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RESEARCH ARTICLE

The Impacts of Innovation Attribute, Business Environment, and Risk Management on the Artificial Intelligence Investment Decision in Oman's Hydrocarbons Industry

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ABSTRACT

Artificial intelligence (AI) has become a pioneering technology in the new era for the hydrocarbon industry across the globe. The objective of this study was to assess the effects of innovation attributes, business environment, and risk management on AI investment decision in Oman's hydrocarbon industry. This study is a quantitative study using a questionnaire addressed to employees of Oman's hydrocarbons industry with a total of 367 respondents. Hypotheses were tested using the Smart PLS 4.0 statistical tool. The results showed that relative advantage of innovation attribute of AI has a significant positive relationship with AI investment decision (coefficient = 0.09, $p < 0.05$). The relationship between the compatibility of the innovation attribute of AI and AI investment decision was significant (coefficient = 0.12, $p < 0.05$). The observability of the innovation attribute of AI has no significant relationship with AI investment decision (coefficient = 0.04, $p > 0.05$). Government factors (coefficient = 0.13, $p < 0.05$), knowledge capability (coefficient = 0.16, $p < 0.05$), risk management (coefficient = 0.14, $p < 0.05$), and economic instability (coefficient = -0.12, $p < 0.05$), have a significant relationship with AI investment decision. Management structure has a significant positive relationship with AI investment decision (coefficient = 0.14, $p < 0.05$). There is no relationship between physical facilities' unobtainability and AI investment decision. The conclusion is that the following factors have a significant relationship with AI investment decision, namely: relative advantage and compatibility of innovation attributes of AI, government and economic factors, knowledge capability, risk management, and management structure.

INTRODUCTION

Oman's hydrocarbons industry is vital to the nation's economy, generating a large amount of income and job opportunities. Artificial intelligence (AI) technologies have gained popularity in recent years to foster decision-making processes, reduce costs, and improve operational effectiveness. This study aims to explore the impacts of AI innovation, business environment, and risk management on AI investment decision in Oman's hydrocarbons industry. Comprehending these facets enables industry stakeholders to make knowledgeable choices regarding the use of AI and optimize the advantages of these technologies. As more businesses utilize AI to automate processes, its popularity has grown in recent years. AI is one of the most cutting-edge technologies that is trending in several industries. Nevertheless, within the past 20 years, there has been a growth in the manipulation of AI. However, AI is leading the fourth industrial revolution in many parts of the world today. The Sultanate of Oman has started to foster digital transformation to improve efficiency and optimize processes. The Oman Vision 2040 is steering innovation in the modern digital economy by encouraging diverse economic evolution and job creation. Moreover, the topic of AI has garnered pointed attention and investment from numerous firms in the recent past (Lui et al., 2021). Furthermore, AI is being applied more and more in the fields of manufacturing, education, healthcare, banking, logistics, and hydrocarbons. This is moving lifestyle toward intelligence and making the working environment more intelligent (Liu et al., 2020).

LITERATURE REVIEW AND RESEARCH HYPOTHESES

Innovation attributes of the innovation diffusion theory (IDT), including relative advantage, compatibility, and observability, are observed to influence innovation adoption (Tan et al., 2009; Li, 2008; M. Islam et al., 2013; A. Mehra et al., 2021). Rogers (2003) describes relative advantage as the degree to which an innovation is perceived as being healthier than the idea that it succeeds. Furthermore, relative advantage is a hotly disputed topic because it affects how quickly users adopt new technology services and products (Mombeuil & Uhde, 2021). According to Pan et al. (2022), the term "relative advantage" indicates the amount of value that innovation can grant to an organization. Moreover, relative advantage refers to the degree to which an innovation is seen to be superior to its predecessors (Pandl et al., 2022). Nevertheless, relative advantage is one of the most important features of innovation in predicting whether a technological breakthrough will be accepted and adopted (Hmoud & Várallyai, 2022). Additionally, the perceived relative advantage of an innovation is the level to which it outperforms the idea it replaces; the larger the perceived relative advantage of an innovation, the quicker it will be implemented (Tsai & Chen, 2022). Therefore, relative advantage reveals that AI innovation is further advantageous in contrast with the existing technology.

