Journal of Sustainable Development of Transport and Logistics
journal home page: https://jsdtl.sciview.net

Angammana, J. S. K., & Jayawardena, A. M. A. (2022). Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka. *Journal of Sustainable Development of Transport and Logistics, 7*(2), 80-110. doi:10.14254/jsdtl.2022.7-2.6.

Scientific Platform
ISSN 2520-2979

Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka

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Article history:

Received: September 19, 2022
1st Revision: September 30, 2022
Accepted: November 10, 2022

DOI:
10.14254/jsdtl.2022.7-2.6

Abstract: This study is focused on the influence that artificial intelligence can bring on warehouse performance. A sample of 329 workers from selected warehouses was used for this study, and a self-administered questionnaire was used to collect data. An index was constructed using the Principal Component Analysis (PCA) method to measure the influence on warehouse performance. Mann Whitney U test and Kruskal-Wallis H test were used to determine the effect of demographic factors on warehouse performance. The association among the variables was identified by employing correlation analysis. A regression analysis was performed to determine the relationship between the identified factors and warehouse performance. When the study tests for the association among the variables, it depicts a positive correlation. Finally, based on the analysis, it illustrates the influence of machine learning, robotics, the Internet of things (IoT), and fuzzy logic on warehouse performance. The warehouse performance was mentioned in three categories: time, inventory, and cost.

Keywords: artificial intelligence, warehouse performance, machine learning, robotics, Internet of things, fuzzy logic

1. Introduction

There is rapid development from the technological perspective in cloud computing and processing, connectivity, and algorithm development in the areas of big data. Artificial intelligence work like a human having standard abilities. This automates human thinking and takes action effectively and efficiently. According to Forbes Insight research, 65% of industry leaders believe that logistics, transportation, and supply chain have unshared in the era of "profound transformation." It states that 36 large, mid and small size organizations have successfully adopted Artificial intelligence for logistics

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and supply chain processes, and also 28% of the survey respondents are at the threshold of bringing artificial intelligence into logistics (Katrine Spirina, 2021). The introduction of artificial intelligence and machine learning has made it easy to cater to the process of logistics.

Additionally, they made numerous modifications such as predictive analysis, autonomous vehicles, smart roads, and automation of warehouses. Further, the studies state that using artificial intelligence will increase productivity by more than 40% by 2035 (Throughput, 2020). There is an immense change in logistics and transportation with the influence of artificial intelligence. There are many advantages to governments and businesses in processing these data using advanced algorithms in recent years. The massive growth of learning algorithms, helped by different technologies like the Internet of things, robotic process automation, computer vision, and natural language processing, have enhanced the growth of artificial intelligence.

In the current scenario, AI can be used in international logistic firms such as Amazon, Echo Global Logistics, HAVI, TTEC, Zebra Technologies, Infor, C3, and Uptake. As a result of globalization, there is competition among companies to become the top-ranked in their respective fields. Everyone should follow modern trends to compete in the global market to live up to the top-ranked competitors. One such trend is Artificial Intelligence (AI).

With the effects of globalization, all countries focused on more profit from their companies or workplaces, which resulted in using machines and IT to enhance production quality. The logistics sector was found to be one of the sectors that practice AI (Crisp Research AG).

Generally, more labor-oriented workplaces will increase time consumption and result in a reduction in profit. Using AI in the field of logistics and transportation will help in collecting quality data with the use of (NLP) Natural Language Processing and (ML) Machine learning. When connected with logistics AI will enable data usage in shipping. AI will further minimize the cost and also maximizes the resources efficiently.

As a new logistics technology generation, AI can reduce labor costs and optimize products and services. AI's logistics optimization and transport control system can help traffic management optimize the logistics management process very well; the computer vision and computer's autonomous learning language improve the factory's safety and warehouse's management efficiency (Xin Zhang, 2021). People tend to transfer to IT-based systems to ease their tasks and earn more profit. Hitachi is one such AI-based work system developed to increase warehouse productivity efficiency. Hitachi Review (2016) states that this will continue to work on expanding the AI system to a wide range of social innovation Business areas like manufacturing and distribution.

In the early stages, the documentation was done by hand on paper which allocated man forced to do tasks; in other words, the tasks were completed manually. Humans cannot analyze massive amounts of data, collect information, and optimally transport a single shipment from one point to another. Here comes the predictive analysis, which comprises more accurate data. While adding more significance, AI can handle and perform these logistic operations accurately.

