Operational Research in Engineering Sciences: Theory and Applications
Vol. 6, Issue 1, 2023, pp. 365-387
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.31181/oresta/0601133

ARTIFICIAL INTELLIGENCE (AI) BASED CONTRACTS PROCUREMENT: EXAMINING THE INFLUENCE OF BIG DATA, MACHINE LEARNING, INTERNET OF THINGS, EMPLOYEE SKILLS & RESOURCES AND LEADERSHIP ON PROCUREMENT COST REDUCTION

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Received: 17 April 2023
Accepted: 26 June 2023
First Online: 11 July 2023

Research Paper

Abstract: *AI is not a single technology but a collection of diverse, powerful technologies that simulate human intelligence and invest in the power of the digital brain. Using AI techniques, big data analytics can be utilized to discover patterns and a wealth of knowledge. Consequently, this study aims to examine the impact of big data, machine learning, personnel, IoT skills, and artificial intelligence in procurement contracts that impact cost savings and improve enterprise performance and productivity by automating previously labor-intensive processes or tasks. One hundred fifty employees from the procurement department of Saudi Organizations were surveyed to collect data. The study's findings demonstrated the importance of big data analytics, the Internet of Things, and digital skills for employees. On the other hand, (machine learning and autonomous driving) had no significant impact on cost reduction.*

Keywords: *Artificial Intelligence (AI), Big Data Analytics (BDA), Internet of Things (IoT), Cost Reduction, Machine Learning (ML), Procurement, Contracts*

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1. Introduction

The main aim of cost saving in most organizations is to keep the business's sustainability continuity. Emerging Artificial Intelligence (AI) technologies, such as big data analysis to predict the demand for contractors (Zhai et al., 2018) or machine learning models to address the contractors' sourcing issue (Luan et al., 2019), have the potential to save money in procurement, according to expert researchers. Nonetheless, contrary to the beliefs of some, AI analytics could be utilized by contractors to balance supply and demand (Chaturvedi, Yu, & Rao, 2018). Emerging AI in contract procurement and supply chain management will reduce supply chain procurement costs (Hamdi et al., 2018).

The demand for business growth in different areas is driven by the change in customer behavior and requirements concerning the high supply chain competition (Porter & Heppelmann, 2014). Therefore, emerging artificial intelligence tools and technology were crucial to maintaining the competitive level by implementing innovation to bring a nontraditional conceptual business model (Downes & Nunes, 2014). Digital transformation became the top priority for management and executive level due to the rapid disruptive change in the business. The fourth industrial revolution 4.0 is advancing rapidly, necessitating organization management and stakeholders to invest more in innovation and new supply chain management strategies to achieve competitive advantages (Schrauf & Berttram, 2016). This research focuses on procurement as a component of supply chain management. The position of contract procurement in supply chain management is crucial for determining the organization's long-term efficiency, effectiveness, and profitability (Liu & Li, 2022). Big data is the backbone of digital transformation, leading to organizational efficiency, effectiveness, and profitability (Bucy, Hall, & Yakola, 2016; Zhong et al., 2016). Applying artificial intelligence in procurement, as part of the supply chain ecosystem, shall lead new level of innovation and collaboration by employees.

Recently, some studies have shown that avoiding AI technology in procurement may lead to supplier selection challenges and determine the current supply and demand for forecasting purposes issues (Luan et al., 2019). Artificial Intelligence has become popular and famous in the media as it reaches a level it did not reach before. Many conferences and summits about Artificial Intelligence and digital transformation were conducted to share the trends and updates of AI applications in many different disciplines, such as health care, education, transportation, and more.

Procurement also could leverage AI and digital transformation through cost-saving and optimizing the process. The supply chain exposes an involvement in every organization sector, and procurement is critical to that process (Carlos, Kahn, & Halabi, 2018). From initiating a customer order to delivering a product or service, the supply chain plays a crucial role in the business flow. As the significance of the supply chain becomes more apparent, this industry attracts local and international investors. For instance, Saudi Arabia recently launched a supply chain strategy to play a significant role in global supply chain activities and services. Such a move would require solid financial projections. AI has demonstrated its ability to reduce supply chain costs in certain instances.

Certain organizations are leveraging the advantage of AI on supply chain and procurement to increase cost reduction (Thomassey & Zeng, 2018). Exposure to the technologies trends is vital to leverage these tools within your organization's use case. In addition, these technologies will facilitate daily tasks and processes.

Some significant factors shall increase the cost reduction of contract procurement within the supply chain field. Understanding the nature of contracts procurement job and environment is the cause of cost saving. Accessing qualified data is another reason organizations cannot leverage AI in procurement for more productivities and cost savings. The big data challenges depend on successfully running big data to create value. Else is only a huge amount of data and documents (Wani & Jabin, 2018). Analyzing big data is a powerful tool only when the data is being used successfully.

This quantitative research aims to analyze the relationship and influence of digitalizing and artificial intelligence in the context of contract procurement cost reduction in organizations and highlight the opportunities and challenges. In addition, the research will highlight procurement as a variable moderator of executive leadership. Contracting procurement may utilize artificial intelligence to achieve an organization's strategic objectives and growth. The contracts procurement division of businesses will pioneer this stage of the fourth industrial revolution. 4.0 to encourage and achieve organization first class level (Johnson & Flynn, 2015).

2. Literature Review

The literature review shall highlight the research dependent variable (DV), cost reduction in contract procurement. After highlighting the DV, the research shall cover the four independent variables (IVs): Big Data Analysis, Machine Learning, the Internet of Things, and Employees' AI skills and resources. Then, this study shall cover executive leadership as the moderator variable. Lastly, the theory of this study shall be the combination of cost reduction, big data, machine learning, the Internet of Things, and employees' skills and resources.