Compatibility as the extent to which an innovation is perceived as relentless with historical practices, existing values, and demands of feasible adopters (Rogers, 2003). Besides, compatibility is mounting between the desired usage and technology, and a skilled partner between the technology and the assignment will head to advanced levels of acknowledgement and utilization (Enholm et el., 2021). Conversely, the technical compatibility of lasting techniques with new AI solution is decisive and has a substantial bearing on AI investment decision (Schaefer et al., 2021). Similarly, according to Tsai and Chen (2022), the extent to which an invention is involved to be dependable with the alive principles, preceding experiences, and needs of possible adopters is branded as compatibility. An innovation that is contradictory with the system's leading values and standards will not be accepted as speedily as one that is compatible.

Observability is the extent to which an innovation supplies visible values that promote risen visibility (Hidayat et al., 2022). However, according to Tsai and Chen (2022), the level to which the consequences of innovation may be perceived by others is stated to as observability and individuals will accept innovations more rapidly if they can see the significance of the invention straightforwardly.

The business environment contains all factors that influence the business, such as the internal power relationships, the organization's strengths, weaknesses, and orientations; government strategies and rules; the economy's nature and economic circumstances; sociocultural factors; demographic trends; natural factors; and worldwide trends and cross-border changes (Cherunilam, 2016). Though, according to Ajaz Khan et al. (2019) the business environment incorporates regulations and supervisory frameworks, standards and rules, governance, and overall trade and investment strategy, as well as commence rules and regulations for business operations that may have a positive or negative impact on the market, business, cost of doing business, investment flow, and output. According to Cherunilam

(2016), AI investment decision is shaped by the internal and the external environment. According to Trisakhon, et al. (2018) in their research painted the meanings of both internal and external environment, the term "internal environment" refers to factors within the organization, and most internal factors are more controllable than external factors since they are structured by the management of the organization. On the other hand, the term "external environment" refers to the factors that can influence an organization and is mostly made up of uncontrollable forces.

Additionally, the external environment is divided into four main classifications: economic, political, technological, social, and cultural. External Business environmental factors, such as government and legal, economic, demographic, socio-cultural, geophysical, and other factors, are often seen as unmanageable by an organization (Cherunilam, 2016). Furthermore, the external environment presents a restricted state of the business's environment and a range of factors influencing conditions and business paths (Borodin et al., 2021).

Government has the power to encourage the acceptance of new technologies and enact laws that either create or remove obstacles to the introduction of novel innovations (Huang & Palvia, 2001). Conversely, government policy stages an essential role in supporting innovation (Lemke,2003). The government's endorsement of breakthrough technology through the provision of supportive infrastructure and legal and regulatory frameworks will expedite its adoption (Li, 2008). Additionally, the support of the government fosters an environment that is conducive to AI and will increase its impact and dissemination (Agrawal & Goldrarb, 2019). Government policies, however, have a significant influence on the overall financial performance of many sectors, and it is difficult for firms to make wise investment decisions when appropriate economic policies are not in place (Al-Thaqeb & Algharabali, 2019). Moreover, the governments of different countries policies might result in either beneficial or negative development (Okere, 2017). Furthermore, government programs afford directives that figure out how AI is created (Enholm et el., 2021).

Positive economics is a critical thought when determining whether to invest in AI solutions (Wolff et al., 2020). A lot of organizations are impacted by important economic issues including inflation, interest rates, and unemployment. These factors have a big influence on how businesses act and make decisions (Kowo & Popoola, 2018). However, investment efficiency can be supported through the thriving provision of capital. As a result, oil prices are important in determining how to allocate the necessary cash, particularly for governments where the price of oil is their primary source of income for their total domestic production. Furthermore, oil price variations have a huge effect on the economics of oil exporting nations, mainly OPEC members (Trang et al., 2017).

The body of literature contains sufficient evidence to demonstrate that AI technology opens new possibilities that have the potential to drastically alter businesses and the economy. (Soni et al., 2020). Technology, on the other hand, refers to the methodical application of organized knowledge to actual challenges (Kowo & Popoola, 2018). They also argue that technology advances at a quick speed, making it difficult to keep up, and that businesses should always be on the lookout for new technologies to integrate into their operations. However, developing a more cost-effective way to influence a resource, system, or item than what was before available is the aim and objective of technological development (Sukharev, 2019).