Route planning can be handled through AI-driven software, which will also reduce any bottlenecks in ports and storage optimization on ocean shipments. Further, in the context of transportation, this will reduce the shortage of truckers, containers, and other equipment, and also, it will reduce the risk of ships waiting offshore for their turn in line at the port for berthing. In order to streamline the logistics operations, the line haul should be optimized through AI. It states that there was a 24.3% increase in the parcel and last-mile logistics with the growth of e-commerce (Transmetrics, 2021). Further, AI allows companies to optimize their fleets in shipping and transportation. The article "Evolution of AI in Logistics and Supply Chain Sector Will Drive more revenue to companies" (2021) states that the ecosystem connected with logistics and AI was valued at USD1.7 bn in 2018 and also expected to reach USD 12 Bn in 2027 when growing at a rate of CAGR of 24%.

Robotics and AI will accumulate the knowledge of humans and make decisions and judgments to interact with humans. This process can help maintain accurate data in the servers and type invoices, and also, this will help distribute data to the unified database. Additionally, warehouse management and proper inventory handling will be at ease by using AI than using the workforce, as AI can store and analyze a large amount of data with zero mistakes. Using robotics by Amazon is a prevalent factor where the robots identify the package and delivery options and packaging. Sri Lanka also should develop logistics and transportation in that perspective to compete with other global companies. So therefore, this study is intended to discuss the influence that AI has in the field of logistics and transportation.

According to Gartner, supply chain organizations expect the machine automation level in their supply chain processes to double in the next five years. (Artificial Intelligence (AI) in Supply Chain and Logistics - ThroughPut. https://throughput.world/blog/ai-in-supply-chain-and-logistics/)

It has been easy to access vital information in logistics companies, such as billing amounts, account information, dates, address, and parties involved with the influence of artificial intelligence (Vashitha Praveen). Using artificial intelligence saves time and money as it helps automate numerous time-consuming processes. Many tech enterprises, such as google, amazon have heavily invested in this technology and leading the field (Kuprenko, Vitaly). Also, it helps in demand forecasting and increases productivity and accuracy. Using artificial intelligence will reduce shipment costs, generating high profits. Furthermore, this will analyze information in decision-making, reducing cycle time, operations, and continuous improvements (Jacobs, Tina 2020).

Nowadays, warehouses are heavily impacted by impressive artificial intelligence systems and devices. Companies like Amazon and Ocado use autonomous robotics for warehouse order fulfillment and other operations. Furthermore, this can monitor the current inventory level and classify and identify the goods stored in warehouses. This will reduce the cost related to human errors and increase speed and accuracy in picking orders, resulting in increased customer satisfaction rates, directly impacting the business's revenue.

In the current situation in Sri Lanka as a country, we had fallen into the depth of an economic crisis starting in 2019 when the bomb blast happened in Easter, and then the Covid 19 virus came into existence. Currently, we are facing huge problems as a country where lots of logistic-related work has been stopped without notice, and many companies that earned huge profits have gone into debt. If we had initiated artificial intelligence in the first place, it would have been a lot easier, and the economic crisis we face today could have been stopped or decreased to some extent.

When addressing AI, this concept is practiced in most countries for logistics and other industries. In the Srilankan context, as a developing country, logistics will help to compete with other countries. Furthermore, proper warehouse management is much needed to cater to the customers on time and with the least cost affected. Numerous warehouses in the country have adopted artificial intelligence in their processes, but some issues cannot be overcome.

Proper warehouse management is much needed to cater to the customers on time and with the least cost. In Sri Lanka, some warehouses practice artificial intelligence in their process, but some have still not adopted it due to a lack of knowledge. Workers undergo severe trauma related to the workload and significant accidents because of improper safety precautions. Warehouses should be designed with safety for labors and also for the goods and materials that are stored. With the current economic crisis Sri Lanka faces, warehouse performance is a must to gain profits. If we can initiate artificial intelligence to some extent, it will be easy for the workers, and there will be huge profits. Some sources are related to Industry 4.0 to warehouse management, but warehouse performance is not addressed as a whole. This research will showcase how warehouse performance will increase when using artificial intelligence.