According to Raz (2008), in supply chain management, organizations have to improve their internal processes and procedures to meet future challenges. Nonetheless, they must comprehend supply chain management to maintain the organization's competitive advantage and reduce costs. In this context, AI, such as big data and machine learning, will be the future focus of the organization. According to Wu et al. (2016), AI in procurement is the research field that aims to reduce supply chain management costs and increase efficiency. IBM's future supply chain opportunity involves three AI drivers that are instrumented, interconnected, and intelligent (Ross, 2016).

Firstly, instrumented is about operational processes in digital transformation and handled by, for example, sensors to reduce cost and risks (IBM, 2009). The AI will also drive the digital transformation and automation of processes by leveraging Big Data, as per Zhong et al. (2016), to support collecting further data. Secondly, the objective of interconnected is to connect the Internet with technology and collaborate with supply chain activities (IBM, 2009). The change in the supply chain model is due to the impact of technology integrity, such as Big Data and the Internet of Things which is an opportunity for organizations to optimize traditional production (Kumar et al., 2016). Third, intelligent is about the supply chain process simulation that technologies implement. This will allow the estimated situation to be examined before its occurrence (IBM, 2009). Okada, Namatame, and Sato (2016) concurred that the supply chain process simulation technology provides an advantage for potential operational scenarios.

2.1 Cost reduction

There are two ways to reduce costs: the first is to avoid cost increases, such as price increases, inflation, or increases in the cost of services and materials provided by contractors, such as maintenance services. The second strategy is to reduce the fixed and variable costs associated with acquiring a service or material (Barrad, 2020). Several factors are involved in cost reduction, such as providing services, materials, projects and after-sales customer services, supply chain, procurement, and logistics & transportation. The total cost of procuring a job or avoiding a potential cost emphasizes reducing the cost in general as it affects the revenue or loss either positively or negatively. However, cost reduction is not always the main target for some organizations, such as the public or healthcare industry. For instance, during the COVID-19 pandemic, most organizations lacked services or products. As a result, the lowest bidder is not the only purchasing objective; securing the flow of required services or materials is equally essential to avoid such operational shutdowns.

Changing from a conventional business model to an intelligent one is advantageous for cost reduction. A business based on digital transformation and artificial intelligence would benefit the organization by allowing it to prioritize its areas of improvement and investment, which will impact its profit or loss. Procurement within an organization aims to acquire market supply to meet operation demands. Intelligence procurement contributes significantly in terms of contract users and providers. Analysis of contracts, supplier performance, and the authorized expenditures limit (AEL) are frequently employed to quantify cost reductions in procurement. By analyzing all information pertaining to contracts, spending per cost center, and the analysis results, an organization or contracts department can determine the strength or weakness of their procurement and where the challenges originate from. Several IT organizations are utilizing artificial intelligence technologies, such as machine learning algorithms, to automate traditional procurement tasks, such as recommending alternative options, to reduce procurement costs (Barrad, 2020).

2.2 AI Technologies

This part of this research highlights the chosen variables of artificial intelligence technologies within contracts procurement and the mediator executive leadership. They utilize information, technology and other resources to produce services or products by either people or machines (Alter, 2013). Every business field has its ecosystem, and this research will focus on the contracts procurement ecosystem. In this research context, artificial intelligence, such as big data, is an important useful source of information that supports procurement to gain added value and development (Richey Jr et al., 2016). For example, big data reduce risk management by avoiding facing fraud.

This theory explains why this research is important, as AI, AI employee skills & resources, and executive leadership are the main elements of this paper. The first AI element is big data, an infrastructure to collect data for analysis. The second element is the employees' AI skills and resources to drive the AI procurement ecosystem. The third element would be the executive leadership of the organization.

Machine learning reduces people's involvement in contract procurement in precisely categorizing the organization's expenditure. Also, artificial intelligence emphasizes developing document management by transforming traditional documents into digital documents by implementing OCR technology to extract important information in contract procurement, such as line item prices, terms & conditions, pricing methods, deduction, etc. Machine learning provides this feature to support the benefit of structured and unstructured data in contract documents for better analysis and function review. Also, Natural Language Processing (NPL) could conduct further advanced tasks by utilizing Machine Learning algorithms such as addressing questions, concerns, and highlighting and summarizing data in the contracts procurement process. Also, Machine Learning may advance contracts procurement by forecasting the cost of services,

3. Big Data Analytics

According to Zhang et al. (2022), Big Data Analytics could enhance organizations' efficiency and cost reduction in managing the data and, in the research case, procurement of contracts. ERP is no longer the main data driver in contract procurement, but Big Data has become a more critical and necessary tool to impact procurement positively. The main idea of Big Data is to analyze larger amounts of information from different sources. Big Data supports companies to address their requirement efficiently by allowing them to conduct predictive and prescriptive analyses that support making the most appropriate decision.

In well-known companies, the process of making an operational or strategic decision is by analyzing data, which is highly important. Organizations usually use these procedures to advance data flow across contract procurement. In addition, such analysis shall help the organization forecast the next procurement requirement that shall support acting appropriately in advance, such as preparing, negotiating, or proceeding.

Big Data's primary objective is to assist with this aspect of the job, such as the expenditure amount against some contracts, the utilized type of line items, the charged cost centers, and the contractors so that the contracts advisor can procure and share daily contractual reports. This information could help the company save money or avoid incurring additional expenses.

There are three analytics techniques: descriptive, predictive and prescriptive (Souza, 2014). The first type is descriptive analytics, which explains and provides the most updated status of large collected information, such as deciding the required value for certain types of contracts by analyzing the expenditure amount for each service and comparing it with future requirements.

The second type is predictive analytics, which collects historical information and applies regression analysis to understand what the upcoming should be expected. For instance, the organization would predict the demand quantity of services for repetitive contracts before the existing agreement's expiry date.

