 interval scale) with the statement that "AI quickly integrates all unit's data for proper easy monitoring and evaluation." About 5.35% assumed a neutral position (scored between 4-6 on a 0-10 interval scale) concerning statement PD 7, not being sure whether AI quickly integrates all unit's data for proper easy monitoring and evaluation. However, 4.81% of respondents had high levels of disagreement (scored between 0-2 on a 0-10 interval scale), while 2.14% expressed moderate levels of disagreement (scored between 2-4 on a 0-10 interval scale) with PD 7.

Inferential Statistics

Table *22* provides the results of the analysis of variance for the responses of study participants to various statements on precision in decision as an effect of AI technology application.

Table 22: Results of Analysis of Variance for Responses of Study Participants to Various Statements on Precision in Decision (PD) as an Effect of AI Technology Application

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Statements on PD	0.1182	6	0.0197	0.001693	1	2.661305
Responses to Statements	11525.15	3	3841.715	330.1799	6.42E-16	3.159908
Error	209.4339	18	11.63522			
Total	11734.7	27				

Statements as a source of variation registered an F value of 0.001693, which is lower than the F critical value of 2.661305 (Table 20). Moreover, the p-value obtained for statements on precision in decision was 1, which is greater than 0.05. These results implied that the various statements on precision in decision as an effect of AI technology application were not significantly different since p-value was greater than 0.05. This implied that the various statements on precision in decision were similar.

Responses as a source of variation obtained an F value of 330.1799 at a p-value of 6.42×10^{-16}, which is less than 0.05. That suggests frequency distribution of the responses provided, was significantly different from one another (since the p-value was less than 0.05) across the various statements on precision in decision as an effect of AI technology application. This meant that respondents viewed precision in decision effect of AI technology application differently. Therefore, it is safe to conclude that the responses given to the various statements on precision in decision as an effect of AI technology application were not similar.

Comparing the Effects of AI Technology Application

Table 23 below compares the effects of AI technology application on occupational safety practices.

Table 23: Effects of AI Application on Occupational Safety Practices

Effects of AI Application	Mean	SD
Reduction of Risk	8.74	0.72
Recognition of Threats and Prevention of Hacking	8.86	0.64
Smarter and Safer Fuel Station	8.82	0.65
Precision in Decision	8.88	0.67

The results in Table 23 show that precision in decision had the highest mean value (8.88) followed by recognition of threats and prevention of hacking (8.86), and smarter and safer fuel station (8.82). Reduction of risk scored the lowest mean value. The preceding suggests that, as far as the downstream petroleum sector in the Greater Accra Region is concerned, the primary effect of AI technology application appears to be precision in decision since it scored the highest mean value of 8.88. That was followed by the recognition of threats and prevention of hacking. Because of the use of several data points, the suggestions and recommendations put forward by the artificial intelligence application tend to be precise. This has increased the precision of decisions made by petroleum companies.

CHAPTER SEVEN

MODEL AI TECHNOLOGY APPLICATION SYSTEM IMPROVED OCCUPATIONAL SAFETY

Introduction

This chapter answers the fourth research question, "what AI technology Application model can be designed for improving occupational safety in the downstream petroleum industry in the Greater Accra Region? The expected outcome for this chapter is that an AI Technology Application based model for improving occupational safety in the downstream petroleum industry in the Greater Accra Region would be synthesized. The rest of the chapter is structured as follows: Section 7.1 presents model testing and data analysis; Section 7.2 discusses model AI technology application for improved occupational safety.

Model Testing and Data Analysis

Table 24 proposes different AI-based models for improving occupational safety systems. The table presents the coefficient of determination (R^2) obtained for each assessed model and the proxy of interest. Occupational safety systems were proxied using reduction of risk, recognition of threats and prevention of hacking, smarter and safer fuel stations, and precision in decision. The coefficient of determination shows the amount of variance that is explained by each of the assessed models. Six models were investigated: OHS policies only and occupational safety systems, execution of OHS policies and occupational safety systems, AI only and occupational safety systems, OHS policies + AI and occupational safety systems, execution of OHS policies + AI and occupational safety systems, and OHS Policies + Execution + AI and occupational safety systems.

The coefficient of determination for all the models recorded a p-value of 0.000, indicating that all the models were statistically significant and considerably explained the variations in occupational safety systems.