This research will showcase how using artificial intelligence in warehouse Performance in the context of SriLanka will reduce the cost and bring high-end profits to the country, which is safer for humans and also more efficient. Different warehouses are taken into consideration. Furthermore, it will also showcase how the time that is consumed can be reduced and how inventory can be managed appropriately. Warehouse performance will increase the profits along with the productivity of the workers, and also, new technologies that can be used will give and enhance the workers' knowledge and let them adopt new technologies.

2. Literature review

Artificial intelligence (AI) is where machines work like humans with human intelligence, sense, and thinking. There are numerous definitions of artificial intelligence, and also, here, it will be illustrated by disparate definitions based on four approaches for its ability to act and think like humans, where humans can think and act rationally (Stuart, 1995). Artificial intelligence can be displayed with two specific dimensions.

Types of artificial intelligence

Artificial intelligence can be classified into different methods. One such way is to classify it according to its capabilities and functionality (point, 2019)

The Ability aspect is known as Type -1 AI, including Narrow Ai, General AI, and Strong AI. Artificial Narrow Intelligence (ANI) is also addressed as weak AI. This can only perform specified narrowed tasks without any thinking ability. The most famous examples of ANI are Alexa of Amazon, Go Google of Google, and Siri of Apple, which perform machine learning, processing of natural language, data mining, or pattern recognition.

General AI or Artificial General Intelligence (AGI) and Strong AI or Artificial Strong Intelligence (ASI) are both considered strong AI. ASI is the intelligence that will be superior to all humans in any filed. There is no such evolution or specific ASI still. When addressing AGI, it is a machine that can perform just like a human with human efficiency.

The functionality aspect is also known as the Type-2 AI, which includes reactive machines, limited memory, theory of mind, and self-awareness.

Reactive machines

When addressing the reactive machines is the basic level of artificial intelligence. Where it does not make any memories and store them, it cannot rely on past experiences to make current decisions. Deep Blue is the best example in this scenario, which is IBM's chess-playing supercomputer defeating the international grandmaster Garry Kasparov (Stuart, 1995). Here, a reactive machine was implied to Deep Blue, where it can identify the pieces and how each piece moves in the chess board by analyzing the current data. This showcases the forecast's optimal next move or decision (Hintez, 2016).

Limited memory

Though this is similar to reactive memory, it still has small memory backed up to give decisions based on prior observations (Dataflair, 2019). The best example is self-driving cars. Future accidents can be prevented by making better decisions as the cars have limited memory, where they can identify civilians crossing the road, steep roads, and traffic signals (Zulaikha, 2019). In the current scenario, self-driving cars are a trend. Where numerous car manufacturers such as Google car, Audi, Tesla, and CMU Navlab.

Theory of mind

This very advanced type of artificial intelligence is not yet in existence, but significant research is taking place in this context. Theory of mind connects with individuals' knowledge of emotions to find solutions. Humans usually work together with their abilities, such as capabilities, goals, and desires. Here, philosophers and psychologists propose that the human mind be implemented to process the information on computers or machines with human thoughts and emotions (Benjamin, 2016).

Self-awareness

This is hypothetical, where machines can make decisions with their self-awareness. Human emotions can be evoked and can control humans' beliefs, desires, capabilities, and goals. This is the last stage of evolution in artificial intelligence which will be catastrophic. This can take over humanity by making sophisticated decisions by outsmarting the human brain.

Machine learning

Arthur Samuel invented the machine learning term in 1959 and pioneered computer gaming. Tom M Mitchell defined machine learning as studying computer algorithms that automatically allow computer programs to improve through experience. (Herzog, Anna, et al. "COVID-19 and the Kidney: A Retrospective Analysis of 37 Critically Ill Patients Using Machine Learning." PLoS One, vol. 16, no. 5, Public Library of Science, May 2021, p. e0251932.) Machine learning algorithms are classified as follows (Luger, 2002):

Concept Learning is created to remember the relevant concepts for future decision-making procedures.

Decision tree Learning assigns data continuously split according to a specific output. The decisions are interpreted by nodes and leaves, where leaves represent the final decision and nodes are a place of breaking data.

Perceptron learning uses a single-layer network "perceptron" to obtain functional knowledge, decrease error and handle decision complications.