The third type of analytics is prescriptive analytics, which combines descriptive and predictive analysis to design the future optimally. There are numerous applications for prescriptive analysis in procurement, including evaluating vendors based on job completion and execution delivered. In addition, prescriptive analytics facilitate the estimation of seasonal demand.

3.1 Machine Learning

Machine Learning is the second AI technology investigated in this research (Kumari & Shukla, 2022). The field of contract procurement faces several obstacles, such as highlighting the essential information for analysis. However, Machine Learning can support the procurement of contracts in this field with its algorithms that can sort and recognize missing contact information. Implementing this Machine Learning feature will necessitate using UNSPC and K-Nearest Neighbor coding. In addition, the contracts procurement planning and estimated required Machine Learning algorithms, such as using Nave, which is based on historical usage, could help advance hypo.

Machine Learning (ML) is an Artificial Intelligent technology that supports transferring the automation process in inquiry and data analysis (Murdoch et al., 2019). For example, when a computer station has developed its ability to use historical data for decision-making purposes or predict the future, it obtains Machine Learning knowledge. Also, Machine learning needs qualified data and valid algorithms to be most effective.

Machine Learning consists of three categories: Supervised, unsupervised, and reinforced learning. First, supervised learning is about a machine being developed with good data to address incomes with results; therefore, more inputs shall provide well results. The second category, unsupervised learning, is about the machine utilizing limited information that is not trained in entities and still provides answers and results. In unsupervised learning, it builds up experience once more examples and cases and trains itself to address further situations.

Thirdly, reinforced learning is similar to unsupervised learning in terms of limited access to data. However, Machine Learning algorithms shall classify the appropriate response once a user questions a specific subject based on the history of actions and the sequences of inputs and outcomes.

The relationship between Artificial Intelligence (AI) and Machine learning (ML) is corresponding; however, they have different perceptions and concepts (Mitchell, 1999). Machine Learning (ML) is about learning historical activities by coding software to support future planning. At the same time, Artificial Intelligence (AI) is about developing a machine that simulates the human brain, such as thinking, questioning, and knowledge states.

3.2 Internet of Things

According to Liu et al. (2022), digital transformation in the field of procurement is an important element to have an excellent achievement within the organization. The study focuses on the outcome of emerging digitalization in procurement and its chances for the firm in the future. The opportunities in the upcoming years depend on the technologies that may be identified in the digital sector. Innovation shall be an element of enhancing the procurement process and procedure in any firm and any sector. According to Berger (2016), "Industry 4.0" and AI are the latest challenges in the field of contracts procurement, and a contracts advisora contracts advisor shall handle it.

One of the main challenges in an organization, generally and in procurement specifically, is transforming to digitalization through AI, such as the Internet of Things (IoT) (Khodadadi, Dastjerdi, & Buyya, 2016). The main AI tools in the Internet of Things technology are RFID, sensors, networks, and cloud computing (Haddud, Dugger, & Gill, 2016). Transferring and connecting the needed data in the Internet of Things is crucial to utilize all the possibilities worldwide. All these tasks and obstacles shall support the procurement ecosystem to raise efficiency by enhancing the procurement and supply chain procedure and limitations (Zolnowski, Christiansen, & Gudat, 2016). Increasing the input data to assist in establishing transparency, follow-up, novel and bright ecosystem in the supply chain field is the procurement duty (Mantey, 2015). However, the main concern would concentrate on cyber-security in increasing connected information to the Internet of Things.

Stephens and Valverde (2013) highlighted in a previous paper the significant need for security in the contracts procurement sector since high amounts of data are digitally transformed and automated. Thus, creating a cybersecurity system in procurement is critical to avoid any security deviation internally or externally (Johnson, 2013). As trust between supplier and customer is essential, from a digitalization perspective, an old-style supplier and customer believe that trust between them is the most significant thing in their relationship (Keith et al., 2016). Hughes and Ertel (2016) mentioned that the firms should utilize earlier methods against the improvement in contracts procurement and the digitalization model of procurement to keep the competitiveness among their contracts emerging innovation and strategy. Automation and outsourcing the operation to allow a firm to focus on its initiatives and strategy shall support reaching the highest benefits from contractors' abilities and skills.

3.3 Employees' AI skills and resources

Teamwork means dual coworkers or more people dealing with each other to reach a shared target (Salas, Burke, & Cannon-Bowers, 2000). While employees collaborate in the firm, each should have their own activity. It is important to capture the employees' success depending on their personality and level of job satisfaction to evaluate the outcomes (Campion, Medsker, & Higgs, 1993). The daily operation activities are the team's key performance indicators (KPI) once they collaborate.

Numerous studies have demonstrated the correlation between teamwork and efficiently achieving goals. Important to note is that the team is comprised of individuals who differ in many ways, complicating communication and collaboration. These challenges within the team would have either a positive or negative impact on the contracts procurement procedure.

In teamwork, certain values and behavior shall be structured in their beliefs and perspective. Teamwork is about understanding each member's character and requirements to manage the activities. Once teamwork values and behavior are designed correctly, employees shall play a role in decreasing the cost by implementing Artificial Intelligence (AI) tools.

3.4 Executive Leadership

Upper leadership is considered in a firm at a high management level. Upper management consists of those in the organization who set the critical judgment and design the company's long-term plan. The upper leadership applies the organization's vision, mission, abilities, and character. Several studies (Dalton et al., 1998) demonstrated the correlation between leadership and management and the variance in company performance. On the other hand, according to some studies, the influence of executives and directors does not affect the firm's outcomes. However, the most recent research indicates a correlation between them (Barsade et al., 2000).