Internal Business Environmental elements, including as management structure, employees, physical facilities, knowledge capabilities, and functional means, such as marketing combination, are frequently viewed as governable because the firm has influence over them (Cherunilam, 2016). Besides, Vlados (2019) defines the internal business environment as all tangible and intangible resources under direct control. Tangible resources refer to an organization's material assets, such as industrial units, buildings, and financial assets. However, intangible resources include non-material assets such as data, the company's reputation, accumulated knowledge, and the general enterprise culture (Valdos, 2019).

Senior management backing is vital for creating a positive atmosphere and providing sufficient funding for organizations to deploy AI innovations (Li, 2008). Nevertheless, according to Cherunilam (2016) management structure is essential in molding corporate decisions; some management structures slow decision-making while others accelerate it. Cherunilam further stated that the professionalism of the board of directors, as the highest level of leadership that establishes the direction for the company's success and oversees its performance, is an important factor in the company's growth and performance. Similarly, agility in operations management led to increased operational efficiency and customer satisfaction, which positively impacted cost considerations (Piya et al., 2020). In this respect, Vlados (2019) states that to flourish and grow, every business must integrate strategic, technological, and managerial factors, with a focus on innovation that will allow the organization to preserve profitability and efficiency.

Management structure is critical to the development of other areas of the organization and innovations. According to Piya et al. (2020), senior management dedication, alignment with strategy, management competence, and information technology incorporation were identified as the primary drivers for offering an agile supply chain.However, agility is the capacity for organizational process adaptation as well as flexible and quick implementation of operational changes, in addition to digitized process reach, customer agility, and inventive awareness (Kohli & Grover, 2008; Barenfanger & Otto, 2015). Moreover, managers of organizations must thus identify the critical success factors that result in the successful adoption of AI in the workplace. If managers possess greater IT expertise and deeper competency, they may exert more influence over the adoption of AI by enterprises (Sun et al., 2018).

Facilities Management (FM) is a multi-disciplinary profession that assists organizations in achieving their strategic goals. It includes a range of non-core services such as management, development, and coordination, as well as buildings and related systems, plants, IT equipment, and furnishings (Safiee et al., 2020). Furthermore, Malik et al. (2020) concluded that there is a relationship between organizational structure, physical facilities, leadership practices, and AI investment decision. It has a promising position in the global economy since of its enormous expansion and significant infrastructure investments (Piya et al., 2020). Organizations also need to assess if their resources, skills, and dedication align with the AI adoption objective (Jöhnk et al., 2021). Finding a comfortable workspace is therefore essential for fostering corporate innovations and decision-making.

Knowledge capability, which can result in considerable cost savings, improvements in human performance, and better competitiveness, is the organized process by which an organization acquires, integrates, and applies knowledge to attain long-term competitive advantage and high efficiency (Candra, 2014). Furthermore, Olusoji and Rose (2020) confirmed that knowledge capability is concerned with the professional knowledge, skills, values, and ethics that are necessary to demonstrate competence. It is defined as the qualities that give the individualistic the chance to perform.

The term "business environment" describes the entirety of all internal and external factors that have an impact on or influence a company. Nonetheless, the business environment is a dynamic concept or reality due to growing notions in business ethics, corporate social responsibility, corporate governance, and consumer citizenship. A strong conceptual and policy framework should also be in place at every organization or management to support the creation and use of business and environmental data in decision-making (Hans, 2018). According to Taiwo (2019), the management must make sound decisions based on accurate forecasting to ensure the company's continued growth and survival. According to the author, choosing an investment is one of the most important business decisions a firm must make to maintain efficiency and competitiveness while also ensuring its long-term viability.

Furthermore, AI is gradually being used in numerous industries to shrink risk and increase operational proficiency (Li et al., 2020). However, the industrial environment, rivals, and laws, in addition to technology, innovations, risk management, corporate strategy, and a few other components, all have an impact on an organization's efficiency (Frederica et al., 2021). Furthermore, in the AI era, data science has shown to be a successful method for automating risk detection (Frederick et al., 2019). Moreover, Zhou and Huang's (2021) study aim to explore the potential applications of AI in risk management within the sports industry. Launching the intelligent risk control project in its entirety and further solidifying risk management capabilities are critical components of risk management planning, according to the authors, as they will open countless opportunities for the business. The authors raised this concern and added that to address future risk management requirements and take preventative action, managers and executors need to reevaluate the risk characteristics of the business environment, integrate established and cutting-edge measurement techniques, embrace new technologies, and develop risk prevention mechanisms.