Bayesian learning allows computers to practice probabilistic functions. Here the probability can be indicated as a statistical index with a scope between zero point (an absolute impossibility) to unity (an absolute certainty) (Michael, 2005).

Reinforcement learning attempts to implement the scenario by identifying specific activities to maximize the payoff. The machine is not permitted to know the hints of acts; instead, it must determine which action would provide the greatest reward.

Artificial Neural Networks (ANN) and Deep Learning are two components of Machine Learning. ANN was created in the shape of a human biological brain to create a computing system that was inspired by knowledge storage, processing methods, and learning capabilities (Haykin, 1999).

The input layer, intermediate layer, and output layer of an ANN can be organized in a multi-layer network. In the intermediate layer, each neuron takes the incoming data and processes it to give a variety of behaviors (hidden layer). Multiple "simple" functions can be transformed into extremely complicated functions in the output layer. Deep learning uses the same concept as ANN but employs several hidden layers in the ANN.

Robotics

To the community, robotics is an important sector of Artificial Intelligence technology. Mechanical, Computer Science and Electrical Engineering are all part of it. Robots are artificial agents that are designed to manipulate heavy things by sensing, picking, moving, and altering their physical properties (Neha, 2018). The majority of robotics was created to make work more accessible and more productive. Traditional Robotics used AI design processes to undertake robot operations in the past.

Nonetheless, in today's Autonomous Robotic approach, robots must be able to improve and govern themselves autonomously and regularly. In many workplaces in the United States, the employment of industrial robots has resulted in considerable labor and product cost savings. They had projected that the cost of human work would be 15% higher than the cost of robotic labor, according to BCG news (Hal Sirkin, 2015).

The initial aspect of robotics focuses on industrial domains like shipping and manufacturing. The robot may be required to move things in various places or to recognize disparate pieces that must be packed in the correct sequence. Furthermore, moving items to and from warehouses is seen as an important function for robots. When industrial robots interact more with people, the flexibility of robots should be added.

The second branch of robotics focuses on service industries such as medical, home, education, and defense. The majority of these robots were designed to aid people in their daily chores. One of the most common examples is vacuum cleaning robots or reconnaissance drones. Furthermore, the use of robots in medicine has increased in areas such as surgery, rehabilitation, and training (F.Mondada, 2018).

Internet of things

Since the Internet of Things inception, academics have begun investigating the potential applications of this technology in various sectors.

In the subject of Supply Chain Management, only a few researches have looked into this implementation (SCM). (Bo Yan, 2016) proposed an IoT-based model that uses RFID to solve the problem of imperfect information and the bullwhip effect in agricultural supply chains. They also introduced two methods of information inquiry for static and dynamic information that aid in increasing supply chain efficiency and improving product authenticity and quality because they allow operators to trace, easily track, and inspect products at any time and at any stage. (Lee, 2011) published a study about warehousing management, including the Internet of things, to ensure smart warehousing for smart logistics in industry 4.0 to enhance the energy effectiveness of warehousing operations and increase worker-employee satisfaction.

(Qu, 2016) suggested a cloud manufacturing-based IoT-based real-time production logistics synchronization system that combined cloud manufacturing and IoT infrastructure to address the dynamics in production logistics operations. They saw the suggested system as an adaptive solution to plan infeasibility caused by execution dynamics and a general way of integrating IoT and cloud manufacturing implementation. (Ding, 2013) introduced a smart WMS based on IoT that uses sensors to offer a large quantity of information on various commodities, allowing for intelligent processing, greater control over storage than the old system, increased efficiency, lower prices, and lower error rates. (Tejesh, 2017) created an inventory management system based on open-source hardware and the Internet of Things. It may be used to track, monitor, and gather data on items, such as the stockroom and product details.

Warehouses are essential in meeting client expectations in today's corporate sector. It is a crucial source of competition since it determines who can supply things quicker while saving money and being more flexible. In this regard, managers must thoroughly grasp storage and how it affects the whole supply chain (Richards, 2017). According to (Trappey, 2017) warehouse improvement may be judged by the accuracy and speed with which needs are met, as well as the reduction of non-value-added operations and effective management. The information integration, which includes critical services for inventory status updates, order management, and product tracking, is another concern.