Leaders could be divided into more specific categories: human resource management, managing qualified employees, personality, and decision-making (McCarthy, 2014). Additionally, there are successful and unsuccessful attitudes and conduct. Successful attitudes and behaviors include assisting employees, being receptive to new ideas, recognizing employees' efforts, etc., whereas unsuccessful attitudes and behaviors include discrimination within the team and a lack of shrinking knowledge.

Regarding leadership, a main concept that shall be emphasized is empowering employees and giving more authorization. By empowering the workforce, this leadership style shall positively impact the organization's performance, not just the performance of employees themselves (Carmeli, Schaubroeck, & Tishler, 2011). This strategy has testified that empowerment enhances the efficiency of employees and that empowerment enhances employees' efficiency (Harris et al., 2014). Empowering employees to make decisions and authorizing them with powers is mainly about empowerment. Empowerment shall influence and enhance the motivation and attitude of the workforce in a firm and increase job satisfaction (Chen et al., 2014). This paper will consider studying the impact of leadership on decreasing the cost of procurement in an organization.

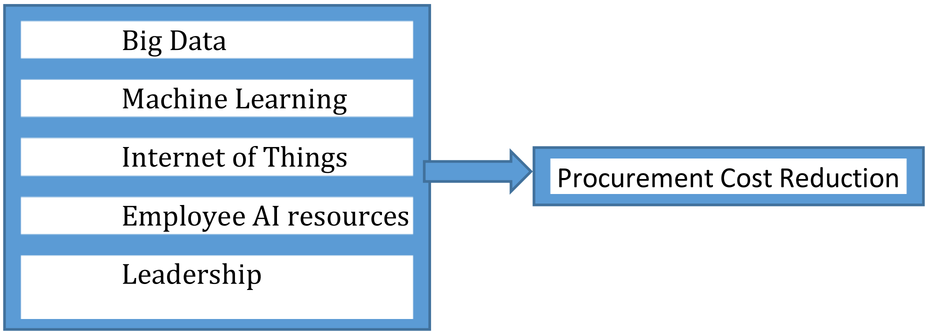

Figure (1) Research Framework

This research framework shows this study's purpose, highlighting the relationship between the independent and dependent variables. As the dependent variable, procurement cost reduction is this research's main concept. Literature in the field of AI Contracts Procurement was consulted to select these particular variables. This study investigates the cost reduction of AI procurement about five factors: big data, machine learning, the internet of things, AI employee resources, and leadership. Additionally, this research framework has generated five hypotheses.

3.5 Hypothesis

Based on the framework, the researcher formulated the following hypothesis:

H1= *Big Data positively affect the contracts procurement cost reduction.*
H2= *Machine Learning positively affects the contracts procurement cost reduction.*
H3= *Internet of Things positively affects the contracts procurement cost reduction.*
H4= *Employee AI resources positively affect the contracts procurement cost reduction.*

H5= *Leadership positively affects the contracts procurement cost reduction.*

4. Methodology

The nature of this study is to test the hypothesis. The research was designed using a quantitative approach explaining in more detail the influence of Big Data, Machine Learning, the Internet of Things, Employees' AI Resources, and Leadership on Contracts Procurement Cost Reduction. The methodology for this research shall focus on the research design and measurement and then develop the questionnaire through the reference from the previous studies, which is related to the research topic. Furthermore, the researcher shall continue with the questionnaire distribution and statistical analysis.

4.1 Sample and population

In this study, the researcher selected individuals involved with procurement and artificial intelligence as his population. The sample represents the entire population to ensure the study has reliability and adds value. The researcher shall conduct the study among employees related to contract procurement from different industries and specializations, which is the study's target population.

The researcher used Simple random sampling to collect data on Procurement employees. The estimated target respondent population for this study is 150 participants. Many employees around the world work in the field of contracts procurement, but the researcher will select only 150 employees to answer the questionnaire and gain insight into the impact of Big Data, Machine Learning, the Internet of Things, Employee AI Resources, and Leadership on the cost reduction of contracts procurement.

4.2 Instrumentation

Data collection for this research primarily depends on the questionnaire the researcher will distribute to the respondent to collect the information. The questionnaire stated in English that it was divided into two sections, with the first section containing the respondent's demographic information (age, level of education, years of professional experience, job function, and industry). While the section included five (5) items measuring the impact of Big Data Analytics on procurement cost reduction, five (5) items measuring the impact of Machine Learning on procurement cost reduction, five (5) items measuring the impact of Internet of Things on procurement cost reduction, two (2) items measuring the impact of Employee Digital Skills and Resources on procurement cost reduction, and five (5) items measuring the impact of Executive Leadership on procurement cost reduction, the section also included two (2) items measuring the impact of Employee Digital Skills and Resources on procurement cost reduction. All the questionnaire items were adopted from previous studies, which rectified the questions' validity.

4.3 Data Analysis Technique

Once the data was collected from the respondent through the questionnaire, the raw data were entered into an Excel file as the statements will be grouped and tabulated to start the statistical analysis. The researcher checked the input data, then analyzed it using the Statistical Package for Social Science (SPSS version 22.0) software for the analysis result. The reliability analysis was conducted to analyze the factors of contract procurement cost reduction.

Besides the descriptive statistics used to get the study result, the researcher shall use the Mean and the Std. Deviation of each statement. Also, Cronbach's Alpha will be used in this study to determine the reliability of the instrument based on the accuracy of the respondent's responses and the interrelationships between the questionnaire items. The researcher also used Chi-square tests, Pearson Correlation, and Regression to explore the relationship between independent and dependent variables. Using descriptive statistics reveals the size of the sample and the subgroup. The quantitative research aims to determine what proportion of the sample population complies with the code.