Table 24: Analysis of Models for Improving Occupational Safety

	Occupational Safety Modes							
Models	Reduction of Risk		Recognition of threats and Prevention of Hacking		Smarter and Safer Fuel Stations		Precision in Decision	
	R^2	p-value	R^2	p-value	R^2	p-value	R^2	p-value
OHS Policies only	0.5745	0.000	0.6420	0.000	0.5858	0.000	0.6278	0.000
Execution of OHS Policies only	0.4910	0.000	0.5288	0.000	0.5707	0.000	0.5956	0.000
AI only	0.5779	0.000	0.5804	0.000	**0.6072**	**0.000**	**0.6916**	**0.000**
AI-based Models								
OHS Policies + AI	0.6279	0.000	0.6705	0.000	0.6461	0.000	0.7305	0.000
Execution of Policies + AI	0.6050	0.000	0.6085	0.000	0.6522	0.000	0.7268	0.000
OHS Policies + Execution + AI	0.6401	0.000	0.6797	0.000	0.6694	0.000	0.7444	0.000

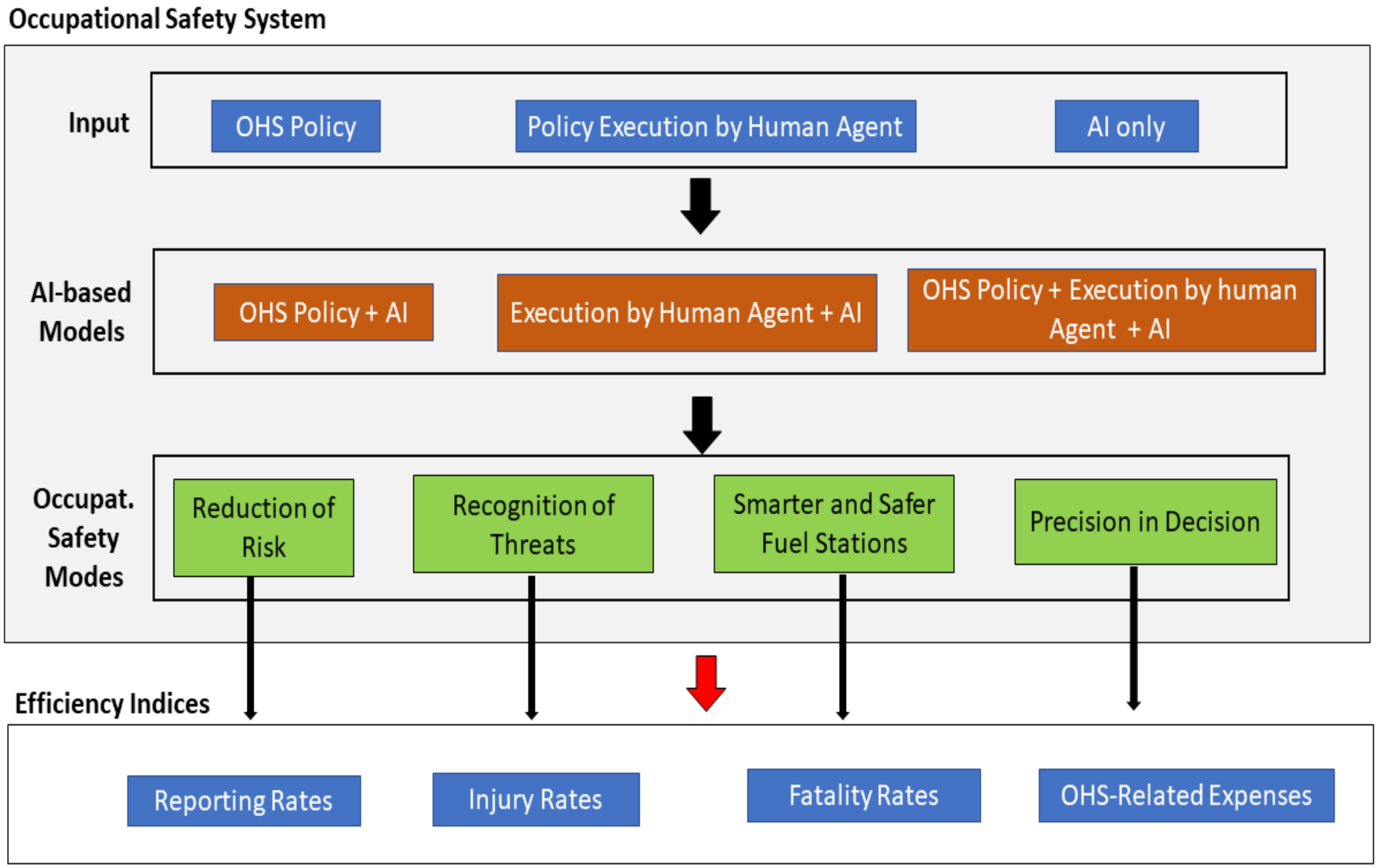
However, some of the models were better at explaining variations in some proxies than other proxies. For example, the AI only model (R-square = 0.5804) was less effective at explaining the variations in recognition of threats, and prevention of hacking when compared to OHS policies only model (R-square = 0.6420), despite being more effective at accounting for the variations in precision in decisions (R-square= 0.6916 compared to R-square of 0.6278), and smarter and safer fuel stations (R-square =0.6072 compared to R-square of 0.5858 for OHS policies only).