IoT may make a warehouse more intelligent in warehousing; it allows for strong collaboration between items and shelves, allowing the product to connect with its location. It also aids in support of decentralized administration as well as the resolution of security and authenticity issues (Richards, 2017). Real-time data from IoT systems may be examined and used in various forecasting models, allowing for more accurate demand forecasting and proactive market response (Yerpude), 2017.

Because a warehouse may hold thousands of items, it should be used to its full potential to guarantee speedy and precise performance across the board to satisfy client needs. IoT in warehousing can potentially have a significant impact since it can be used to minimize manual interference and monitor several operations in real-time. IoT makes the warehouse smarter; it can link everything, allowing for the analysis of the massive quantity of data collected from these connections and turning it into insights to aid decision-making and enhance overall performance.

Fuzzy logic

People typically transfer information using natural languages commonly used in human civilization, such as English, French, Finnish, Vietnamese, etc. Although natural language has limitations, such as accuracy and ambiguity, humans can grasp what others are trying to say. As a result, scientists and mathematicians are working to construct machines that can comprehend and process information like the human brain.

Nonetheless, the primary issue is how the computer can comprehend and interpret knowledge expressed in natural language. To accomplish this goal, scientists must develop a mathematical logic theory that can accurately describe the meaning of pluralistic sentences.

The clauses in conventional logic contain only apparent values like true/false or yes/no. For example, "Today is rainy" is valid if it rains today. This phrase is false if it is not valid. Despite this, several clauses provide ambiguous information. For example, because the degree of a good person is difficult to evaluate accurately, the phrase "Anna is a decent person" contains unclear facts. Fuzzy data refers to clauses that involve erroneous or missing information.

Professor Lofty Zadeh created an adequate theory of fuzzy logic and fuzzy logic set in 1965 (Zadeh, 1968). Humans were able to appraise ambiguous proposals because of this technology. As a result, some information is transmitted to machines using natural language, and the machines can interpret the meaning of such information rather well. Expert opinion is used as input data in fuzzy logic to categorize "excellent" and "poor" portions of each variable (Tanaka, 1997)

Concept of warehouse

The warehouse is addressed as a central location, as it has both inbound and outbound processes. It is simply a building where the products can be stored, packed, and engaged for shipping preparations (loading and unloading). It plays an intermediate role in the supply chain, affecting both the cost and service of the supply chain (Kiefer, 1999).

Warehouse management

Warehouse management is implementing principles to a warehouse's day-to-day activities like receiving and organizing the warehouse space, managing labor, managing inventory, and order fulfillment (Abby, Jenkins, 2020). Though the warehouse operations are invisible to the customers, they play a vital role in satisfying the customer with on-time delivery. Warehouses with best practices ensure they efficiently and effectively serve the customer.

Artificial intelligence in warehouse management

Warehouse Management System (WMS) is a computer system that reduces warehouse process complexity through machine learning. As the studies state, WMS is used to support the needs of the supply chain, including activities such as distribution and manufacturing. This is always user-friendly, and the ERP system suits all businesses (Abby, Jenkins, 2020).

Customer order placement has changed with technological development warehouses have to cater to satisfy customers with their best performance to hold their positions in the market. When moved to the cloud, the warehouse can cater to the customer with visibility, scalability, and market reactivity (Oracle). This will further reduce the costs of errors, and no upgrades will be needed where it will also be an additional cost.

Warehouse safety and security

Warehouse operations should be backed by security and safety management. Operating a safe and secure warehouse will reduce the risk of occupational injury and provide a good work environment that values employee health and well-being. Companies can utilize various warehouse safety and security management practices to improve industrial safety (Ibrahim, 2020).

Performing a warehouse risk assessment includes assessing the state of available equipment for employees, physical pressures on workers, racking and falling item judgment, calculating warehouse vehicle traffic patterns, and worker safety heights while using ladders, forklifts, or elevators.

- To safeguard the items, remove any potential hazards: Theft, pilferage, heat and humidity, vandalism, fire, power outages, and violence are all possible risks.
- Identifying hazardous zones: Warning signs must be placed in dangerous areas to alert workers.
- Staff training: The company should develop employee understanding of safety and security management and remedies in case of a worker breakdown.

Warehouse waste management

Although waste management appears to be a crucial aspect of the warehousing operation, it may be overlooked or given less attention during the design stage. Building a long-term waste management plan for a warehouse may be difficult and expensive, but it will pay off in the long run with various long-term advantages and tremendous environmental influence.