5. Data analysis:

5.1 Demography data

Table 1. Age group

	category	Frequency	Percent
age	<25	20	12.7
	25-35	73	46.5
	36-45	54	34.4
	>45	10	6.4
	Total	157	100

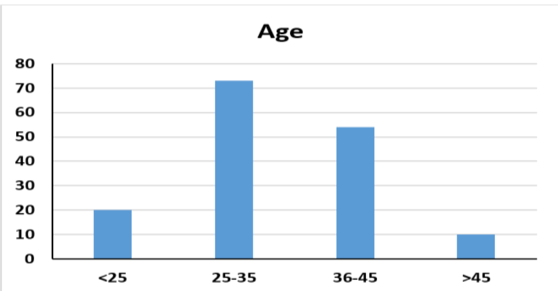

Figure (2): classification of the data according to age group

Figure (2): Classifications of the data according to age When the participants of the research study were asked about their age, it was found that the maximum number of respondents were of the age group of 25-35 years (46.5%, N= 73), they were followed by the participants belonging to the age group of 36-45 years (34.4%, N=54), and the participants belonging to the age group of <25 years 12.7%. The least number of people were below the age group of >45 years (6.4%, N= 10). This shows that the respondents who have taken part in this research study have an equal distribution across the different age groups; hence, more mature and reliable answers could be obtained.

5.2 Years of Experience Level

Table 2. Years of Experience Group

	category	Frequency	Percent
experience	<10	56	35.7
	10-14	54	34.4
	15-20	42	26.8
	>20	5	3.2
	Total	157	100

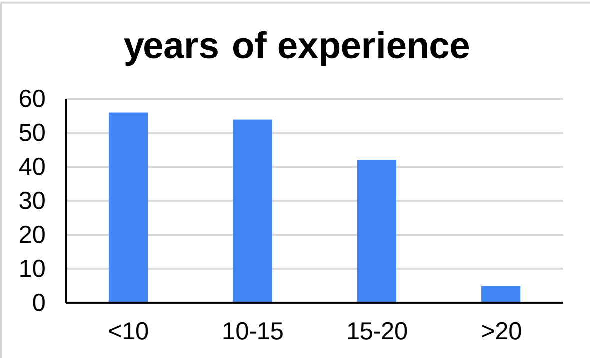

Figure (3): classification of the data according to years of experience group

Figure (3): Classifications of the data according to years of experience When the participants of the research study were asked about their years of experience, it was found that the maximum number of respondents were of the age group of <10 years (35.7%, N= 56), they were followed by the participants belonging to the age group of 15-20 years (26.8%, N=42). The participants in the age group of >20 years are 3.2%.

5.3 Educational Level

Table 4. Educational Level

	category	Frequency	Percent
educational	High school	14	8.9
	Diploma	24	15.3
	Bachelor's degree	72	45.9
	Master's degree	37	23.6
	Doctoral of Philosophy	10	6.4
	Total	157	100

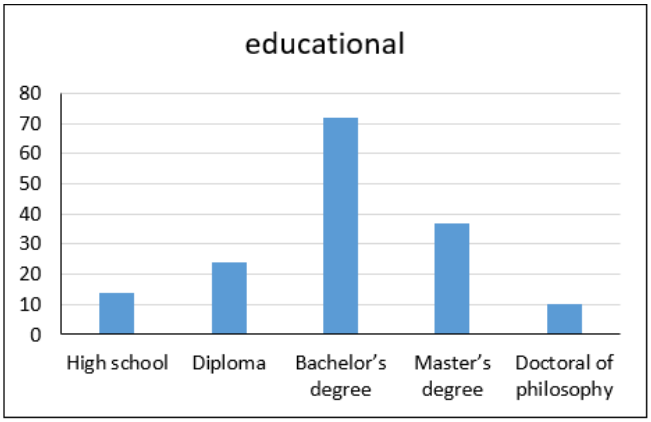

Figure (4): classification of the data according to educational group

Figure (2): Classifications of the data according to education When the participants of the research study were asked about their education, it was found that the maximum number of respondents have the Bachelor's degree (45.9%, N= 72), the participants followed them have the Master's degree (23.6%, N=37), and the participants have Diploma 15.3%. The least people have a Doctoral of Philosophy (6.4%, N= 10). This shows that the respondents who have taken part in this research study have an equal distribution across the different educational groups, and hence more mature and reliable answers could be obtained.

5.4 Job area

Table 5. Educational Level

	category	Frequency	Percent
Job area	Supply Chain	29	18.5
	Logistics / Transportation	13	8.3
	Finance /Accounting	34	21.7
	Contracts Procurement	65	41.4
	Law	16	10.2
	Total	157	100

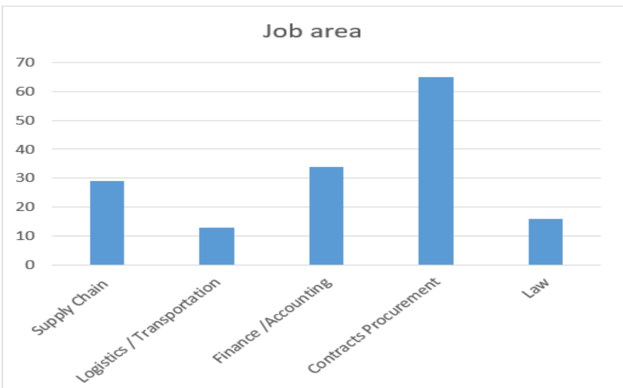

Figure (5): classification of the data according to educational group

Figure (5): Classifications of the data according to Job area When the participants of the research study were asked about their Job area, it was found that the maximum number of respondents were Contracts Procurement (41.4%, N= 65), they were followed by the participants work at Finance /Accounting (21.7%, N=34), and the participants have Supply Chain 18.5%. The least people worked in Logistics / Transportation (8.3%, N= 13). This shows that the respondents who have taken part in this research study have an equal distribution across the different Job areas; hence, more mature and reliable answers could be obtained.