Since all the models examined were found to significantly explain the variations in the occupational safety systems proxies, any of them could be used to enhance occupational safety systems. However, further analysis showed that the AI based models appeared to be far more effective in explaining the variations in occupational safety systems than the OHS policies only and occupational safety systems model, execution of OHS policies and occupational safety systems model, and AI only and occupational safety systems model. Among the AI based models, the findings indicate that the most effective seem to be OHS Policies + Execution + AI, and occupational safety systems model. This presupposes that occupational safety systems of downstream petroleum firms would be better served by formulating occupational health and safety policies unique to their context, executing those policies, and applying artificial intelligence technologies to augment the impact of the formulated OHS policies and the execution of those OHS policies.

Model AI Technology Application System for Improved Occupational Safety

Based on the results in the preceding section, an AI-based model is sure to considerably improve occupational safety in the downstream petroleum sector.

Figure 10: Framework for Model AI Technology Application for Improved Occupational Safety



System Characteristics

The proposed occupational health and safety system comprises inputs, AI-based models, occupational safety modes, and efficiency indices.

1. Input: These are the signals that the AI-based occupational safety system will rely on to act. It comprises OHS policy, policy execution by human agent, and the AI algorithm (i.e., AI only).

Components of Input

OHS Policy: This input determines the boundaries of what the system should and would consider an occupational risk.

Policy Execution by Human Agent: This input spells out the specific actions the human agent is recommended to take to mitigate or eliminate the identified OHS risk.

AI only: This input represents the AI algorithm that is responsible for controlling the automations required to carry out specific OHS actions, in response to incidents that the OHS policy has deemed a risk. An example is the automation processes that triggers the sprinklers to release showers to douse the source of the fire, when there is a fire outbreak.

2. AI-based Models: This layer of the system contains models that determine exactly how internal and external signals from the environment of a downstream petroleum business, like a fuel filling station, will be processed and acted upon.

This layer of the system comprises OHS Policy + AI, Policy Execution by Human Agent + AI, and OHS Policy + Policy Execution by Human Agent +AI.

OHS Policy + AI: This AI based model works by fully automating OHS practices and procedures encapsulated in the OHS policy. This model can, thus, be considered as full automation without input from human agent as regards executing OHS-related actions. In this model, the AI is given permission to creatively formulate its own data-driven OHS policies without further input from a human agent.

Policy Execution by Human Agent + AI: This AI-based model combines execution of policy-informed OHS actions by human agents and by artificial intelligence algorithms and their associated smart devices. In this AI-based model, the AI is allowed to creatively formulate its own data-driven OHS policies subject to review and with input from a human agent. This model can, therefore, be considered as semi-autonomous as it partially relies on AI.

OHS Policy + Execution by Human Agent + AI: This AI-based model combines execution of policy-informed OHS actions by human agents and by artificial intelligence algorithms and their associated smart devices. In this AI-based model, OHS policy is regularly reviewed by human agents and new OHS policies added as and when necessary. In this model, the new OHS policy additions may or may not be informed by data.

3. Occupational Safety Modes: This layer of the system presents four different occupational safety modes namely reduction of risk, recognition of threats, smarter and safer fuel stations, and precision in decision (Refer to Chapter 6 for detailed explanations of these modes). The type of occupational safety mode selected depends on the unique occupational safety need and safety priority of the firm. A petroleum firm that prioritizes risk reduction will most likely opt for reduction of risk as occupational safety mode of choice.

5. Efficiency Indices: This layer of the system looks at four output indices namely injury rates, reporting rates, fatality rates and OHS related expenses. These indices measure the extent to which an AI based model in conjunction with an occupational safety mode is performing.

The injury rate has to do with the frequency of injuries. The lower the injury rates the better. The reporting rate has to do with how often safety incidences are reported. A higher reporting rate may suggest that safety in the firm may not be really "up to scratch." Fatality rate suggests the proportion of people who may have died from a workplace accident or injury, by virtue of the AI based model and occupational safety mode selected. Meanwhile, OHS related expenses measures the amount of money spent by the firm in resolving cases of safety issues such as medical bills and compensations.

CHAPTER EIGHT

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

The chapter focuses on the summary of the study, the conclusions drawn from the findings, and recommendations. Section 8.1 presents the summary of findings, while section 8.2 presents the conclusions of the study.

The study set out to analyze artificial intelligence technology application and occupational safety to improve occupational safety in downstream petroleum performance in the Greater Accra Region. The specific objectives of the study are to describe the state of AI technology application and occupational safety in the Greater Accra Region; examine determinants of AI technology application in the downstream petroleum sector; evaluate effects of AI technology application on occupational safety in the downstream petroleum sector within the Greater Accra Region; synthesize a model AI technology application system for improved occupational safety.

Summary of Findings

State of AI Application and Occupational Safety

The areas of application of AI technology examined were theft and fraud, cyber security, threats recognition, risk assessment, predictive analytics of the environment, compliance with safety rules, operational efficiency.

Predictive analytics of the environment recorded the highest mean value of 8.72. This was followed by cyber security with a mean value of 8.66, and compliance with safety rules in third place recording a mean value of 8.54. A test of statistical significance showed that the difference between the mean values for predictive analytics of the environment and cyber security was statistically insignificant (t = 0.6098; p = 0.5427). However, the difference between the mean values for predictive analytics of the environment and compliance with safety rules was found to be statistically significant (t = 2.3368; p = 0.0205).

