Role Of Digital Technologies In Enhancing Procurement Performance : An Empirical Study

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ABSTRACT:

This study investigates the role of digital technologies in procurement performance, to support organizations making better technology investment decisions. It has identified eighteen technologies that exhibit potential for use in procurement, while narrowing the study focus on three specific technologies, namely: E-procurement as basic mature technology, in addition to Robotic Process Automation (RPA) and Artificial Intelligence (AI) for the purpose of automating additional procurement activities.

The study also investigates the main dimensions of procurement performance and methods for measuring them.

This study is applied to the manufacturing sector in Egypt through use of a five-scale Likert questionnaire to examine the role of digital technologies in procurement performance.

The study found a statistically significant positive relationship between the independent variables of E-procurement, Robotic Process Automation (RPA), and Artificial Intelligence (AI), and the dependent variable procurement performance.

The study recommends utilizing E-procurement solutions to automate procurement activities. Robotic Process Automation (RPA) can be utilized in automating routine activities, reducing costs, and enhancing reliability. Artificial Intelligence (AI) can provide a competitive edge by increasing the percentage of purchase orders delivered on time. Other digital technologies can be considered for comprehensive automation and digital transformation of the procurement function.

Keywords: Digital Technologies, E-procurement, Robotic Process Automation (RPA), Artificial Intelligence (AI), Procurement Performance.

مستخلص البحث:

تبحث هذه الدراسة دور التقنيات الرقمية في أداء المشتريات، لدعم المنظمات في اتخاذ قرارات تكنولوجية استثمارية أفضل. وقد حددت الأدبيات ثمانية عشر تقنية تظهر إمكانات للاستخدام في المشتريات، ولكن ركزت الدراسة على ثلاث تقنيات محددة، وهي: المشتريات الإلكترونية ، بالإضافة إلى أتمتة العمليات الروبوتية (RPA) والذكاء

الاصطناعي (AI) لغرض أتمتة أنشطة المشتريات الإضافية. كما تبحث الدراسة الأبعاد الرئيسية لأداء المشتريات وطرق قياسها.

تم تطبيق هذه الدراسة على قطاع التصنيع في مصر من خلال استخدام استبيان ليكرت بخمسة مقاييس لفحص دور التقنيات الرقمية في أداء المشتريات. وقد وجدت الدراسة علاقة إيجابية ذات دلالة إحصائية بين المتغيرات المستقلة للشراء الإلكتروني وأتمتة العمليات الروبوتية (RPA) والذكاء الاصطناعي (AI) والمتغير التابع أداء المشتريات.

توصي الدراسة باستخدام حلول المشتريات الإلكترونية لأتمتة أنشطة المشتريات. كما يمكن الاستفادة من أتمتة العمليات الروبوتية (RPA) في أتمتة الأنشطة الروتينية وخفض التكاليف وتعزيز الموثوقية. فيمكن للذكاء الاصطناعي أن يوفر ميزة تنافسية من خلال زيادة نسبة أوامر الشراء التي يتم تسليمها في الوقت المحدد. ويمكن النظر في التقنيات الرقمية الأخرى لتحقيق الأتمتة الشاملة والتحول الرقمي لوظيفة المشتريات.

الكلمات الرئيسية: التقنيات الرقمية، الشراء الإلكتروني ، أتمتة العمليات الروبوتية (RPA)، الذكاء الاصطناعي (AI)، أداء المشتريات.

1. INTRODUCTION

To thrive in the marketplace and gain a competitive advantage, industries must allocate resources toward the adoption and integration of cutting-edge technologies (Chandrasekara et al, 2020). Recently, businesses have been compelled to pay close attention to the principles of the 4th Industrial Revolution, particularly digitalization, due to its potential influence on critical organizational aspects such as profitability and competitiveness (Viale & Zouari, 2020). The growing discussion around the digital revolution and the emergence of disruptive competitive advantages has given rise to the conceptualization of a business vision known as Industry 4.0 (Glas et al., 2016).

The performance of the procurement process involves enhancements in purchasing performance, which encompass cost reduction, lead time reduction, quality improvement, and inventory management (Mishra et al., 2013). Procurement practices can influence procurement performance, specifically cost, time, satisfaction, quality, stock, and value. Firms are enhancing their procurement practices by leveraging the latest technologies, thereby aiming to enhance company performance through improved efficiency in the entirety of their procurement process (Lindskog and Wennberg, 2002).

In the current study, the new digital technologies that evolved during the fourth industrial revolution will be explored while investigating their potential role in managing the procurement function and how these technologies can impact procurement performance, aiming at supporting decision-makers and procurement professionals in deciding the feasibility of utilizing these technologies and the expected return on investment measured through potential impact on enhancing reliability and responsiveness while reducing the cost.

2. LITERATURE REVIEW

2.1 Digital technologies

2.1.1 Digitization, Digitalization, and Digital Transformation concepts

Digitization, digitalization, and **digital transformation**, these terms are frequently employed interchangeably, and the perception of their interchangeability highlights the prevailing ambiguity surrounding the essence of digital transformation (Maltaverne, B. 2017). Within the broader realm of digital transformation, there are new terminologies that emerge in scholarly literature, like "digitization" and "digitalization" (Bumann, J., & Peter, M. ,2019). However, it is important to note that these three terms have different definitions (Bloomberg, J., 2018).

The concepts of **Digitization, digitalization,** and **digital transformation** are summarized and visualized in the following figure:

Figure 1: Digitization, Digitalization and Digital Transformation

Source: Maltaverne (2017)

Digitization is the process of transitioning from analogue to digital form involves converting data without introducing any fundamental alterations to the underlying mechanism (Gartner, 2022). According to Ross (2017), the process of digitization is considered an essential operational requirement in order to facilitate the broader concept of digitalization.

Digitalization refers to the utilization of digital technologies (Srai & Lorentz, 2019). The aforementioned definition aligns with the definition provided by Gartner (2022), which characterizes digitalization as the use of digital technology to transform a business model and create new opportunities for generating revenue and value.

Digital transformation refers to the process of organizational transformation that is initiated by the adoption of technology-driven digital disruptions and is driven by the actors involved (Nadkarni and Prügl, 2021). The occurrence of this phenomena leads to the formation of new marketplaces, clients, and firms (Maltaverne, 2017).

2.1.2 The Industrial Revolutions (1.0, 2.0, 3.0, 4.0, 5.0) There are four main industrial revolution stages (Nasution, 2020), in addition to a recent declared 5th revolution by the European Commission (Xu, et. al. 2021).