5.5 Industry Type

Table 6. Industry Type

	Category	Frequency	Percent
Company Industry	Manufacturing	17	10.8
	Oil & Gas	41	26.1
	Banking	31	19.7
	IT	17	10.8
	Tourism	4	2.5
	Others	47	29.9
	Total	157	100

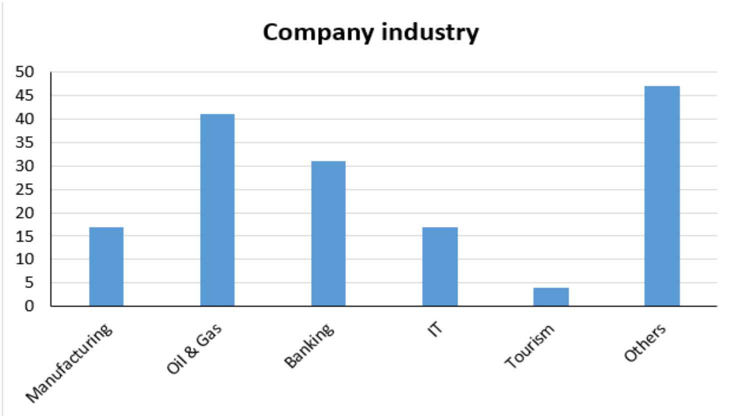

Figure (6): classification of the data according to educational group

Figure (6): Classifications of the data according to Company Industry When the participants of the research study were asked about their Company industry, it was found that the maximum number of respondents work in the Others sector (29.9%, N= 47), they were followed by the participants work at Oil & Gas (26.1%, N=41), and the participants work Manufacturing 10.8%. The least people worked in Tourism (2.5%, N= 4). This shows that the respondents who have taken part in this research study have an equal distribution across the different Company industries; hence, more mature and reliable answers could be obtained.

6. Correlation

A correlation of 0 indicates no relationship at all, 1.0 indicates a perfect positive correlation, and -1.0 indicates a perfect positive correlation. In interpreting the value between 0 and 1, different authors suggest a different interpretation of coefficient correlation. However, according to Cohen (1988), interpretations of the correlation coefficient are as follows:

r = 0.10 to 0.29: Small correlation
r = 0.30 to 0.49: Medium correlation
r = 0.50 to 1.00: Large/strong correlation

Correlation analysis was conducted to test whether there is a relationship and its strength among variables. The results for correlation for all variables are depicted in Table 4.3.

Table (11): Pearson Correlation for Independent Variables and Dependent Variable

	big	**Machin**	**Internet**	**employ**	**Executive**	**cost**
Big Data Analytics	1					
Machine Learning	.309**	1				
Internet of Things	.256**	.638**	1			
Employee Digital Skills	.212**	.431**	.623**	1		
Executive Leadership	.301**	.475**	.636**	.450**	1	
Cost Reduction	.333**	.501**	.641**	.524**	.473**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table (11) Correlation analysis refers to the strength and direction of the linear relationship between two factors. The degree of correlation refers to the strength and significance of a relationship between them. A bivariate association was performed to achieve it, calculating the Pearson correlation coefficient with the degree of importance. A value of 1 or -1 means that the factors can be accurately determined interchangeably, and 0 indicates no relationship between them. Finally, the results of the analysis are presented in Table 3. The Bivariate Pearson's correlation test suggested that there was a positive significant correlation (i.e., association) between Big Data Analytics, Machine Learning, Internet of Things, Employee Digital Skills and Executive Leadership Ranging between ($r = 0.212$ to 0.638, $p < 0.010$). Also, the analysis using the Bivariate Pearson's correlation test showed that the correlation of the independent variables and cost reduction ranged between ($r = 0.333$ to 641, $p < 0.010$).

6.1 Regression analysis

The significance and strength of the relationship between the independent variables (Big Data Analytics, Machine Learning, Internet of Things, Employee Digital Skills, and Executive Leadership) and the dependent variable (Cost Reduction) were determined using multiple regression analysis. Regression yields an equation that represents the most accurate prediction of a dependent variable given a set of independent variables. It is a useful technique for simultaneously analyzing the relationship between a single dependent variable and multiple independent (predictor or explanatory) variables. The summary of the regression results is shown in Tables 12-14.

Table 12 Model Summary of independent variables and Cost Reduction.

R	R Square	Adjusted R Square	Std. Error of the Estimate
.688	0.473	0.455	0.42

The preceding table shows that the adjusted R square value is 0.455%. This value can be interpreted as the proportion of the Cost Reduction's change or total variation that independent variables can explain. Consequently, if we convert this value to a percentage, independent variables explain 47.3% of the total variance in Cost Reduction. In context, the remaining 52.7%, not explained by independent variables, is explained by other factors not included in this model.

Table 13: ANOVA of Content independent variables and Cost Reduction

	Sum of Squares	df	Mean Square	F	Sig.
Regression	24.36	5	4.87	27.07	.000
Residual	27.17	151	0.18		
Total	51.5	156			

As shown in the preceding table, the significance level is 0.000 with an F statistic of 27.07. Consequently, there is a statistically significant relationship between the independent variable and Cost Reduction. This suggests that this model with independent variables and Cost Reduction is significant.