From this literature review, several factors could lead to the implementation of AI solutions in the hydrocarbon industry, namely, innovation attributes, business environment, and risk management. However, very few studies have been published about investments in AI technology in Oman's hydrocarbons industry, according to a review of pertinent literature. Thus, there is a need for empirical work to flesh out the details. However, after referring to the previous literature reviews, the hypotheses were formulated as follows:

H1a: Relative advantage of innovation attribute of AI will apply a significant influence on AI investment decision.

H1b: Compatibility of innovation attribute of AI will apply a significant influence on AI investment decision.

H1c: Observability of innovation attribute of AI will apply a significant influence on AI investment decision.

H2a: Government factors have a positive effect on AI investment decision.

H2b: Economic factors instability have a negative effect on AI investment decision.

H2c: Technological factors have a positive effect on AI investment decision.

H2d: Management structure has a positive effect on AI investment decision.

H2e: Physical facilities unobtainability have a negative effect on AI investment decision.

H2f: Knowledge capability has a positive effect on AI investment decision.

H3a: Risk management has a positive effect on AI investment decision.

This study's literature reviews suggest the research structure, which is depicted in Figure 1.

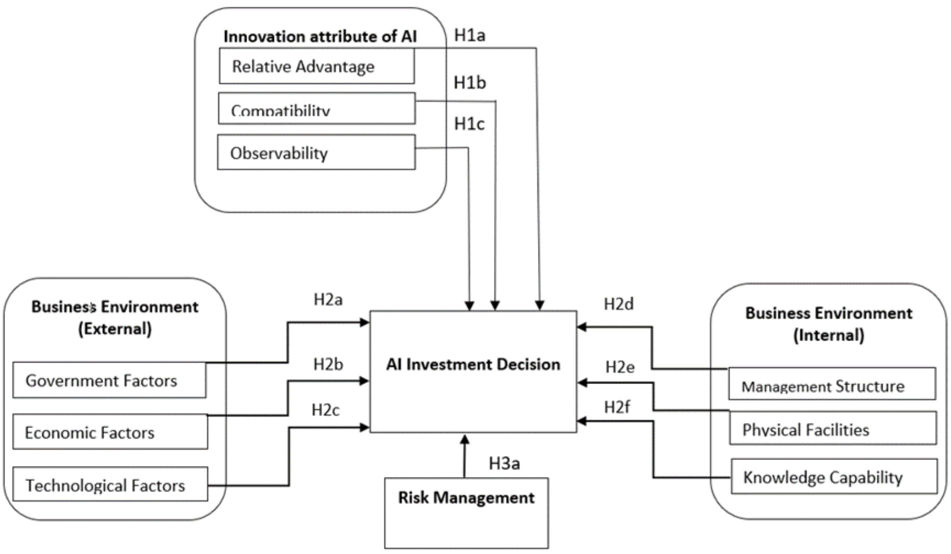

Figure1: Research Framework

DATA, MEASUREMENT, AND METHODS

A research design is essentially the framework or strategy for a study that serves as a guide for gathering and interpreting data and as the blueprint for data gathering, measurement, and analysis (Valunaite & Sliogeriene, 2020). However, the research design specifies how participants are chosen, which variables are included and how they are manipulated, how data is collected and evaluated, and how superfluous variability is managed to answer the main research problem (Dannels, 2018). Likewise, the most significant decision a researcher takes is research design, which is fundamental to research in science, social science, and many other fields (Abutabenjeh & Jaradat, 2018). The research design used in this study is a cross-sectional quantitative survey. In contrast to longitudinal research, which requires the recurrent collection of similar samples over a long period of time, this approach allows a researcher to gather data from a single sample at a specific point in time (Williams, 2017). The random sample size from the identified population was calculated using a table created by Krejcie and Morgan (1970). According to the table, the appropriate sample size is N = 367 (for 8000 employees working in a major hydrocarbon industry). Study variables have been specified by previous studies. The conceptual framework includes 10 elements, namely: relative advantage, compatibility, observability, government factors, economic factors, technological factors, management structure, physical facilities, knowledge capability, and risk management. Awang et al. (2016) highlight that operating a measuring model with a 10-point scale using structural equation modelling is more efficient than using a 5-point Likert scale for the same model and quantity of data sets in identifying how much the respondent agrees or disagrees with specific questions. However, in this research, a 10-point scale, ranging from 1 (strongly disagree) to 10 (strongly agree), is applied to measure the factors. The sampling in this study was carried out by distributing online questionnaires, with a total sample of 367 respondents. The design used in this study is hypotheses testing using the Smart PLS 4.0 statistical tool (Version 4.0.9.5).

RESULTS