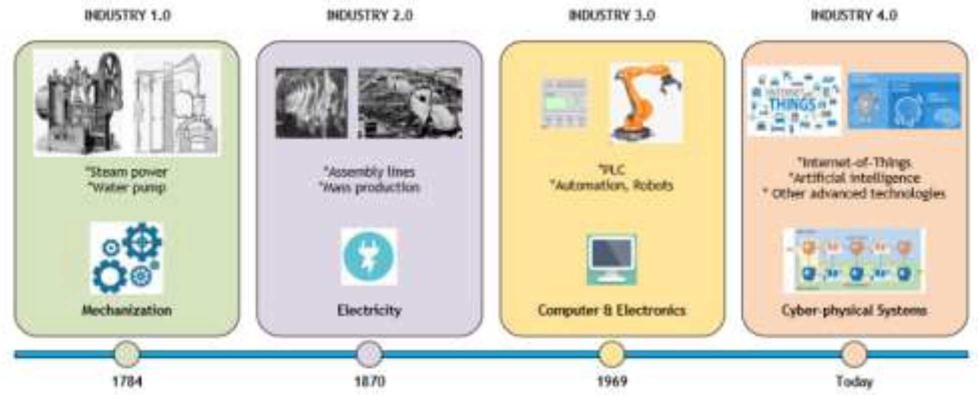


Figure 2: Industrial revolution stages

Source: Mubarok, (2020)

Industry 1.0: During the early 19th century, a novel technological development emerged in the form of water steam-powered machinery, which served to partially supplant the reliance on animals. Simultaneously, these machines provided assistance to workers in various capacities (Nasution, 2020). The first stage of industrialization was marked by a significant transition from manual manufacturing methods to automated operations powered by steam or water energy (Xu et. al. 2021).

Industry 2.0: In the early 20th century, electricity sparked a new industry and corporate enthusiasm. Machine-driven vehicles, ships, railroads, and certain equipment consume oil. The new administrative model for this stage has established numerous management programs to improve manufacturing facility efficiency and effectiveness by dividing labor into interconnected phases and assigning personnel by stage. Every job is optimized with improved work methods to improve quality. (Nasution, 2020).

Industry 3.0: In light of the progression of electricity's introduction, further technological developments have resulted in the widespread proliferation of electronic devices. Several to its initial iteration, the machine underwent several updates to enhance its performance, hence enabling the incorporation of personalized programs tailored to the user's specific interests. The emergence of the Third Industrial Revolution marked the incorporation of field-level computers, such as the Programmable Logic Controller (PLC), and advanced communication technologies within the manufacturing process, hence enabling the automation of production (Xu et al., 2021).

Industry 4.0 concept was first promoted at the Hanover Fair in 2011, as documented by Drath and Horch (2014). The origins of the Fourth Industrial Revolution, commonly referred to as Industry 4.0, can be attributed to its emergence as a project inside the high-tech policy framework of the German government in 2011. The emergence of Industry 4.0 was mostly observed in the manufacturing industry, where there was a convergence of physical production technologies with digital technologies, including big data, artificial intelligence (AI), and cloud computing (Fatorachian and Kazemi, 2018). The digital transformation associated with Industry 4.0 is distinguished by the adoption and integration of certain digital technologies (Indri et al., 2018).

Industry 5.0 : In 2021, The European Commission declared the advent of Industry 5.0, marking a significant milestone a decade after the inception of Industry 4.0. Industry 4.0 is commonly regarded as a paradigm characterized by its reliance on technology, while Industry 5.0, in contrast, places a greater emphasis on values (Xu, X., et al. 2021). The fundamental concept underpinning Industry 5.0 is around the selection of technologies guided by an ethical rationale that prioritizes the support of human values and needs. This approach goes beyond solely considering the technical or economic capabilities of technologies (Müller, 2020).

2.1.3 Enabling digital technologies to industry 4.0 and 5.0

The successful implementation of digital transformation necessitates the use of emerging technologies and software paradigms in order to efficiently oversee the process and stay abreast of technological progress (Srai, & Lorentz, 2019). The Boston Consulting Group (BCG) established a comprehensive framework consisting of nine core principles that underpin the notion of Industry 4.0, thereby delineating the foundations of technological advancement. The list includes Industrial Internet-of-Things, cloud computing, cybersecurity, Big data and analytics, horizontal and vertical system integration, advanced robotics, additive manufacturing, augmented reality, and simulation (BCG, 2015).

Several further technologies have subsequently emerged. According to the study conducted by Mubarok (2020), the inclusion of three additional sophisticated technologies, specifically knowledge graph, blockchain, and digital-twin, was seen. The specified nine technologies, as proposed by BCG, were supplemented with an additional 12 advanced technologies as demonstrated in the following figure.

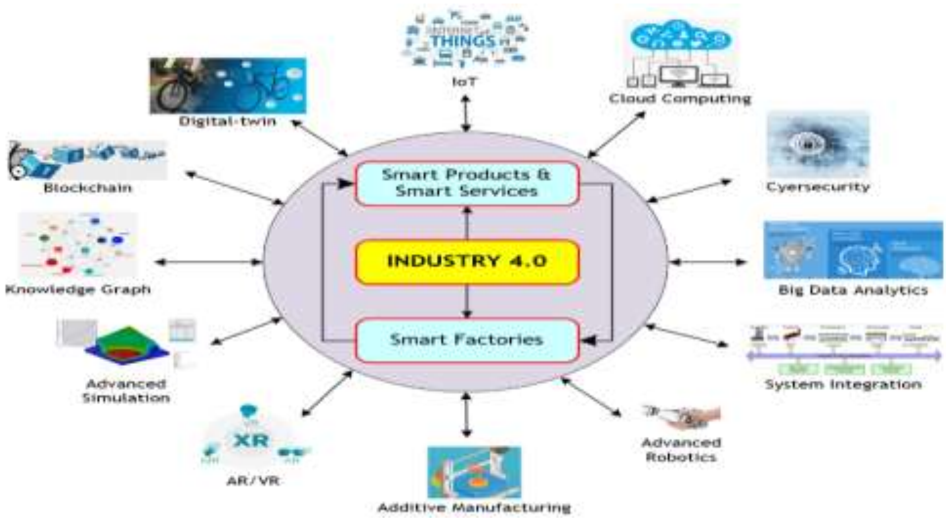


Figure 3: Advanced technologies driving Industry 4.0 vision

Source: Mubarok, (2020).

Maddikunta et al. (2022) reported several advances in Industry 5.0 enabling technologies. These advancements include edge computing, digital twins, cobots, and collaborative robots. Edge computing involves the distribution of data processing closer to its origin. Digital twins enable the instantaneous simulation of tangible objects and intricate systems. The Internet of Everything (IoE), big data analytics, blockchain, 6G, and other upcoming technologies, along with Network Slicing (NS), extended Reality (XR), and Private Mobile Network (PMN), contribute to the development and implementation of Industry 5.0 and its applications.