Table 14: Coefficients of independent variables and Cost Reduction

	Unstandardized Coefficients	**Std. Error**	**Standardized Coefficients**	**t**	**Sig.**
	B		Beta		
(Constant)	0.51	0.34		1.502	0.135
Big Data Analytics	0.148	0.06	0.155	2.453	**0.015**
Machine Learning	0.109	0.089	0.096	1.218	0.225
Internet of Things	0.405	0.105	0.374	3.845	**0.00**
Employee Digital Skills	0.135	0.062	0.166	2.167	**0.032**
Executive Leadership	0.092	0.073	0.098	1.255	0.212

Concerning the above table, it's possible to derive the values to develop the model equation reflecting the effect of the independent variables on the dependent variables under consideration. The level of significance (α) relates to the probability of rejecting the null hypothesis. In independent variables and Cost Reduction research, significance is generally accepted at 0.05 (5%) (Hair et al., 2010). Accordingly, 0.51 is the constant (β_0), 0.148 is the slope (β1), where this Beta value is a significant effect at a 0.05 significant level (as depicted in the table, the significance value is 0.000, which is less than 0.05). 0.405 is the slope (β3), where this Beta value is a significant effect at 0.05, also Based on these figures derived from the above table. 0.135 is the slope (β4), where this Beta value is a significant effect at a 0.05.can be generated as, where the slop β2 and β5 have no significant effect at an (α=0.05)

6.2 Hypothesis Testing:

***H1**= Big Data Analytics positively affect Cost Reduction*

The analysis also shows that out of four predictors, Big Data Analytics was associated with predicting Cost Reduction (β = 0.148, t = 2.453, p-value 0.015). Since the standard coefficients (Beta) are 0.148, the regression equation model is Y = 0.51+ 0.148X (Y = Cost Reduction, X = Big Data Analytics). Based on the above regression equation, we can predict that if the level of job characteristics increases by one unit, the level of Cost Reduction will increase by 0.148 units.

***The H3**=Internet of Things positively affects Cost Reduction.*

The analysis also shows that out of four predictors, the Internet of Things was associated with predicting the level of Cost Reduction (β = 0.405, t = 3.845, p-value 0.000). Since the standard coefficients (Beta) are 0.148, the regression equation model is Y = 0.51+ 0.405 (Y = Cost Reduction, X = Internet of Things). Based on the above regression equation, we can predict that if the level of job characteristics increases by one unit, the level of Cost Reduction will increase by 0.405 units. Thus, we conclude that the Internet of Things is the most important factor influencing Cost Reduction among these three independent variables.

***H4**= Employee Digital Skills positively affect Cost Reduction*

The analysis also shows that out of four predictors, Employee Digital Skills were associated with predicting Cost Reduction (β = 0.135, t = 2.167, p -value= 0.015). Since the standard coefficients (Beta) are 0.148, the regression equation model is Y = 0.51+ 0.135X (Y = Cost Reduction, X = Employee Digital Skills). Based on the above regression equation, we can predict that if the level of job characteristics increases by one unit, the level of Cost Reduction will increase by 0.135 units.

Table 4.15: Summarized Results for all Hypothesis Analysis

Hypothesis		Result
H1	Big Data Analytics positively affect Cost Reduction	Supported
H2	Machine Learning positively affects Cost Reduction	Not Supported
H3	The Internet of Things positively affects Cost Reduction	Supported
H4	Employee Digital Skills positively affect Cost Reduction	Supported
H5	Executive leadership positively affects Cost Reduction	Not Supported

7. Discussion

Artificial intelligence is one of the intelligent technological applications that perform cognitive functions associated with human minds, such as learning, interaction, and problem-solving, and the development of artificial intelligence systems is rapid and ongoing. Initial technological progress has been slow in discussing AI systems and dimensions such as management Big data, the Internet of things, and employee skills and resources. Numerous scientists then resorted to emergency measures, separating the routine executive tasks machines could perform from the complex administrative tasks assigned to human resources.

Cost Reduction is positively affected by Big Data Analytics. Big data analytics assists businesses in cost management. Large amounts of data can be evaluated for patterns, trends, exceptions, and outliers through data visualization, allowing for improved decision-making. The organization can obtain better acceptable outcomes and analyze vast information to make better decisions. Businesses can use the data at hand to recognize trends to gain a competitive advantage and seize opportunities. Numerous examples of business evaluations lead to the best business decisions. Early detection of potential risks in the business environment is possible. An organization can continue to monitor all expenses and compare them to its established goals. In addition to the benefits and opportunities of utilizing big data and big data analytics for cost control, there are also risks.

The ability of machine learning algorithms to analyze vast amounts of data to identify trends and patterns enables businesses to make informed inventory decisions. This can reduce waste, improve efficiency, and reduce the risk of stock shortages or excess inventory. Machine Learning (ML) is a subset or component of AI that uses data to develop task-specific solutions. Moreover, the problem solvers are professionally trained models that effectively resolve business-related issues. The ML models are provided with vast amounts of data and information derived from linear algebra and probability theory. As the models do not comprehend the common human language, they only comprehend computer language and concepts derived from theory.

In addition to this, machine learning and AI offer numerous benefits for the growth and development of a variety of businesses. Machine learning aims to identify the structure of information and data and transfer it to models that people can use. The primary objective of this study is to determine the significance of machine learning and its effects on business management in the current digital era. In addition, the study examines the need or demand for AI and ML in the contemporary business world. The concept of machine learning allows users to lock their phones with their faces, share photos with their friends using a fingerprint lock, and many other technologies convert the text of images into movable text. In the modern world, there is a growing demand for machine learning (ML) and artificial intelligence (AI) installed and developed devices that allow customers to operate the devices remotely. This study demonstrated that big data does not reduce costs due to the extensive time, effort, and expense required to analyze and process big data. Technicians were required to rely on artificial intelligence systems that could learn, infer, and respond to situations that were not programmed into the machine using complex algorithms and using cloud computing technologies to complete their work and work on it.