According to Roberts and Priest (2006), reliability describes the extent to which a specific test, technique, or tool, such as a questionnaire, would provide identical findings under varied conditions, provided nothing else has changed. Moreover, reliability is the ability of an instrument to consistently measure the characteristics of a variable or construct (LoBiondo & Haber, 2013; Price et al., 2015). Before examining the results, it is essential to run reliability tests on the measurement scale to make sure the outcomes are reliable and that the items or questions used to measure a certain construct are operating consistently. There are numerous methods for evaluating reliability, such as test-retest reliability, alternative forms of reliability, and internal consistency (Downing, 2004; Hair et al., 2014; Polit, 2014; Torkzadeh & Doll, 1991).

Internal consistency estimates are among the most utilized forms of reliability coefficients because they are easily derived from a single delivery of a test (Henson, 2001). According to Hajjar (2018), internal consistency measures the constancy of outcomes across components inside a test. Cronbach's alpha is the most used internal consistency metric, which is generally defined as the mean of all conceivable split-half coefficients. Furthermore, the internal consistency reliability test determines how all the components of the test relate to each other (Christmann & Van, 2006). Likewise, it is applied to groups of components proposed to measure diverse aspects of the same topic. Its method works because each component addresses only one aspect of a topic. However, when numerous diverse elements are used to gather information about a certain construct, the data set is more reliable.

According to Tavakol and Dennick (2011), there are several reports on acceptable alpha values ranging from 0.70 to 0.95. A low alpha value may be caused by a small number of questions, inadequate inter-relatedness between items, or heterogeneous conceptions. However, if a low alpha is caused by a weak correlation between items, some should be updated or deleted. The simplest way to detect them is to compute the correlation of each test item with the overall score; items with low correlations (around zero) are removed. Moreover, if alpha is excessively high, it may imply that some items are redundant because they are testing the same question in multiple contexts. Thus, a maximum alpha value of 0.90 is recommended (Streiner, 2003). Furthermore, according to Tavakol and Dennick (2011), when the items in a test are associated, the value of alpha rises. However, a high coefficient of alpha does not automatically imply a high degree of internal consistency. This is because the length of the test influences alpha. If the test length is too short, the value of alpha is reduced. Therefore, to boost alpha, more similar items testing the same concept should be added to the test.

Cronbach's alpha assumes that all items on the scale measure the same underlying construct and have equal weights. It may produce erroneous results if items measure various sub-constructs or if the relationships between items are not uniform (Cronbach, 1951). Moreover, Cronbach's alpha can be affected by item phrasing. Even if the underlying construct being assessed hasn't changed, changing the wording of an item can cause changes in the alpha value (Peters, 2014). Likewise, Cronbach's alpha presupposes that all pairs of items have the same inter-item correlations. This assumption, known as tau-equivalence, may not be correct in all circumstances (Zumbo, 2007). In addition, Cronbach's alpha can be affected by the number of response categories for each item. If the response categories are limited, the alpha values may be lower (Revelle & Zinbarg, 2009). However, Cronbach's alpha tends to increase in proportion to the number of elements in the scale. This means that scales with more things may boost the alpha value artificially, even if the items aren't genuinely more dependable (Raykov, 1997). Furthermore, Cronbach's alpha presupposes unidimensionality, which means that all items assess a single underlying dimension. If the notion is multidimensional, Cronbach's alpha might not adequately reflect dependability (Dunn et al., 2014). The item loadings were all above the acceptable benchmark of 0.70. The results prove the reliability of the measurement model.