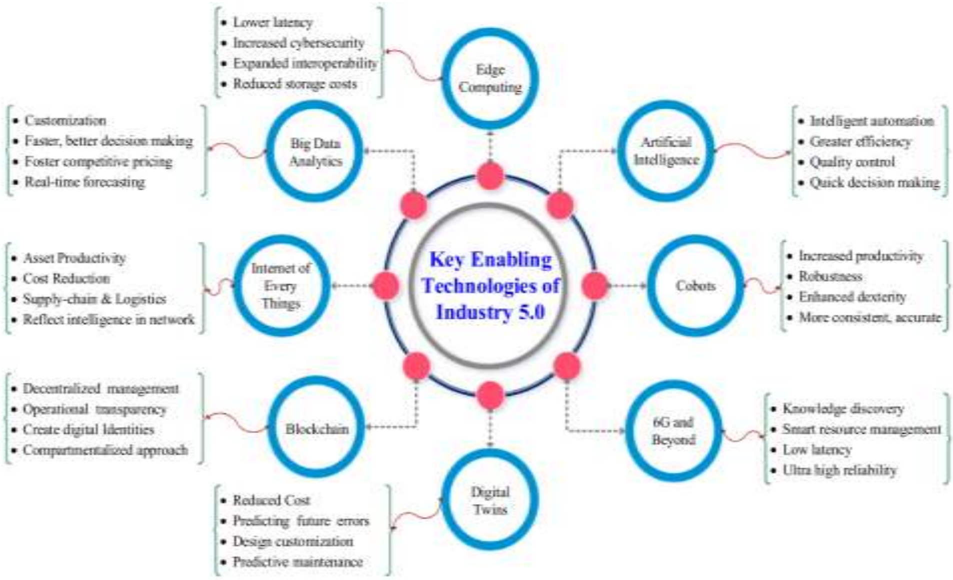


Figure 4: Key enabling technologies in connection with Industry 5.0

Source: Maddikunta, et. al (2022)

2.1.4 Procurement 4.0 and most relevant technologies to procurement function.

Procurement 4.0 aims to improve supply chain performance by creating new value propositions and meeting changing company needs. Procurement using Industry 4.0 principles (Chandrasekara, et. al. 2020). Industry 4.0's cross-organizational automation doesn't replace procurement. Instead, Procurement 4.0 strategically ensures collaboration in a dynamic Industry 4.0 framework of rapidly changing organizational boundaries with contractual solutions and instruments to improve supply chain performance, such as standardization (Glas, & Kleemann, 2016). According to research by IBM, cloud, cognitive computing, and predictive data analytics are Chief Procurement Officers' top three technology investments over the coming three years. IBM created a natural language processing virtual buying assistant. The “three bids and a buy” process for non-catalogue indirect goods and services can be handled by this virtual assistant. Not only does this improve user experience. Both buyer and seller benefit from greater quality, data consistency, and efficiency (Booth, & Sharma, 2019).

Digital procurement practices encompass the application of sophisticated digital technology in the realm of procurement. There is a clear differentiation between basic and advanced digital technology. Fundamental digital technologies essentially comprise e-procurement, which refers to the electronic process of requesting, placing orders, and acquiring goods and services between businesses (B2B) using the internet. (Srai and Lorentz, 2019).

Organizations have used buyer-side e-Request for quotation systems and electronic marketplaces for over a decade to expedite internal and external procurement. There are several e-procurement options on the market, and upcoming technologies like RPA could automate more work (Högel et al., 2018).

AI, Big Data, and the IoT automate operational tasks and allocate resources to more strategic projects led by human agents, making them essential to procurement (Bienhaus, & Haddud, 2018). However, current research implies that procurement uses emerging technology less (Handfield et al., 2019).

Allen (2019) surveyed 200 procurement functions in the UK, working in organizations employing over 1,000 people in operations, telecommunications, finance, and retail. Over 70% of procurement employees perceived limited digitalization in the procurement domain. This digitalization gap cost enterprises roughly £2 million annually. The survey indicated that procurement teams spend 1/3 of their time on clerical tasks and inefficient paper-based procedures. The majority of 80% also reported time constraints when making strategic contributions.

Chandrasekara and Wickramarachchi (2020) reviewed industry 4.0 procurement optimization literature. Eight Industry 4.0

technologies were associated with procurement optimization in this study. Analytics Big data/Cognitive, IoT/RFID, RPA/AI, Cloud Computing, Internet/EDI/web-based platforms, Blockchain, Automated Vehicles, and Mobile technologies are covered in this study. In another research by Srai, & Lorentz, (2019), a total of nine digital technologies that offer advantages have been identified as being pertinent to the value drivers of procurement. These technologies encompass the Internet of Things, social media, cloud computing, big data analytics, cognitive computing/artificial intelligence, mobile technologies, virtual/augmented reality, blockchain, and additive manufacturing.

The research of Weenink, (2022) determined the applicability of several technologies, including e-Tendering programs, BI, Cloud Computing, API Management Software, OCR, Blockchain, IoT, RPA, and AI, in the different stages of procurement management. Nevertheless, certain applications exhibit greater efficacy compared to others.

The above examined studies (Weenink, 2022; Chandrasekara, et al. 2020; Srai and Lorentz, 2019; Bienhaus, & Haddud, 2018; Högel et al., 2018) have identified eighteen technologies with potential application in procurement, which are summarized in the following table:

Table 1: Technologies with potential application in procurement

#	Technology
1	Additive manufacturing (or 3D printing)
2	Artificial Intelligence
3	Application programming interface (API)
4	Autonomous Vehicles
5	Augmented reality (AR)
6	Business intelligence (BI) services
7	Blockchain
8	Big data analytics
9	Cloud Computing
10	e-procurement
11	Electronic Data Interchange (EDI)
12	The Internet of Things (IoT)
13	Mobile technologies
14	Optical Character Recognition (OCR)
15	Radio frequency identification (RFID)
16	Robotic process automation (RPA)
17	Social media
18	Virtual reality (VR)

Source: Prepared by the researchers

This study will focus on examining the role of selected digital technologies representing both the basic technologies widely applied in procurement, in addition to the application of advanced technologies with potential impact on procurement in the near future.

As for the basic technology application, this study will examine the role of E-procurement as the basic digital technology used in procurement for many years (Srai and Lorentz, 2019).

2.1.5 E-procurement, Robotic Process Automation (RPA), Artificial Intelligence (AI)

According to ASCM dictionary (2022), E-procurement encompasses a range of tools and software that streamline various tasks related to the development of buy orders, management of orders, communication, document transfer, tracking procurement progress, and logistics. E-procurement was reported in the study by Gartner as the most mature technology application in procurement (Gartner, 2022), which was also identified in the study by Weenink, (2022) among technology applications with the highest potential impact on the organization and will enhance the overall performance of the company (Kim, et al., 2015).