The Web of Things In researching the quality of services to learn more about the impact of IoT, researchers discovered few studies that focused on the Internet of Things or electronic banking services or even new technology's effect on service quality in banks, whereas others focused on traditional bank services. The Internet of Things consists of a global network of interconnected sensor devices with unique identifiers whose purpose is to collect data. Data will be transmitted over the Internet and stored in a database, aiding businesses in various areas, including inventory management and demand forecasting based on historical consumption patterns. Moreover, real-time data enables managers to rely on output forecasts and make decision-making adjustments to prevent further losses to the organization. Real-time insights enable organizations to anticipate errors and rapidly respond to any problem.

IoT technology assists bank decision-makers in locating solutions and increasing productivity with minimal human intervention and broad scope. IoT represents a development in M2M by connecting devices to the internet and multiple networks, enabling employees to respond rapidly, creating new revenue streams, and improving operational efficiencies and service delivery Liu et al. (2022). Responsiveness is a factor of service quality in Internet banking that enables employees to respond rapidly to a customer's request while saving time and money for both parties. Emphasis is placed on demonstrating awareness and sensitivity to questions.

Most organizations are attempting to reduce expenses and increase profits, and Employee skills are the ideal place to begin." Following is a list of suggestions for enhancing employee skills in any organization: Regardless of the industry in which an organization operates, focusing on employee skills is one of its most important aspects. As the costs of employee skills are one of the primary expenses for increasing employee efficiency, improving it can significantly impact a startup organization, particularly when employee skills development methods are utilized. One of the primary advantages of utilizing employees' skills is reduced expenses. To put things in perspective, higher employee skills can increase administrative efficiency by up to 21%, save 30% in time and money, and reduce errors.

According to one report, improved job satisfaction, productivity, and performance directly result from technically integrated employee skills support. Technology adoption for developing employee skills is high in ten of the fourteen industries recently surveyed, including automotive, e-commerce, health, pharmaceuticals, hospitality, knowledge process outsourcing, retail, and telecom. This is a huge victory for startups, as most of them will be establishing themselves on the market. This is due to Employee's tremendous skill growth over the past few years, which has enabled her to jump gears and make informed decisions for her organization. Lastly, from the employee's perspective, it is also necessary to increase the technological skills of employees in the workplace. Even daily, we have adapted to rapid technological advancements with relative ease. Technology improves employee engagement, particularly in remote work and mixed working systems.

Nevertheless, the advantages of utilizing artificial intelligence outweigh its risks, particularly in business applications (4). To monitor the attitudes of public relations professionals toward the paths of employing artificial intelligence applications in Egyptian banks following the theory of job replacement by artificial intelligence to make the right decisions or uncover deception and money laundering. Cost reduction becomes a widely adopted operating strategy not only for specific organizations but also for organizations with a general corporate strategy for cost leadership and for many industry sectors for which cost reduction is a general strategy. This study found that big data and big data analytics help businesses control costs by analyzing cost data, comparing actual and target costs, and making cost-control-related business decisions. Businesses can use the data at hand to identify trends to gain competitive advantage and opportunities. Numerous business evaluation examples can be implemented to make the best business decisions. Workplace hazards can be identified early on. There are numerous risks associated with using big data and big data analytics, including security risks associated with the data held, data quality concerns, and the quality of big data analytics. Big data analytics and big data for enterprise cost control are most effective when combined with large databases and cloud service applications. This enables a person to gather more information and utilize different types of data from multiple sources to identify specific opportunities to control cost, generate new insights, manage risk, and predict future outcomes. The Internet of Things enables remote sensor data access, monitoring, and control of the physical world.

Moreover, the combination of data capture and analysis enables organizations to develop and enhance services that can't be provided by isolated systems. Although there is limited research in the e-commerce field on the Internet of Things, our review indicates that stories and benefits have been the primary focus. According to research, the benefits range from the political to the operational levels.

Specifically, the benefits of e-commerce can be attributed to improving the efficiency, effectiveness, and flexibility of services; reducing costs; empowering citizens more effectively; increasing government transparency; enforcing regulations more effectively; improving planning and forecasting; and enhancing health and safety procedures. The Internet of Things enables remote sensor data access, monitoring, and control of the physical world. There may be future consequences in addition to the intended benefits. Data privacy issues, data security issues, weak or uncoordinated data policies, weak or uncoordinated data management, conflicting market forces, costs, interoperability and integration issues, IoT acceptance, trust issues, lack of adequate knowledge regarding IoT, and IoT infrastructure limitations can be specifically attributed to the disadvantages. Problems with information and data management

7.1 Implications:

The applied significance of this study is highlighted by its attempt to influence the perceptions of institution workers in leadership and management, as well as the significance of employing artificial intelligence in all Saudi Arabian industries. In addition, it is hoped that everyone will benefit from this study by gaining knowledge about the reality of employing artificial intelligence and making decisions to improve this reality. It may benefit planners by revealing obstacles to the application of artificial intelligence, allowing them to devise solutions. It may also be useful for educational institution administrators to improve the use of artificial intelligence. Scientists and researchers will be better able to comprehend the role of the independent variables in the big data study of Internet of things Employee skills and their effect on the dependent variable, cost reduction, as a result of this study. In addition, the findings of this study will demonstrate the disparity between these variables and their impact on cost reduction.

7.2 Limitation of Study and Future Research Directions:

Multiple variables may influence contract procurement cost reduction. Artificial Intelligence is one of the key contributors to procurement cost reduction. In this study, the researcher will focus solely on the impact of AI on reducing procurement costs. The only limitation in the research field is procurement. First, the results of this study will assist another researcher in the context of artificial intelligence and the factors that facilitate its implementation and adoption in Saudi Arabia, who will lead the way in this regard. The second point is to consider the other Independent non-significant factors and monitor the reasons why these factors are marginalized, such as Machine

Learning and Executive Leadership, which can justify the application of artificial intelligence.

Acknowledgment: This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia [Grant 3944]

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