Any measurement process must be validated using a range of various sorts of evidence to establish the psychological constructs being tested (Landy, 1986). According to Punch (1998), validity expresses the degree to which a measure correctly represents the concept it declares to measure. Validity relates to how well a study measures or evaluates the ideas it claims to investigate (Colliver et al., 2012). It entails making sure that the techniques employed to gather information and make judgments are suitable, trustworthy, and consistent with the goals of the study. Validity establishes the reliability and veracity of study findings as well as their relevance to actual circumstances (Cook et al., 1979; Cook et al., 2002; Campbell, 1963).

Convergent validity tests whether there is a positive correlation between various measurements of the same construct, demonstrating that the underlying concept is truly being captured. This kind of validity aids in proving that various approaches or indicators work together to precisely assess the same concept (Campbell & Fiske, 1959). Moreover, convergent validity is a concept in psychometrics that evaluates how well several evaluation components or scales are meant to measure the same construct or assess the same underlying concept. In other words, it looks at how highly different measures or indicators of the same construct are connected to one another. A high level of convergent validity means that the measures are reliably capturing the same underlying construct (Bagozzi & Yi, 1988). According to Kock (2014), convergent validity is an indicator of the effectiveness of a measurement tool, which is often a collection of question statements. A measurement tool has effective convergent validity if the respondents recognize the question-statements connected with each latent variable in the identical way that the question-statements' makers projected.

Convergent validity involves an examination of the relationships between question statements and latent variables employing loadings and cross-loadings. Factor loadings are the coefficients of the question statements with the primary latent variable. In contrast, cross-loadings are the coefficients of the question words with the other latent variables (Amora, 2021). However, convergent validity is measured by calculating the average variance extracted (AVE) from each construct with the outer loadings of the indicators. It is calculated as follows:

$$\text{AVE} = \left(\frac{\sum_{i=1}^{M} l_i^2}{M} \right)$$

The outer loadings should be bigger than 0.708, since the square of that value shows that the construct score accounts for at least 50% of the variable's variation (Henseler et al., 2015). The AVE is a summary convergence indicator generated from the variance retrieved for all elements loading on a single construct. The rule of thumb for appropriate convergence is an AVE > 0.50, which indicates that the construct score includes more than half of the indicator variance (Hair et al., 2017). However, the assessment of convergent validity for formative measurement methods is significantly different because internal consistency reliability is not appropriate. To assess convergent validity for formatively measured constructs, extra reflectively measured variables must be included in the nomological net of each formative construct in the survey. According to Hair et al. (2017), formatively measured constructs are assessed in addition to convergent validity based on the size and statistical significance of the indicator weights as well as the collinearity between indicators. Table 1 represents a summary result of the reliability test and convergent validity.

Table 1: Construct Reliability and Convergent Validity

Constructs	Cronbach's Alpha	AVE
Compatibility	0.836	0.593
Economic Factor	0.804	0.61
Government Factor	0.882	0.628
Investment Decision	0.885	0.542
Knowledge Capability	0.847	0.54
Management Structure	0.899	0.589
Observability	0.862	0.573
Physical Facilities	0.866	0.635
Reliability	0.845	0.519
Risk Management	0.817	0.523
Technological Factor	0.859	0.647

The bootstrap approach (in Smart PLS) is used to test the significance of the structural path with 5000 subsamples and a significance level of 5%. To determine significance levels, Hair et al. (2014) employ the p-value, which is defined as "the probability of incorrectly rejecting a true null hypothesis". According to Table 2, only 7 of the 10 paths were significant ($p < 0.05$), and the remaining 3 were not.

In the paths of innovation attribute of AI, all the paths were significant with positive relationships, apart from the path between observability and investment decision, which has a positive non-significant relationship. The path regarding external factors only found one path that was not significant between technological factors and investment decision. Economic factors instability has a significant negative relationship with investment decision. Likewise, the paths with internal factors were all significant except for the path between physical facilities and investment decision. The path regarding risk management was found to be significant, with a positive relationship.