For advanced digital technologies, this study will examine the role of Artificial Intelligence (AI) and Robotic Process Automation (RPA) technologies in automating additional procurement tasks (Högel et al., 2018) through supporting daily business, administrative tasks, and operational tasks (Chandrasekara, et. al., 2020), and their potential effect on procurement performance.

According to the Gartner glossary (2023), Artificial Intelligence (AI) involves the application of advanced analytical and logic-based techniques, such as machine learning, to understand events, streamline decision-making, and carry out activities. Although Robotic Process Automation (RPA) is a technological solution that enables users to configure one or more scripts, also known as bots, to execute predetermined keystrokes in an automated manner. As a consequence, the bots possess the capability to imitate or replicate specific tasks (such as transaction steps) within a larger business or IT process.

The application of artificial intelligence (AI) in procurement enables the automation of manual, repetitive, and tactical processes, thereby enabling professionals to allocate their attention towards strategic objectives. Artificial intelligence (AI) can also contribute to the provision of analytical insights and enhance the accuracy of price predictions (Sammalkorpi, & Teppala, 2019).

The implementation of Robotic Process Automation (RPA) in procurement can yield significant effects on conventional procurement practices by improving time allocation and automating internal procedures, ultimately resulting in heightened stakeholder contentment (Viale, & Zouari, 2020).

Artificial intelligence (AI) and Robotic process automation (RPA) technologies were identified to have the highest potential impact on procurement according to study by Weenink, (2022), where these technologies are expected to get more mature and to have broad market applicability in procurement within 2 to 5 years according to study by Gartner (2022).

2.2 Procurement performance

2.2.1 Dimensions of Procurement Performance

The process of procurement, which involves the acquisition of goods or services from an external provider, holds significant significance inside an organization. In order to assess the effectiveness of an organization's execution of this task, it is important to evaluate all relevant Key Performance Indicators (KPIs) related to procurement (Abolbashari, et al, 2018).

Procurement performance is attained by acquiring goods or services at the most advantageous cost to fulfill the buyer's requirements in terms of quality, quantity, timeliness, and location (Munyimi, 2019). Association for Supply Chain Management (2016) has identified five main performance attributes for the supply chain, including reliability, responsiveness, agility, costs, and asset management efficiency. These performance attributes include a number of metrics used to present a strategic direction and measure the performance. It should be noted that an attribute, in and of itself, lacks measurability and instead serves the purpose of establishing strategic direction.

2.2.2 Procurement performance measurement and evaluation

Lysons and Farrington (2016) define procurement performance evaluation as a methodical assessment, employing either quantitative or qualitative approaches, carried out over a defined timeframe to measure the degree to which procurement economies, efficiency, and effectiveness align with corporate or operational goals and objectives. Measuring and evaluating organizational performance could be conducted by identifying KPIs, developing monitoring and evaluation frameworks, and adapting strategies based on feedback and learning. (Frank and Mohamed, 2024)

Abolbashari et. al (2018) has developed the following model aiming to assess and enhance procurement performance in organizations.

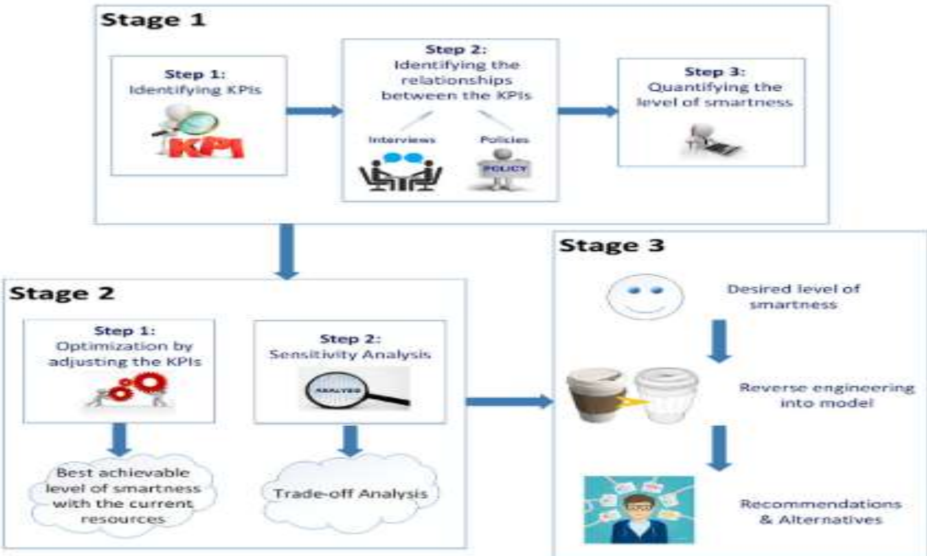


Figure 5: The Smart Buyer framework for procurement excellence

Source: Abolbashari et al. (2018)

Based on the aforementioned study conducted by Abolbashari et al. (2018), a total of five procurement professionals were interviewed to determine the key performance indicators (KPIs) which are considered crucial to evaluating procurement performance. These professionals agreed that the following KPIs were most important for procurement performance including: cost, value for money, cycle time, quality satisfaction, forecast accuracy, effectiveness, and efficiency.

2.2.3 Procurement Key Performance Indicators (KPIs)

According to the KPI institute (2012), a KPI is an indicator that is chosen to monitor the performance of a strategic target, outcome, or key result area that is crucial for the success and growth of the company as a whole.

Abolbashari, et al. (2018) selected Cycle, Supplier performance, Agile, Quality, Supplier selection, Sustainability, and Training as the primary procurement KPIs based on domain experts. Internal KPIs determine a company's procurement performance.

In primary research by The KPI institute (2012), the procurement performance measures were identified and grouped into subcategories, such as Cost management, Savings, Order processing, Invoicing, Purchasing Profitability, and Supplier Management. This report compiles the most popular 25 KPIs used by the Procurement function.

The SCOR model's Source process measurements are another key procurement KPI reference because they are related to the main procurement operations like ordering, delivering, receiving, and transferring raw materials, subassemblies, products, and services.

2.3 Potential impact of adopting digital technologies on procurement performance

The deployment of Industry 4.0 applications may result in substantial costs, which could make them financially unattainable for a wide range of stakeholders. Therefore, it is crucial to ensure that procurement managers have a comprehensive understanding of the benefits linked to the implementation of these technologies before committing any resources to the digitization of the procurement process (Jahani, et al., 2021).