- Waste reduction in warehouses may save space, time, and money.
- The reputation of the warehouse will improve if recycling procedures are used successfully. Customers are growing more environmentally conscious and value business operations based on this issue.
- Collecting and storing garbage in the proper manner and location contributes to a cleaner and safer workplace, lowering labor accident rates and maintaining employee health.

Performance

Performance cannot be defined objectively; this concept refers to the follow or way a particular task is done. There can be both good and bad performance in any scenario. Performance measurement is the process of quantifying the efficiency and effectiveness of an action or a particular activity (Neely, 1995).

Performance measurement will identify if the process is flowing correctly if there are any issues where it generates poor performance, and how this can be mitigated and improved performance through various solutions. It measures performance, avoids certain inconveniences, monitors customer relations, controls processes and costs, and maintains quality (Ackerman,2003). Performance indicators, or KPIs, are the main instruments used to measure performance rates or levels.

Warehouse performance indicators

There are numerous steps in the process of a warehouse and different types, etc., so a warehouse must measure its customers to make the process efficient and effective also, the indicators can be compared with the current values with the standard values. There are different types of KPIs addressed in past research when it is connected to warehouse performance.

One hundred thirty indicators are identified to assess the warehouse performance, including storage surface, storage volume, storage racks, number and characteristics of docks, pallets per hour, pallets per square meter, opening hours, and customer assistance (Krauth AL, 2005).

Order fulfillment rate, inventory management, and warehouse performance are three indicators used by John Mill (2007) to measure warehouse performance.

A software tool introduced by Colson & Dorigo (2004) will allow the selection of public warehouses according to a criterion that includes storage surface and volume, dangerous items, the possibility of temperature control, separation of storage areas, geographical distance to highway connection, trains, waterways, certification, opening hours and use of technology.

There are three leading warehouse key performance indicators: time, inventory, and cost (Frazelle, 2002). This study will be based on these three indicators to identify the impact on warehouse performance through artificial intelligence.

One of the most important aspects of warehouse operations is inventory management. Raw materials, work in progress, all production supplies, and finished items all make up a significant amount of a company's assets (Max Muller, 2003). Inventory management refers to ensuring that a company's items are always available. It is responsible for coordinating and administering the flow of commodities required for the operation of the business. Inventory management is also in charge of stock ordering, and reordering, product sorting, inventory prediction analytics, and ensuring safe stock is available from the manufacturer or supplier.

Artificial intelligence is being used in a wide range of industries, including inventory management. It helps warehouse departments better regulate the normal tasks of inventory management by providing significant insights for firms, capturing the newest trend from client demand, and analyzing vast amounts of data. Many AI systems have been utilized to comprehend a wide range of real-time inventory management issues that affect inventory stock levels. AI may foresee scenarios based on the data acquired, offer acceptable solutions, and even act independently or with human approval.

Robots and drones

This is the most recent step of the inventory management revolution. Many warehouses are already using robots in their operations systems. These robots have employed artificial intelligence (AI) to attain high speed and precision in manufacturing, sales, and transportation. The more advanced a robot is, the more tasks it can accomplish. There is a barrier to the capacity of robots to perceive all aspects of the environment in the early stages of using them in supply chain and warehouse operations. Both moveable and non-movable things are included in the element. Warehouse robots are equipped with pre-programmed navigation and various optical, audial, and thermal sensors to detect and measure temperature in the surrounding region.

Thanks to an AI revolution, warehouse robots have been re-programmed with more complex AI-aid and machine learning systems that enable them to assess observed data and make decisions based on their resources.

Manual Counting

Before the Industrial Revolution, manual counting was performed to calculate the number of products sold or leaving the warehouse in a day. After each day, shopkeepers and merchants would tally the units sold to calculate how many products were sold. Furthermore, merchants frequently estimate future demand based on their intuition and previous job experiences. Manually counting the inventory would take hours, if not days, if the supply was overwhelmed. This approach is prone to mistakes and has a low level of accuracy.