Table 2: Path Coefficients

Paths	Original sample	T statistics	P values
Innovation Attribute of AI			
Compatibility-> Investment Decision	0.12	2.5	0.01
Observability -> Investment Decision	0.04	0.91	0.36
Relative Advantage -> Investment Decision	0.09	2.07	0.04
External Factors			
Economic Factor -> Investment Decision	-0.12	2.54	0.01
Government Factor ->Investment Decision	0.13	2.09	0.04
Technological Factor -> Investment Decision	0.05	0.99	0.32
Internal Factors			
Knowledge Capability-> Investment Decision	0.16	3.24	0.00
Management Structure ->Investment Decision	0.14	3.07	0.00
Physical Facilities -> Investment Decision	0.05	1.09	0.28
Risk Management			
Risk Management -> Investment Decision	0.14	2.91	0.00

DISCUSSION

This study hypothesised that there is a positive relationship between the management structure and AI investment decision. The results The reliability and validity of the research were assessed, and the results demonstrated that it is reliable and valid. Cronbach's alpha was employed to assess reliability. There are numerous publications on acceptable alpha values ranging from 0.70 to 0.95, according to Tavakol and Dennick (2011). Therefore, data scores greater than 0.70 in Cronbach's alpha confirm that the used scale is reliable. The convergent validity was assessed by using the average variance extracted (AVE). The AVE values were between 0.519 and 0.673, above the standard of 0.5 recommended by Chin (1998) and Hair et al. (2017). The bootstrap process (in Smart PLS) was used to examine the significance of the structural path with 5000 subsamples, a significant level of 5%, and the p-value to determine the significance level. Out of 10 paths, only 7 paths were determined to be significant ($p < 0.05$), supporting the relevant hypothesis, whereas the remaining 3 were not (see Table 2).

The path between the relative advantage of the innovation attribute of AI and AI investment decision was significant, which supports the corresponding hypothesis. The relative advantage of the innovation attribute of AI has a significant positive relationship with AI investment decision (Path coefficient = 0.09, $p < 0.05$), in turn supporting H1a. Likewise, the path between the compatibility of the innovation attribute of AI and AI investment decision was significant. The compatibility of innovation attribute of AI has a significant positive relationship with AI investment decision (Path coefficient = 0.12, $p < 0.05$), revealing support for H1b. On the other hand, the observability of the innovation attribute of AI has no significant relationship with AI investment decision (Path coefficient = 0.04, $p > 0.05$), H1c. The results showed that only relative advantage and compatibility of the intended AI system will play a major role in adopting an AI investment decision. The results of the quantitative analysis carried out in the hydrocarbons industry in Oman offer insightful information on the factors that influence AI investment decision in this industry. The findings of this study show that those in charge of making decisions in the hydrocarbons sector understand how critical it is to smoothly incorporate AI into the existing operational frameworks. In addition, this research emphasizes the necessity of using AI solutions to enhance current workflows, systems, instruments, and procedures. Moreover, it implies that those making decisions are more likely to spend money on AI solutions that are flexible enough to be quickly integrated and tailored to the needs and limitations of the hydrocarbons industry in Oman.

Government factors (Path coefficient = 0.13, $p < 0.05$) and economic factors instability (Path coefficient = -0.12, $p < 0.05$) have a significant relationship with AI investment decision, confirming supports for H2a and H2b. On the other hand, there is no relationship between technological factors and AI investment decision (Path coefficient = 0.05, $p > 0.05$), which declines the H2c.The study's findings agreed with this expectation and implied that government factors positively impacted the independent variable of this study. Furthermore, the expected impact of Oman's government on AI investment decision in the hydrocarbons industry is consistent with the larger framework of policies and programs designed to foster technical innovation and economic growth in Oman. The participants on this study believed that the government of Oman is crucial in forming frameworks, offering incentives, and influencing regulations to promote the uptake of cutting-edge technology like artificial intelligence. However, at the study's start, it was anticipated that economic factors would be determined in modeling AI investment decision in Oman's hydrocarbons industry. Besides, the study's results have aligned with this anticipation and meant that economic factors positively impacted the AI investment decision. This expectation stemmed from the knowledge that market dynamics, financial considerations, and economic conditions are important factors that influence investment plans in a variety of industries, including the hydrocarbons industry in Oman. On the other hand, the results imply that AI investment decision is not affected by technological factors in Oman's hydrocarbons industry. Furthermore, the hydrocarbons industry in Oman appears to be justified by the effects of technological factors, which points to several possible dynamics at work. Besides, it might be an indication of the industry's level of maturity since the AI technologies on offer are thought to be somewhat uniform or standardized. Nonetheless, under such circumstances, technological distinctions among AI solutions might not be considered by decision-makers as important factors for making AI investments.