There is growing evidence, both in theory and practice, indicating that digital technologies can facilitate the transformation of various functions within supply chains. The present surge of technological breakthroughs, commonly referred to as the Industry 4.0 revolution, holds the potential to not only eliminate clerical and administrative duties, but also to automate, optimize, and enhance processes and information for increased efficiency (Seyedghorban, et al. 2020).

Leading corporations have achieved notable enhancements in operational efficiencies and financial gains through the adoption of digital technologies in the procurement process (Kosmol, et.al., 2019).

Digital procurement solutions provide the potential to enhance efficiency and enable procurement teams to assume a strategic role. By automating purchasing operations, these solutions liberate resources that can be allocated to more strategic endeavours (Radell, & Schannon, 2018).

The study conducted by Bauer and Göbl (2019) demonstrated that procurement departments who have embraced digitalization to a greater extent experience enhanced efficiency and reduced reliance on administrative and manual chores. Consequently, this leads to a rise in procurement efficiency.

Bag et al. (2020) conducted a study that suggests the Procurement 4.0 approach has a favorable impact on the intention of buyers to enhance company operations and performance optimization.

While the study conducted by Hallikas et al. (2021) has provided further empirical evidence for the existence of positive and statistically significant relationships between digital procurement capabilities, data analytics capabilities, and supply chain performance. The research undertaken by Sánchez-Rodríguez et al. (2019) has additionally proven a positive association between electronic procurement (e-procurement) and the efficacy of procurement processes, as well as the overall performance of businesses. Kim, et al. (2015) have also confirmed in a study that e-procurement has a beneficial impact on the performance of firms.

The utilization of electronic marketplaces in supply chains offers various advantages, such as the ability to assess performance and reduce supply delays and transaction costs (Allal-Chérif, & Babai, 2012).

Procurement 4.0 has numerous advantages to organizations, including the facilitation of daily procurement tasks and administrative responsibilities, heightened operational efficiency, improved decision-making capabilities, enhanced overall efficacy, and greater profitability for businesses (Bienhaus and Haddud, 2018).

The implementation of Procurement 4.0 technology offers more transparency, thereby effectively mitigating supply bottlenecks. Furthermore, the presence of accessible data regarding market intelligence and worldwide supplier pricing trends will grant purchasers the additional benefit of effectively managing supply chain expenses inside remanufacturing operations (Bag, et. al., 2020).

The research conducted by Seyedghorban, et al. (2020) employed a case study methodology to examine three companies that varied significantly in terms of their level of digital advancement in procurement. This study presented a comprehensive analysis of the advantages associated with the digitization of procurement processes. The findings indicate that digitalization offers numerous benefits, such as decreased costs and lead times, enhanced performance, and improved efficiency in various aspects, including agility, sustainability, and flexibility.

3. RESEARCH PROBLEM

Using technology could help organizations improve efficiency and reduce costs, but the return on investment must be justified in terms of performance improvement and cost savings, as well as determining which technology has the highest impact on performance and should be prioritized for use. Otherwise, organizations can incur investment costs for underperforming technologies or miss out utilization of other more effective technologies with better potential to improve the organizational performance.

To solve this problem, this study investigates the role of digital technologies in procurement performance, to support organizations making better technology investment decisions.

4. RESEARCH OBJECTIVES

The research aims to achieve the following objectives:

- To investigate the digital technologies that can be adopted in procurement.
- To examine the main dimensions of procurement performance and how to measure them.

- To discuss the potential impact of adopting digital technologies on procurement performance.

5. METHODOLOGY

5.1 Study Population, Sample, and Data Collection

This field study was conducted on the research population (target population) including individuals working in procurement and supply chain management in manufacturing companies operating in Egypt.

The total number of registered manufacturing companies within the Egyptian private sector is nearly 93,600 institutions according to the Federation of Egyptian Industries. The population size is 93,600 individuals considering the main individual carrying out procurement activities to support the company operations. This identified population number will not affect the sample size calculation since it provides the same sample size of an unknown or unlimited population.

The sample size was determined according to the following equation:

$$n = \frac{z^2 p(1-p)}{e^2}$$

whereas:
Z = the standard scores corresponding to the confidence level **95%** which can be used in social research, and the standard level corresponding to the confidence level **95%** equals **1.96.**

p = Percentage of those who are subject to study in the study population **50%.**

(1-p) = Percentage of those who do not have the subject of study in the study population **50%.**

e = The amount of error allowed at the estimate of **5%** is the percentage of error allowed in social research.

n = sample size

By applying the previous formula, researcher found that the sample size is at least **384** individuals in target population.

The used questionnaire contains 36 statements, divided into six variables (3 independent and 3 dependent)

The first section is the independent variables which included three selected basic and advanced technologies: E-procurement, Robotic Process Automation (RPA), and Artificial Intelligence (AI). While the second section is for the dependent variables, which focused on three major performance attributes Reliability, Responsiveness and Cost. The questionnaire statements were determined according to the objectives of the study and adopted from four main relevant studies by Sánchez-Rodríguez, et al (2019), Viale, & Zouari, (2020), Sammalkorpi, & Teppala, (2019), and Bienhaus, & Haddud, (2018),

A Likert scale was used as a five scale. (5) referred to strongly agree (4) agree (3) neutral (2) disagree and (1) strongly disagree. This indicated that (5) strongly agree referred to a very high degree of acceptance, while (1) strongly disagree refers to a very low degree of acceptance.

5.2 Hypotheses Development

Based on the problem of the study and its objectives, the **Hypotheses** can be expressed as follows:

Main Hypothesis:

There is a significant effect of utilizing digital technologies on procurement performance**.**

This hypothesis can be sub-divided into the following hypotheses:

Hypothesis 1:

There is a significant effect of utilizing e-procurement on procurement performance**.**

Hypothesis 1.1:

There is a significant effect of utilizing e-procurement on Reliability.

Hypothesis 1.2:

There is a significant effect of utilizing e-procurement on Responsiveness.

Hypothesis 1.3:

There is a significant effect of utilizing e-procurement on Cost.

Hypothesis 2:

There is a significant effect of utilizing Robotic Process Automation (RPA) on procurement performance.

Hypothesis 2.1:

There is a significant effect of utilizing Robotic Process Automation (RPA) on Reliability.

Hypothesis 2.1:

There is a significant effect of utilizing Robotic Process Automation (RPA) on Responsiveness.

Hypothesis 2.1:

There is a significant effect of utilizing Robotic Process Automation (RPA) on Cost.

Hypothesis 3:

There is a significant effect of utilizing Artificial Intelligence (AI) on procurement performance.

Hypothesis 3.1:

There is a significant effect of utilizing Artificial Intelligence (AI) on Reliability.