Punch Card

When efficiency and mass manufacturing became critical company goals, the industrial revolution ushered in a comprehensive overhaul of the inventory management process. The punch card system, developed by Harvard University academics in the 1930s, was used to monitor inventory from the factory to the warehouse and finally to the point of sale. Punch cards could be matched to available brochure items that were readable by computers thanks to the little holes in the paper. Nonetheless, this strategy was prohibitively expensive and labor-intensive to remain extensively utilized and to keep up with increasing commercial issues.

The barcode

In the 1940s and 1950s, the first barcode was developed, which used ultraviolet light-sensitive ink and a scanner to amass item labels and manage inventories. The advancement of computer and software technology from the 1980s to the 1990s has made the barcode system more flourishing and efficient nowadays. Manual inventory tracking was replaced by scanning technology, although humans still did data entry into systems.

AI research and development have received much attention in recent years. Many large AI initiatives have been developed to aid human life and industrial activity. According to Felix and Dirk (2019), AI was first used in sorting systems that relied on optical sensors and circuitry to discern gray levels in the 1970s and 1980s.

The electrical circuit uses a ratio between these values to apply a rules-based judgment on whether to keep or reject the material. Customized camera technology was combined with object identification in the early 1990s to categorize and assign each pixel to a particular material class.

Artificial neural networks became popular in the 2000s for detecting and sorting data processing mistakes. The class of this AI was instigated in numerous sectors based on its capacity to define clusters in multidimensional space. In the supply chain, for example, standard applications are enhanced to maximize inventory sorting as follows:

- Autonomous scanning robot (ASR)
- Articulated robotic arms (Assembly line robot)
- Automated guided Vehicles (AGVs)

Autonomous scanning robot (ASR)

Inventory circulation is traditionally one of the most time-consuming tasks in the warehouse regarding handling and verifying inventory. There may be a human resource restriction regarding inventory management in warehouses with large volumes. As a result, AI is an efficient and automated way of control. Autonomous scanning robots are one of the most common applications for inventory monitoring (ASR). Each inventory will be allocated a Radio Frequency Identification (RFID) tag with a microchip that stores information about the item, including the barcode, function, magnetic security strip, tracking, and identification (al, 2010). The ASR roams the warehouse, scanning RFID codes, which the microchip transmits to the warehouse management system. The ASR scanning robot uses maps and sensors to drive more flexible paths and scan more precisely. The acquired data from the robot will provide particular inventory counts at pre-determined periods or intervals, allowing you to better plan for future purchases and decrease overstock rack space.

Robotic arm

An articulated robotic arm has rotary joints that allow it to perform various pre-programmed actions with great precision and speed. Robotic arms are extensively employed in industrial facilities and logistics warehouses for duties such as placing-picking items, welding, and packaging. Assigning these articulated robotic arms to repetitive tasks frees up human personnel and allows them to focus on more challenging tasks (Homyak, 2019)

Several businesses are now developing and testing increasingly advanced AI-powered robotic arms to improve their intelligence, productivity, and accuracy, which are still constrained in several technological areas. The available articulated robotic arms in warehouses worldwide are limited in their ability to classify products of diverse sizes, shapes, and materials (Vincent, 2017).

The main advantages of articulated robotic arms are their consistency and consistent speed. The mobile robotic arms may be tailored to meet the individual production needs of various organizations, and they might be AI-powered to do more complicated and numerous tasks. Aside from that, the articulated robotic arms' design is versatile and small, making them perfect for usage in various warehouses, independent of storage capacity. Furthermore, the robotic arms help with inventory management and productivity output.

Automated guided vehicles

AGVs of various types were first published in 1954. (Bahari, 2014) define an AGV as a programmable mobility vehicle that transports merchandise from one spot to another on the facility floor within a warehouse without the assistance of an accompanying human. To avoid obstructions, AGVs rely on tracks or magnetic strips in pre-determined travel pathways or coupled to sensor camera vision.

Forklifts, unit loads, and tow (driverless trains) are AGVs utilized in warehouses for distribution, fulfillment, and production. It is in charge of moving huge and heavy items such as pallets, rolls, racks, trolleys, and containers, among other things. Adding additional AI to AGVs now provides various benefits to inventory management, such as reducing labor costs, tracking, and increasing safety (Benevides, 2016). Order fulfillment, inventory management, and warehouse productivity are the most common indicators to evaluate warehouse performance (Ramaa, 2012).