Management structure has a significant positive relationship with AI investment decision (Path coefficient = 0.14, $p < 0.05$), which supports H2d. In contrast, there is no relationship between Physical facilities unobtainability and AI investment decision (Path coefficient = 0.05, $p > 0.05$), failing no evidence in support for H2e. Disposition to value Knowledge capability has a significant positive relationship with AI investment decision (Path coefficient = 0.16, $p < 0.05$), revealing support for H2f. of those data analysis show a significant relationship between the management structure and AI investment decision. Hence, the results support the claim that the management structure will impact AI investment decision. Management structure is critical in the decision-making process for firms' investments in artificial intelligence. The organization often includes several layers, including executive leadership, middle management, and frontline supervisors, each with its own set of tasks and decision-making power.

This study hypothesised that there is a negative relationship between physical facilities' unobtainability and AI investment decision. The results of the data analysis show no significant relationship between physical facilities unobtainability and AI investment decision. The Oman hydrocarbons industry does not necessarily have the essential infrastructure to be able to start an artificial intelligence investment, but rather they can seek help and partnership with Internet service providers available in the country to reduce expenses and speed up the application of artificial intelligence. The outcomes of this study support this trend, as decision-makers in the hydrocarbons industry in Oman intend to seek the help of Internet service providers to provide the required structure to invest in the field of artificial intelligence on a broad scale to include all the hydrocarbons industry's activities.

Finally, regarding the path between risk management and AI investment decision, the results indicate that the relationship between them is significant (coefficient = 0.14, $p < 0.05$), hence supporting H3a. At the beginning of this study, it was predicted that risk management would play a key role in affecting AI investment decision. The study's findings agree with this belief and indicate that risk management positively impacts AI investment decision. Nonetheless, Oman's hydrocarbons industry operates in a dynamic and complex environment that is full of risks, including price volatility, operational hazards, and geopolitical instability. Thus, to reduce these uncertainties and protect AI investment, effective risk management strategies are necessary.

CONCLUSION

The present results achieved the purpose of the research that examined the effect of artificial intelligence innovation, business environment, and risk management on artificial intelligence investment decision in the hydrocarbons industry in Oman. This study has demonstrated that the relative advantage and the compatibility of the innovation attribute of AI have a significant positive relationship with AI investment decision. Conversely, the observability of the innovation attribute of AI has no significant relationship with AI investment decision. However, government factors, knowledge capability, risk management, and economic instability have a significant relationship with AI investment decision. Likewise, management structure has a significant positive relationship with AI investment decision. In conflict, there is no relationship between physical facility unobtainability and AI investment decision.

It was discovered that few studies have been conducted on the subject of AI investment in Oman's hydrocarbons industry based on the primary research on appropriate literature reviews. Additionally, this study will significantly advance the body of knowledge about AI investments and how they affect the efficiency of an organization's operations. The study's practical contribution is that various companies and the public sector in Oman can utilize the research framework for AI investment decision to revamp their AI investment frameworks, thereby improving the operational efficiency of their businesses. The findings of this study will support the government's adoption of AI investment policies for other industries per Oman's Vision 2040, which will benefit policymakers.

The research findings may be limited due to the peculiar character of Oman's hydrocarbons industry. While the insights gained from analyzing this specific environment are valuable, generalizing them to other businesses or locations may be difficult due to the hydrocarbons sector's unique characteristics and dynamicsWe found that a big challenge in performing this research was a lack of comprehensive and up-to-date data regarding artificial intelligence investment in Oman's hydrocarbons industry. The sensitivity of the industry and the potential for confidentiality in investment decisions make it difficult to collect crucial data, including investment levels and rates of technology adoption.

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