Hypothesis 3.2:

There is a significant effect of utilizing Artificial Intelligence (AI) on Responsiveness.

Hypothesis 3.3:

There is a significant effect of utilizing Artificial Intelligence (AI) on Cost.

5.3 Statistical Analysis of Survey Methods

The researchers used the statistical analysis program IBM SPSS version 27 in humanitarian and social research when analyzing the questionnaire’s data. The following statistical methods were used to derive the results from the collected questionnaire data:

- Cronbach’s Alpha measure is used to verify stability and reliability for each variable of the whole data set.
- Applying descriptive statistics for each set of statements and for each variable to determine the importance of each statement and for each variable.
- Use one-sample t-test to identify the trend of answers for each statement and each variable.
- The application of Pearson's coefficient of correlation is utilized as a diagnostic method to determine the magnitude and direction of the relationship between each set of variables.
- Applying multiple regression model to estimate the best model which can explain the data well.

Table 2. Results of Validity and Reliability to Variable of Knowledge Management.

Symbol	Statements	Cronbach's Alpha	Validity
X_1	E-procurement (9 items)	0.91	0.95
X_2	Robotic Process Automation (RPA) (9 Items)	0.86	0.93
X_3	Artificial Intelligence (AI)) (9 Items)	0.90	0.94
Y_1	Reliability (3 Items)	0.85	0.92
Y_2	Responsiveness (3 Items)	0.68	0.83
Y_3	Cost (3 Items)	0.69	0.83
Minimum Value		0.68	0.83
Maximum value		0.91	0.95

The previous tables show the results of Alpha (Cronbach): This is a model of internal consistency, based on the average inter-item correlation. The results of the reliability tests are presented in the previous Table. All the items have a Cronbach alpha value range greater than 0.6 thus, the measurement of the variables is valid and reliable (Nunnally and Bernstein, 1994).

Table 3: Descriptive statistics and relative rank for study variables

Symbol	Variables	Mean	SD	CV	Rank
Independent variables					
X_1	E-procurement X_1	4.28	0.61	14.20%	2
X_2	Robotic Process Automation (RPA) X_2	4.14	0.57	13.66%	1
X_3	Artificial Intelligence (AI) X_3	4.19	0.61	14.53%	3
Dependent variables					
Y_1	Reliability Y_1	4.13	0.68	16.52%	3
Y_2	Responsiveness Y_2	4.15	0.60	14.46%	1
Y_3	Cost Y_3	4.16	0.64	15.36%	2

For the **independent variables**; depending on the coefficient of variation value, it was found that the smallest coefficient of variation was **13.66%** for the most important independent variable was X_2 "***Robotic Process Automation (RPA)***" with mean equals **4.14** and standard deviation equals **0.57**; while the largest coefficient of variation was **14.53%** for the less important variable was X_3 "***Artificial Intelligence (AI)***" with mean equals **4.19** and standard deviation equals **0.61**.

For the **dependent variables**; depending on the coefficient of variation value, it was found that the smallest coefficient of variation was **14.46%** for the most important dependent variable was Y_2 "***Responsiveness***" with mean equals **4.15** and standard deviation equals **0.60**; while the largest coefficient of variation was **16.52%** for the less important variable was Y_1 "***Reliability***" with mean equals **4.13** and standard deviation equals **0.68**.

T-test of study variables

The t-test was employed to assess the pattern of responders within the population for each variable under investigation. The subsequent table illustrates the aforementioned findings.

Table 0: T-test results of study variables

Symbol	Variable	t-test value	P-value
X1	E-procurement	47.6	0.000
X2	Robotic Process Automation (RPA)	46.2	0.000
X3	Artificial Intelligence (AI)	44.3	0.000
Y1	Reliability	38.1	0.000
Y2	Responsiveness	43.3	0.000
Y3	Cost	41.1	0.000

The analysis of the data reported in Table 4 indicates that the null hypothesis will be rejected at a 95% confidence level for all variables investigated in the study. This discovery presents empirical support indicating that the respondents generally exhibit an agreement regarding the variables investigated in the survey.

5.4 Hypotheses Testing

5.4.1 Pearson's coefficient of Correlation

The researchers analyzed the Pearson's correlation coefficient between the study variables to determine if there is correlation between them. The researcher reached the following results:

Table 5: Coefficient of Correlation between study variables

Variables		E-procurement X_1	Robotic Process Automation (RPA) X_2	Artificial Intelligence (AI) X_3	Reliability Y_1	Responsiveness Y_2	Cost Y_3
E-procurement X_1	Pearson Correlation	1					
	P-Value						
Robotic Process Automation (RPA) X_2	Pearson Correlation	0.682	1				
	P-Value	0.000					
Artificial Intelligence (AI) X_3	Pearson Correlation	0.705	0.812	1			
	P-Value	0.000	0.000				
Reliability Y_1	Pearson Correlation	0.592	0.880	0.697	1		
	P-Value	0.000	0.000	0.000			
Responsiveness Y_2	Pearson Correlation	0.665	0.856	0.727	0.607	1	
	P-Value	0.000	0.000	0.000	0.000		
Cost Y_3	Pearson Correlation	0.605	0.693	0.741	0.670	0.569	1
	P-Value	0.000	0.000	0.000	0.000	0.000	

Based on the data shown in the preceding table, there is a significant correlation between the ***Independent variable dimensions*** and the dependent variable.

5.4.2Multiple Regression Analysis

Multiple regression analysis was applied to study the effect of the independent variables on each dependent variable. The multiple regression stepwise method was utilized to determine the most important independent variables. The multiple regression models can be as follows:

$$Y_1 = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \varepsilon$$

$$Y_2 = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \varepsilon$$

$$Y_3 = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + \varepsilon$$

Given that ε denotes the error term in the regression model. The following table shows the ANOVA table of stepwise regression for each dependent variable.

Table 6: ANOVA test and coefficient of determination of Regression models for each dependent variable

Dependent Variable	SOV	Sum of Squares	df	Mean Square	F	Sig.
Reliability Y1	Regression	171.79	1	171.79	1704.00	0.000
	Residual	49.80	494	0.10		
	Total	221.59	495			
R Square	77.53%					
Adjusted R Square	77.48%					
Responsiveness Y2	Regression	130.77	2	65.38	723.68	0.000
	Residual	44.54	493	0.09		
	Total	175.31	495			
R Square	74.59%					
Adjusted R Square	74.49%					
Cost Y3	Regression	115.13	3	38.38	226.36	0.000
	Residual	83.42	492	0.17		
	Total	198.55	495			
R Square	57.99%					
Adjusted R Square	57.73%					

Table 6 shows that the ANOVA analysis conducted on multiple regression models indicates that the entire model demonstrates statistical significance, as evidenced by the Sig value being lower than the predetermined Alpha level of 5% for each dependent variable. Additionally, the presented table illustrates that:

- The coefficient of Determination R^2 and adjusted R^2 are **77.53%** and **77.48%** respectively for the multiple regression model of the first dependent variable ***Reliability*** Y_1.
- The coefficient of Determination R^2 and adjusted R^2 are **74.59%** and **74.49%** respectively for the multiple regression model of the second dependent variable ***Responsiveness*** Y_2.
- The coefficient of Determination R^2 and adjusted R^2 are **57.99%** and **57.73%** respectively for the multiple regression model of the third dependent variable ***Cost*** Y_3.