Operational efficiency, and theft and fraud, thus, seem to be the least important areas of consideration when downstream oil companies are deploying AI technology in occupational safety practices, since operational efficiency recorded the lowest mean value of 8.38 followed by Theft and fraud (8.48).

Concerning operational efficiency, most respondents (41.18 %) had a high level of agreement with the notion that AI was used by firms to cut down on costs. The desire to cut down on costs seemed to be greater than that for time savings, and prevention of quality failures.

When it comes to compliance with safety rules, 51.34% of the survey respondents indicating that they had high levels of agreement with the statement, “My firm uses AI to improve compliance with safety rules (CSR1)” compared with the 48.66% recorded for the statement, “My firm uses AI to reduce accidents caused by lack of compliance with safety rules.” The apparent strong concern for improving compliance with safety rules may have a lot to do with reducing accidents caused by lack of compliance with safety rules.

A paired t-test showed that the difference between the mean values for predictive analytics of the environment and compliance with safety rules was statistically significant, as evinced by a p-value of 0.0205, which is below 0.05. The preceding suggests that downstream petroleum companies' attitude towards the deployment of AI for predictive analytics of the environment, and cyber security is markedly different from that exhibited towards compliance safety. Since operational efficiency got the lowest average Interval scale score, it appears to be the area where downstream petroleum companies in Ghana's Greater Accra Region use AI technology the least, when it comes to ensuring occupational safety practices.

The commonest area of AI application in the Greater Accra Region's downstream petroleum sector tended to be predictive analytics of the environment, as evinced by it obtaining the highest mean value of 8.72. The preceding result meant that the ability to predict what could happen in the operating environment (predictive analytics of the environment) under certain hazardous conditions matters most to downstream petroleum companies than any other thing.

Concerning risk assessment, most respondents had a high level of agreement with the statement, "Our AI is used to accurately assess the risk associated with our operations. Downstream petroleum firms seem to consider threat detection and categorization of identified threats equally important and both far more critical than security sensor implementation and neutralization of identified threats. 82.35 % of respondents either had moderate or high levels of agreement with the notion that AI technology is used to make their company's internal network difficult for bad actors to hack or penetrate, while 43.85 % had a moderate level of agreement and were of the view that AI is used to improve their firm's cyber security. Downstream petroleum firms seem to be keener on improving cyber security than making internal network difficult for bad actors to hack or penetrate, since more survey respondents (86.63%) either had moderate or high levels of agreement with the notion that AI technology is used to improve their firm's cyber security compared to the 82.35% percentage frequency for CS1. This could be because the digital environment is "trembling" in the face of ever-evolving hacking targets and methodologies.

Determinants of AI Technology Application

The petroleum downstream firms seeking to adopt AI technology in their firms would first consider innovativeness, followed by the rest. Despite the traditional resistance of the petroleum industry towards new technologies, 88.78% either had moderate or high levels of agreement with the statement, "I do not mind trying new things." The mean value for innovativeness (8.54) was found to be significantly higher than that for risk aversion (8.36), as evinced by a p-value of 0.0218 ($t = 2.3124$), per the results of a paired t-test. This presupposes that employees of downstream petroleum firms are open to accepting AI technology introductions. 35.83 % of respondents had a high level of agreement with the statement, "I am enthusiastic and open about AI usage," while 54.55% had moderate level of agreement with the statement, thus making the majority. About 8.56% of respondents were neutral, even though technology has heavily influenced modern society. The results of the study showed that respondents appeared rather more trusting of AI than enthusiastic about it, since a greater proportion of respondents had a high level of agreement with the statement, "I have trust in the usefulness of AI," when compared to a similar response to the statement, "I am enthusiastic and open about AI usage," which recorded a proportion of 35.83%.

About 34.2% had a high level of agreement with the statement, "I don't feel I am going to be out of a job if I adopt the AI system," while 56.15% had moderate level of agreement with that statement. This meant that 90.35% of respondents did not feel their jobs were under threat because of AI adoption. It, therefore, stands to reason that, such individuals would have no problem accepting AI. Notwithstanding, 9.65% of respondents did not share those same sentiments, as 6.42% expressed a neutral stance and 3.21% had a moderate level of disagreement with the statement above.

About 31.55% of respondents had high level of agreement with the statement, "I am willing to explore new technologies without fear of technology failure," which is comparatively lower than the percentage frequency reported for the statement, "I don't feel I am going to be out of a job if I adopt the AI system." The preceding suggests that personal incentives may be a stronger motivational factor for AI acceptance than fear of technological failure.

Although a high percentage of respondents indicated that they considered AI technology usage an acceptable risk, it was not clear whether respondents fully appreciate the wide range of risks associated with AI usage.