5.4.3Multiple Regression Models

The following table shows the output of the stepwise multiple regression model for each dependent variable:

Table 7: Coefficients of Stepwise multiple regression models for each dependent variable

Dependent Variable	Model	Coefficients	t-value	Sig.
Reliability Y_1	Constant	-0.243	-2.268	0.002
	Robotic Process Automation (RPA) X_2	1.056	41.280	0.000
Responsiveness Y_2	Constant	0.175	1.618	0.006
	Robotic Process Automation (RPA) X_2	0.803	24.258	0.000
	E-procurement X_1	0.150	4.901	0.000
Cost Y_3	Constant	0.479	3.217	0.001
	Artificial Intelligence (AI) X_3	0.495	8.807	0.000
	Robotic Process Automation (RPA) X_2	0.263	4.463	0.000
	E-procurement X_1	0.121	2.688	0.007

Table 7 shows the following:

For the first dependent variable *Reliability* Y_1:

The most important independent variable with the highest positive effect on the dependent variable was ***Robotic Process Automation (RPA)*** X_2**.** The other two independent variables do not make any significant effect on ***Reliability*** Y_1**.** The suggested multiple regression model can be expressed as follows:

$$Y_1 = -0.2438 + 1.056 X_2$$

For the second dependent variable *Responsiveness* Y_2:

The most important independent variable with the highest positive effect on the dependent variable was ***Robotic Process Automation (RPA)*** X_2**.** Then the second important independent variable was ***E-procurement*** X_1**.** The independent ***Artificial Intelligence (AI)*** X_3 do not make any significance effect on ***Responsiveness*** Y_2**.** The proposed multiple regression model can be formulated as follows:

$$Y_2 = 0.175 + 0.150 X_1 + 0.803 . X_2$$

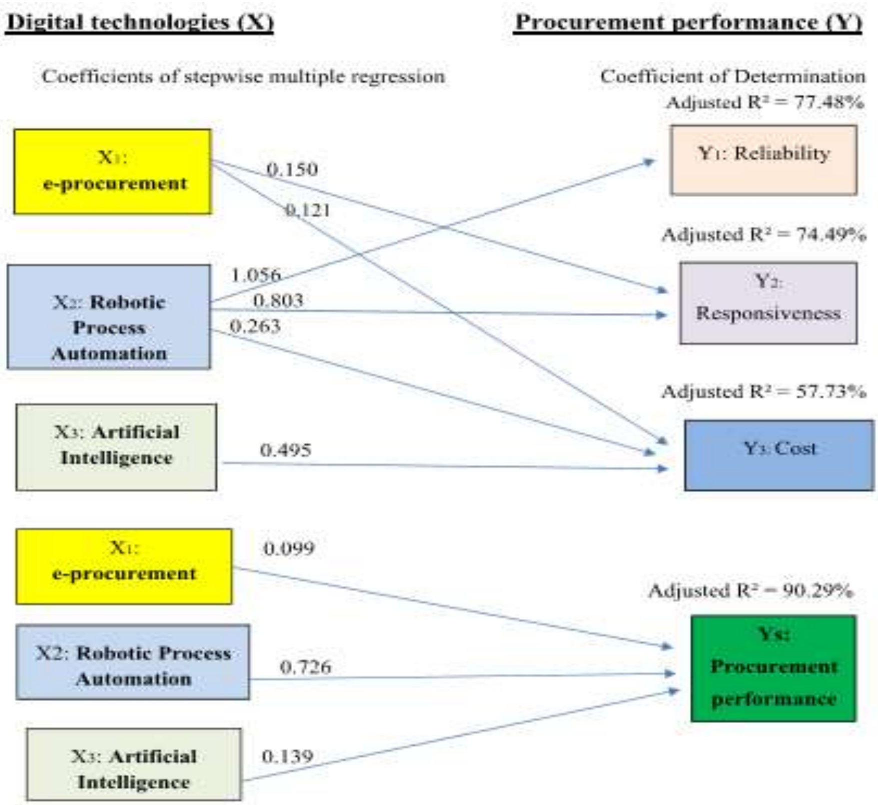
For the third dependent variable *Cost* Y_3:

The most important independent variable with the highest positive effect on the dependent variable was ***Artificial Intelligence (AI)*** X_3**.** Then the second important independent variable was

Robotic Process Automation (RPA) X_2. Then the third important independent variable was ***E-procurement X_1.*** The proposed multiple regression model can be formulated using this formula:

$$Y_3 = 0.497 + 0.121X_1 + 0.263.X_2 + 0.495X_3$$

5.4.4 Research Model



6. RESULTS

According to the conducted statistical analysis and hypothesis testing, the results can be expressed as follows:

<u>6.1 The first hypothesis:</u>

- Pearson's coefficient of Correlation between the independent variable ***E-procurement*** and the dependent variables ***Reliability, Responsiveness, and Cost*** were **0.592, 0.665, and 0.605** respectively, which are positive and moderate relationship**.** The test of significance were **0.000** for all these pairs; which is smaller than the significance level used in social studies Alpha **5%**. So; there is statistical evidence that there is a significant, moderate, and positive relationship.
- Pearson's coefficient of Correlation between the independent variable ***E-procurement*** and the dependent variable ***Procurement Performance*** was **0.717** which is positive and moderate relationship**.**
- A stepwise multiple regression analysis was conducted to determine the most important independent variables (***E-procurement*** X_1, ***Robotic Process Automation*** X_2 and ***Artificial Intelligence*** X_3) with the highest positive effect on the dependent variables (***Reliability*** Y_1, ***Responsiveness*** Y_2, and ***Cost*** Y_3). The suggested multiple regression models can be expressed as follows:

$$Y_1 = -0.2438 + 1.056X_2$$

$$Y_2 = 0.175 + 0.150X_1 + 0.803.X_2$$

$$Y_3 = 0.497 + 0.121X_1 + 0.263.X_2 + 0.495X_3$$

- A multiple regression analysis was carried out; where ***E-procurement X_1, Robotic Process Automation (RPA) X_2 and Artificial Intelligence (AI) X_3*** are independent variables and ***Procurement Performance Y_s*** is a dependent variable. The estimated linear regression model can be expressed as follows:

$$Y_s = 0.126 + 0.099X_1 + 0.726.X_2 + 0.139X_3$$

The regression coefficient of ***E-procurement*** was **0.099** so; as ***E-procurement*** increased by one-unit ***Procurement Performance*** will increase by **0.099** units.