34.76% of respondents had a high level of agreement with the statement, “I like to go along with what I know works,” while 54.55% of them agreed. The preceding suggests that 89.31% of respondents would like to be sure that the AI technology to be adopted really works before they accept it.

35.83 % of respondents had high level of agreement with the statement, “I think about the changes I will have to make in the implementation of AI technology at my workplace,” while 53.48% had moderate level of agreement with the statement. This meant that 89.31% of respondents think about the changes they will have to make in the implementation of AI technology at their workplace.

38.50% of respondents had high level of agreement with the statement, “I understand where technology fits in the process of running a platform,” while 48.66% agreed with the statement, suggesting that the better the technical knowledge of respondents, the more likely they are to accept AI.

About 34.22% had high level of agreement with the statement, “Social influences within my network play a key role in my acceptance of new technology,” while 54.55% agreed with that statement (Table 12). This suggests that 88.77% of respondents appear to be greatly influenced by their social network when it comes to their acceptance of new technology. It, therefore, stands to reason that, such individuals would have no problem accepting AI if their social networks either okays it or are familiar with AI applications.

Of the three organizational factors considered in the study, leadership was the one organizational factor that elicited the greatest proportion of had high level of agreement (40.64%) responses, while of the three organizational factors considered in the study, technology adoption culture was the one organizational factor that had the greatest proportion of moderate level of agreement responses.

Of the fifteen (15) constructs or factors investigated, four of them namely technology attitudes, trust, social norms, and technology adoption culture, were observed to be significant determinants of AI acceptance in the downstream petroleum sector. These findings were supported by Roberts et al.'s (2021) Psychological Technology Adoption Framework.

Furthermore, the above immediate findings seem to suggest that acceptance of new technologies is influenced by psychological factors and appears to occur at the individual level. This means that downstream firms will do well to analyse AI acceptance at the individual and psychological level.

Therefore, when considering organizational factors like the technology adoption culture, which was observed to be a statistically significant determinant of AI acceptance, it will be wise to find out how well the various individuals, especially those with direct oversight of the AI technology application, have been influenced by the organization's technology adoption culture. Ignorance of such considerations could spell doom for the AI technology project.

AI is a socially interesting technology with little in the way of actual user experience, so potential users are still influenced by the opinions of others when deciding whether to adopt AI technology.

Since technology attitudes, and trust fall under the attitude factors; social norms under social factors; and technology adoption culture under organizational factors, this suggests that attitude factors, social factors and organizational factors may well be significant determinants of AI acceptance and application in downstream petroleum sector. Cognitive factor, per the findings of this study, had no significant influence on AI acceptance.

The “say so” or views of individuals regarding the deployment of AI technologies in downstream petroleum firms really matter. This is where the agency theory and stakeholder theory come into play. With agency theory, a principal may pass a policy, but if the agent suffers from conflicts of interest, the desired outcome may not be realized. For any new policy or intervention to work, stakeholders must be consulted; this forms the crux of the stakeholder theory.

Effects of AI Technology Application on Occupational Safety

About 48.66% had high level of agreement with the statement, “AI as part of the built system of the fuel station has helped to alert staff of impending dangers such as fire outbreaks (RR1).” The preceding response formed the majority, indicating how vital artificial intelligence is in alerting staff of downstream petroleum firms of impending disasters such as fire outbreaks. This notion is further buttressed by 31.55% of the respondents who agreed with the statement that "AI as part of the built system of the fuel station has helped to alert staff of impending dangers such as fire outbreaks."

About 47.06% had high level of agreement with the statement, "AI has helped to predict fire outbreak in fuel stations." The preceding response formed the majority, showing how artificial intelligence has helped to predict fire outbreaks in fuel stations.

About 48.66% had high level of agreement with the statement, "AI has prevented criminals from hacking into the operation system of the fuel station." The preceding response formed the majority, showing how essential artificial intelligence is in preventing criminals from hacking into the operation system of the fuel station.

Of the six statements examined under recognition of threats and prevention of hacking as an effect of AI technology application, statement RTPH 5 (i.e., AI has assisted in managing the transaction between clients and the staff of the fuel stations) registered the highest level of neutral responses, underscoring the level of uncertainty among respondents concerning the item.

The various statements on the different AI technology application effects such as reduction of risk, recognition of threats and prevention of hacking, smarter and safer fuel stations, and precision in decision making were not significantly different since the p-value was greater than 0.05.

Precision in decision had the highest mean value (8.88) followed by recognition of threats and prevention of hacking (8.86), and smarter and safer fuel station (8.82). Reduction of risk scored the lowest mean value.

The preceding suggests that, as far as the downstream petroleum sector in the Greater Accra Region is concerned, the primary effect of AI technology application appears to be precision in decision since it scored the highest mean value of 8.88. This was followed by the recognition of threats and prevention of hacking.

Model AI Technology Application for Improved Occupational Safety

Occupational safety systems were proxied using reduction of risk, recognition of threats and prevention of hacking, smarter and safer fuel stations, and precision in decision.