So; the first hypothesis "There is a significant effect of utilizing e-procurement on procurement performance" can be accepted with confidence level 95%.

6.2 The second hypothesis:

- Pearson's coefficient of Correlation between the independent variable ***Robotic Process Automation (RPA)*** and the dependent variables ***Reliability, Responsiveness, and Cost*** were **0.880, 0.856, and 0.693** respectively, which are positive and strong relationship for first two variables and positive moderate relationship for third variable**.** The test of significance were **0.000** for all these pairs; which is smaller than the significance level used in social studies Alpha **5%**. So; there is statistical evidence that there is a significant, moderate, and positive relationship.

- Pearson's coefficient of Correlation between the independent variable ***Robotic Process Automation (RPA)*** and the dependent variable ***Procurement Performance*** was **0.940** which is positive and strong relationship
- A stepwise multiple regression analysis was conducted to determine the most important independent variables (***E-procurement X_1, Robotic Process Automation X_2*** and ***Artificial Intelligence X_3***) with the highest positive effect on the dependent variables (***Reliability Y_1, Responsiveness Y_2***, and ***Cost Y_3***). The suggested multiple regression models can be expressed as follows:

$$Y_1 = -0.2438 + 1.056 X_2$$

$$Y_2 = 0.175 + 0.150 X_1 + 0.803.X_2$$

$$Y_3 = 0.497 + 0.121 X_1 + 0.263.X_2 + 0.495 X_3$$

- A multiple regression analysis was carried out; where ***E-procurement X_1, Robotic Process Automation (RPA) X_2 and Artificial Intelligence (AI) X_3*** are independent variables and ***Procurement Performance Y_s*** is a dependent variable. The estimated linear regression model can be expressed as follows:

$$Y_s = 0.126 + 0.099X_1 + 0.726.X_2 + 0.139X_3$$

The regression coefficient of ***Robotic Process Automation (RPA)*** was **0.726** so; as ***Robotic Process Automation (RPA)*** increased by one-unit ***Procurement Performance*** will increase by **0.726** units.

So; the Second hypothesis "There is a significant effect of utilizing Robotic Process Automation (RPA) on procurement performance" can be accepted with confidence level 95%.

6.3 The third hypothesis

- Pearson's coefficient of Correlation between the independent variable ***Artificial Intelligence (AI*** and the dependent variables ***Reliability, Responsiveness, and Cost*** were **0.697, 0.727, and 0.741** respectively, which are positive and moderate relationship**.** The test of significance were **0.000** for all these pairs; which is smaller than the significance level used in social studies Alpha **5%**. So; there is statistical evidence that there is a significant, moderate, and positive relationship.
- Pearson's coefficient of Correlation between the independent variable ***Artificial Intelligence (AI)*** and the dependent variable ***Procurement Performance*** was **0.834** which is a positive and strong relationship**.** The test of significance was **0.000** for this

pair; which is smaller than the significance level used in social studies Alpha **5%**. So; there is statistical evidence that there is a significant, strong, and positive relationship.

- A stepwise multiple regression analysis was conducted to determine the most important independent variables (***E-procurement*** $\boldsymbol{X_1}$, ***Robotic Process Automation*** $\boldsymbol{X_2}$ and ***Artificial Intelligence*** $\boldsymbol{X_3}$) with the highest positive effect on the dependent variables (***Reliability*** $\boldsymbol{Y_1}$, ***Responsiveness*** $\boldsymbol{Y_2}$, and ***Cost*** $\boldsymbol{Y_3}$). The suggested multiple regression models can be expressed as follows:

$$Y_1 = -0.2438 + 1.056X_2$$

$$Y_2 = 0.175 + 0.150X_1 + 0.803.X_2$$

$$Y_3 = 0.497 + 0.121X_1 + 0.263.X_2 + 0.495X_3$$

- A multiple regression analysis was carried out; where ***E-procurement*** $\boldsymbol{X_1}$, ***Robotic Process Automation (RPA)*** $\boldsymbol{X_2}$ ***and Artificial Intelligence (AI)*** $\boldsymbol{X_3}$ are independent variables and ***Procurement Performance*** $\boldsymbol{Y_s}$ is a dependent variable. The estimated linear regression model can be expressed as follows:

$$Y_s = 0.126 + 0.099X_1 + 0.726.X_2 + 0.139X_3$$

The regression coefficient of ***Artificial Intelligence (AI)*** was **0.139** so; as ***Artificial Intelligence (AI)*** increased by one-unit ***Procurement Performance*** will increase by **0.139** units.

So; the Third hypothesis "There is a significant effect of utilizing Artificial Intelligence (AI) on procurement performance" can be accepted with confidence level 95%.

7. RECOMMENDATIONS AND FUTURE RESEARCH

7.1 Recommendations

Based on the findings and conclusions of this study, the researchers recommend the following:

- Widely utilize the e-procurement solution as basic and mature technology to automate day-to-day procurement activities, especially when aiming to increase the procurement reliability for having all purchase orders delivered in full for being the most important performance measure in addition to increasing responsiveness and reducing operating costs.
- Adopt and expand usage of the Robotic Process Automation (RPA) technology to automate additional routine, repetitive, and time-consuming activities for all purchasing categories, especially when aiming to reduce the cost of processing purchase orders and enhance reliability.
- Gain a competitive edge by utilizing the rapidly advancing technology of Artificial Intelligence (AI), especially when aiming to increase the percentage of purchase orders delivered on time, which is the most important performance measure related to the use of Artificial Intelligence (AI).

- Having an autonomous procurement model, investigate and consider adopting other relevant digital technologies (in addition to e-procurement, RPA, and AI) for comprehensive automation and digital transformation of the procurement function, where applicable, to increase procurement performance in terms of reliability, responsiveness, and cost, giving priority to the highest impact technologies with the least implementation cost.

7.2 Future Research

Based on the study's conclusions and recommendations, the researchers suggest the exploration of the following areas for further research:

- Study the role of other digital technologies on procurement performance, which was not examined in the current study.
- Study the impact of digital technologies on an organization's capability to be more agile and efficient in managing assets.
- Develop and validate a business model for autonomous procurement function, utilizing applicable digital technologies.
- Investigate future job roles and requirements considering the rapid advancements of digital technologies.

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