The coefficient of determination shows the amount of variance that is explained by each of the assessed models. Six models were investigated: OHS policies only and occupational safety systems, execution of OHS policies and occupational safety systems, AI only and occupational safety systems, OHS policies + AI and occupational safety systems, execution of OHS policies + AI and occupational safety systems, and OHS Policies + Execution + AI and occupational safety systems.

The coefficient of determination for all the models recorded a p-value of 0.000, indicating that all the models were statistically significant and considerably explained the variations in occupational safety systems.

Some of the models were better at explaining variations in some proxies than other proxies. For example, the AI only model (R-square = 0.5804) was less effective at explaining the variations in recognition of threats, and prevention of hacking when compared to OHS policies only model (R-square = 0.6420), despite being more effective at accounting for the variations in precision in decisions (R-square= 0.6916 compared to R-square of 0.6278), and smarter and safer fuel stations (R-square =0.6072 compared to R-square of 0.5858 for OHS policies only).

Occupational safety systems of downstream petroleum firms would be better served by formulating occupational health and safety policies unique to their context, executing those policies, and applying artificial intelligence technologies to augment the impact of the formulated OHS policies and the execution of those OHS policies.

Conclusions

State of AI Application and Occupational Safety

- Predictive analytics of the environment was found to be the most common area of AI Technology Application in the downstream petroleum industry, followed by cyber security and compliance with safety rules.
- When downstream oil businesses are adopting AI technology in occupational safety procedures, it was found that operational efficiency and theft and fraud were the areas of consideration that were given the least amount of importance.

Determinants of AI Technology Application

- Technology attitudes, trust, social norms, and technology adoption culture were observed to be significant determinants of AI acceptance in the downstream petroleum sector.
- Acceptance of new technologies in the downstream petroleum sector is influenced by psychological factors and appears to occur at the individual level.

Effects of AI Application on Occupational Safety

- The primary effect of AI technology application in the downstream petroleum sector appears to be precision in decision.
- Recognition of threats and prevention of hacking appears to be the secondary effect of AI technology application in the downstream petroleum sector.

Model AI Technology for Improved Occupational Safety

- Occupational health and safety policies in the downstream petroleum sector are influenced by context. One downstream petroleum firm may regard recognition of threats and prevention of hacking as more important than other occupational safety modes, while another firm may feel smarter and safer fuel stations are what it needs the most.
- A novel framework for model AI technology application for improved occupational safety was developed comprising of the following system characteristics: inputs, AI-based models, occupational safety modes, and efficiency indices. The framework is shown in figure 10 aboves.

Recommendations

Considering the fact that predictive analytics of the environment was found to be the most common area of AI application in the downstream petroleum industry, it is recommended that players in the downstream sector invest resources into training and building the capacity of staff in things that pertain to predictive analytics of the environment. In this way, such firms would derive maximum benefit from their AI technology applications.

Because the acceptance of new technologies in the downstream petroleum sector is influenced by psychological factors and appears to occur at the individual level, it is strongly advised that oil and gas firms engage staff members at the individual level when trying to introduce new technologies like AI technology applications.

It is recommended that formulation of occupational health and safety policies of downstream petroleum firms be done in such a way that it is unique to their context, executing those policies, and applying artificial intelligence technologies to augment the impact of the formulated OHS policies and the execution of those OHS policies.

It is further recommended that as a policy by the regulator all players in the downstream petroleum industries should ensure to embed in all their installation AI compliant systems to improve and ensure safety.

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APPENDIX 1: Output of Multiple Linear Regression on the Determinants of AI Acceptance and AI technology Application

Source	SS	df	MS			
				Number of obs	=	187
				F(15, 171)	=	8.42
Model	5.13912649	15	.342608432	Prob > F	=	0.0000
Residual	6.9571302	171	.040684972	R-squared	=	0.4249
				Adj R-squared	=	0.3744
Total	12.0962567	186	.065033638	Root MSE	=	.20171

new_FirmApplyAI	Coef.	Std. Err.	t	P>|t|	Beta
Obj2_PF1_Innovative~s	.0181104	.0298806	0.61	0.545	.0533809
Obj2_PF1_RiskAversn	-.0489577	.0344583	-1.42	0.157	-.1401846
Obj2_AF1_TechAtt	-.0887067	.0350028	-2.53	0.012	-.2269647
Obj2_AF2_Trust	.1030464	.0342106	3.01	0.003	.3038706
Obj2_MF1_PersonInce~s	.0131428	.0298035	0.44	0.660	.036136
Obj2_MF2_FearTechFa~e	-.0205874	.0346605	-0.59	0.553	-.0577519
Obj2_CF1_RiskPercp	-.0140355	.030313	-0.46	0.644	-.0440552
Obj2_CF2_TechKnowle~e	.0114046	.0339674	0.34	0.737	.0335315
Obj2_CF3_PercepOfCe~y	.0137759	.0322899	0.43	0.670	.0371587
Obj2_CF4_PrevExp	.0082655	.0321467	0.26	0.797	.0219938
Obj2_SF1_SocialInfl	.0341211	.0358224	0.95	0.342	.0942424
Obj2_SF2_SocialNorms	.0822819	.0319457	2.58	0.011	.2440899
Obj2_OF1_Leadership	-.0177601	.0318291	-0.56	0.578	-.0528679
Obj2_OF2_CollabCult~e	.009373	.0337325	0.28	0.781	.0260049
Obj2_OF3_TechAdoptn~e	.1067045	.028823	3.70	0.000	.3282188
_cons	1.045309	.1211379	8.63	0.000	.

APPENDIX 2: Questionnaire

ARTIFICIAL INTELLIGENCE TECHNOLOGY APPLICATION AND OCCUPATIONAL SAFETY PRACTICES IN THE DOWNSTREAM PETROLEUM INDUSTRIES IN THE GREATER ACCRA REGION, GHANA

I am Abban, a PhD candidate of the Institute of Development and Technology Management, Cape Coast, who is currently working on a research project seeking to establish the role of artificial intelligence (AI) technology application in occupational safety practices in the downstream petroleum sector in the Greater Accra Region.

I would like to seek your kind assistance by answering the questionnaire. All information shall be held confidential, and it is strictly for academic purpose only. Thank you for your support and cooperation. No response can be traced back to you.

Section A: Background of Respondents

1. Sex of the respondent? Female [ ], Male [ ]

2. Age of the respondent? ……………

3. What is your highest level of education? (Indicate the highest)

(a) PhD [ ] (b) Masters [ ] (c) Bachelor Degree [ ] (d) Diploma/HND [ ]

(e) Certificate [ ] (f) No formal Education [ ]

4. Your position/job title ……………………………………………

5. How long have you been with your firm? ………………..

4. Does your firm apply artificial intelligence technology in its operations?

(a) Yes [ ] (b) No [ ]

Section B: Explore Areas of Application of AI Technology in Occupational Safety Practices in Downstream Petroleum Industry in the Greater Accra Region

10. Instructions: Please read each statement carefully and rate your response using the following interval scale: 0 – 10, with **0** being **no level of agreement** and **10** being **the highest level of agreement**.

0 1 2 3 4 5 6 7 8 9 10

(Reducing level of agreement) (Increasing level of agreement)

	Variables	Interval scale (pls tick the box that matches your rating										
		0	1	2	3	4	5	6	7	8	9	10
1.	**Operational Efficiency**											
	My firm uses AI to cut down on costs (OE1)											
	My firm uses AI to prevent quality failures. (OE2)											

	My firm uses AI to save time (OE3)												
2.	**Compliance with Safety Rules**												
	My firm uses AI to improve compliance with safety rules (CSR1)												
	My firm uses AI to reduce accidents caused by lack of compliance with safety rules (CSR2)												
3.	**Predictive Analytics of the Environment**												
	AI helps my firm to prevent many occupational health and safety hazards before they happened (PAE1)												
	The predictive power of AI is used to help												

	my firm save a lot of money that would have otherwise been used to do repairs and damage control (PAE2)												
3.	**Risk Assessment**												
	Our AI is used to accurately assess the risk associated with our operations (RA1)												
	Our AI is used to provide insights that inform management of the severity of the risk so that management can take appropriate actions (RA2)												
4.	**Threats Recognition**												
	Our AI is used to recognize threats (TR1).												

	My firm uses AI to implement security sensors to track and decipher information on potential fires outbreaks (TR2).											
	Our AI is used to neutralize identified threats such as putting on water sprinklers when sensors detect smoke (TR3).											
	Our AI is used to categorize identified threats in order of severity (TR4).											
5.	**Cyber security**											
	AI technology is used to make my company's internal network difficult for bad actors to hack or penetrate (CS1)											

	My firm deploys AI technology to improve the company's cyber security (CS2).											
6.	**Theft and Fraud**											
	My firm uses AI to reduce the occurrence of theft and fraud at the workplace (TF1)											
	My firm uses AI to increase accountability (TF2)											
	My firm uses AI to increase transparency (TF3)											

Section C: Determinants of AI acceptance and application in occupational safety practices within the Greater Accra Region's downstream petroleum industry.

11. Instructions: Please read each statement carefully and rate your response using the following interval scale: 0 – 10, with **0** being **no level of agreement** and **10** being **the highest level of agreement**.

0 1 2 3 4 5 6 7 8 9 10

(Reducing level of agreement) (Increasing level of agreement)

	Variable	Interval scale (pls tick the box that matches your rating										
		0	1	2	3	4	5	6	7	8	9	10
1.	**Personality Factors**											
	I do not mind trying new things such as AI (Innovativeness) (PF1)											
	I am not risk averse to AI usage in company operations (Risk aversion) (PF2)											
2	**Attitude Factors**											
	I am enthusiastic and open about AI usage (Technology attitudes) (AF1)											

	I have trust in the usefulness of AI (Trust) (AF2)											
3.	**Motivation factors**											
	I don't feel I am going to be out of a job if I adopt the AI system. (Personal incentiveness) (MF1)											
	I am willing to explore new technologies without fear of technology failure (Fear of technological failure) (MF2)											
4.	**Cognitive factors**											
	I consider AI technology usage an acceptable risk (Risk perception) (CF1)											
	I understand where technology fits in the process of running a platform (Technical knowledge) (CF2)											

	I like to go along with what I know works (Perceptions of certainty) (CF3)											
	I think about the changes I will have to make in the implementation of AI technology at my workplace. (Previous experience) (CF4)											
5.	**Social factors**											
	Social influences within my network play a key role in my acceptance of new technology (Social influences) (SF1)											
	At the workplace, I am expected to behave in a certain way (Social norms) (SF2)											
6.	**Organizational factors**											
	Firm leadership is able to get every member of the											

	firm onboard any new initiative (Leadership) (OF1).											
	As a firm, we look to other industries to see what they're doing and how can we translate their experience *(Collaboration culture)* (OF2)											
	New technology like AI has really been part of the core strategy of the company, and everybody lives and breathes this *(Technology adoption culture).* (OF3)											

Section D: Effects of AI Application on Occupational Safety Practices in the Downstream Petroleum Sector within the Greater Accra Region.

12. Instructions: Please read each statement carefully and rate your response using the following interval scale: 0 – 10, with **0** being **no level of agreement** and **10** being **the highest level of agreement**.

0 1 2 3 4 5 6 7 8 9 10

(Reducing level of agreement) (Increasing level of agreement)

	Variable	Interval scale (pls tick the box that matches your rating										
1.	**Reduction in Risk**	0	1	2	3	4	5	6	7	8	9	10
	AI as part of the built system of the fuel station has helped to alert staff of impending dangers such as fire outbreaks. (RR1)											
	AI has helped to predict fire outbreak											

	in fuel stations. (RR2)											
	AI system has helped automated transmission of fuel from transport to the fuel station by reducing the risk of fire outbreaks (RR3).											
	AI system has reduced the number of risks between staff and the discharge of fuel from transport to the fuel stations. (RR4)											
	AI systems have produced an operation free of risk for effective business transaction between different companies in the											

	downstream petroleum industry (RR5).											
2.	**Recognize Threats and Prevent Hacking**											
	AI has prevented criminals from hacking into the operation system of the fuel station (RTPH 1)											
	AI has assisted in detecting early fire outbreaks in the fuel stations (RTPH 2)											
	AI has helped the prevention of fire outbreak in and around the fuel stations (RTPH 3)											
	AI has assisted in the discharge of fuel											

	from the depot to the fuel station (RTPH 4)											
	AI has assisted in managing the transaction between clients and the staff of the fuel stations (RTPH 5).											
	AI has enhanced quick transfer and transmission of data from one fuel station to the other for faster intervention (RTPH 6)											
3.	**Smarter and Safer Fuel Station**											
	AI has assisted fuel station to transact business with clients through their machines without											

	human involvement (SSFS 1).											
	AI has reduced the risk of fire outbreaks at the fuel station through no involvement of human beings in the transaction line (SSFS 2).											
	AI has supported management to introduce smart cards for their clients (SSFS 3).											
	AI has assisted in free risk fuel station for safer environment to do business (SSFS 4)											
	AI has assisted in non-human interaction in the purchases of fuel by											

	clients at the fuel stations (SSFS 5)											
4.	**Precision in Decision**											
	AI support quick and precise decision (PD 1)											
	AI support management with the needed information at the right time to achieve the goals of the organization (PD 2)											
	AI gives smart and calculable data for detailed analysis (PD 3)											
	AI detect errors in data very fast for quicker resolution of faults (PD 4)											

	AI gives quicker alert and inform staff on operational risks (PD 5)											
	AI transmit data and other valuable information to technical staff for an informed operational planning (PD 6)											
	AI quickly integrate all unit's data for proper easy monitoring and evaluation (PD 7)											

Section E: AI-based Model for Improved Occupational Safety System

13. Instructions: Please read each statement carefully and rate your response using the following interval scale: 0 – 10, with **0** being **no level of agreement** and **10** being **the highest level of agreement**.

0 1 2 3 4 5 6 7 8 9 10

(Reducing level of agreement) (Increasing level of agreement)

	Statements	Interval scale (pls tick the box that matches your rating										
		0	1	2	3	4	5	6	7	8	9	10
	Formulation of policies on occupational safety is the best way to improve occupational safety system (Policies)											
	Execution of policies on occupational safety is the best way to improve occupational safety system (Execution)											
	The use of artificial intelligence (AI) technologies is the best way to improve occupational safety system. (AI)											
	Formulation of policies on occupational safety and their execution is the best way to improve											

	occupational safety system (Policies + Execution)											
	Formulation of policies on occupational safety and their execution together with the use of AI technologies is the best way to improve occupational safety system (Policies + Execution + AI)											