The lead time, receiving time, queuing time, order processing time, delivery lead time, and equipment downtime is a category of time that measures warehouse performance (Li et al., 2009). Measures including cost as a proportion of sales, lines or cases processed per person-hour, response time, and shipment accuracy have been used to evaluate performance in the warehouse and distribution industries (Forger, 1998).

The costs will be reduced by computerizing or applying artificial intelligence. The expenses of ordering and holding goods and the associated documentation are included in inventory costs. This cost is considered by management when deciding how much inventory to maintain on hand. This can lead to changes in the order fulfillment rate for consumers, as well as changes in the flow of the manufacturing process. Economic (i.e., revenue vs. cost) and technical (i.e., outputs vs. inputs) methods to warehouse performance monitoring are two related but separate techniques (Johnson et al, 2010)

Artificial intelligence (Li et al., 2009) can cut inventory costs by lowering lead times through faster processing and scheduling supplies delivery when needed rather than before, which incurs a cost for retaining inventory. Inventory costs include ordering, carrying, and shortage (MBA school team, 2021).

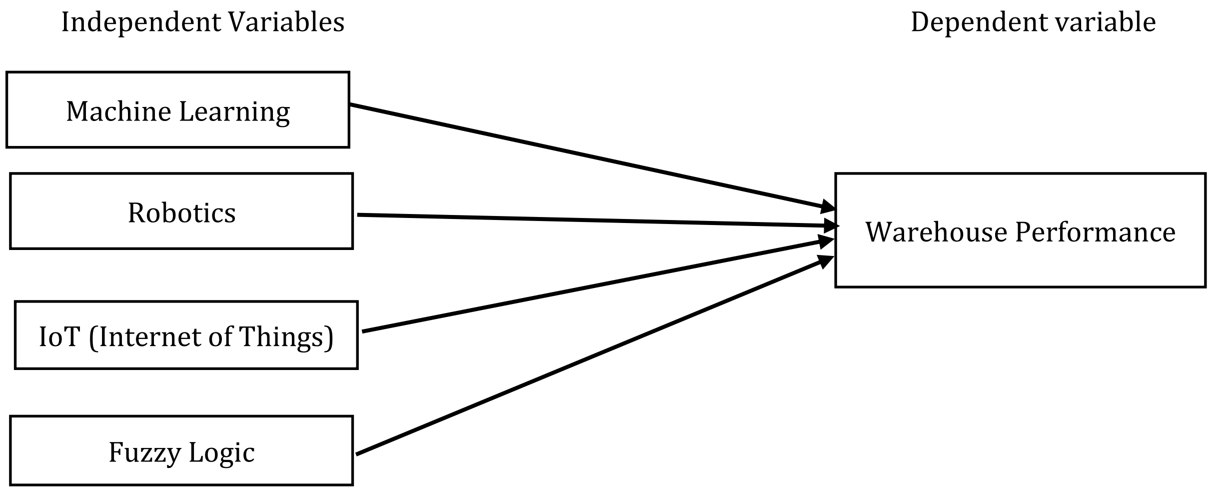
We separate the following characteristics in the sphere of warehousing: investment and operational expenses, volume and mix flexibility, throughput, storage capacity, reaction time, and order fulfillment quality (Rouwenhorst et al., 2000).

Order taking and customer service, inventory storage and maintenance, shipping, and product tracking to assure delivery are all costs associated with fulfilling consumer orders. Understanding how a firm organizes and processes orders and the costs associated with doing so helps business leaders develop budgets, monitor staff, and identify areas where cost savings may be realized (Jessica, Jhones).

3. Methodology

This particular research study discusses the influence of artificial intelligence on warehouse performance. Therefore, the conceptual framework of this study indicates that the influence of artificial intelligence is the independent variable which consists of the Internet of Things (IoT), RFID, and Automation/Robotics as per the literature reviews mentioned above. The dependent variables are lead time reduction, inventory optimization, and cost optimization.

Figure 1: Conceptual framework



Hypothesis development

According to the created theoretical framework hypothesis is an essential factor in analyzing the above-mentioned independent variables to explore and express how the influence of artificial intelligence on the independent variables will affect the performance of the warehouse. The hypothesis and null hypothesis are developed as follows:

H0(1)- There is no significant influence of machine learning on warehouse performance
H1(1) - There is a significant influence of machine learning on warehouse performance
H0 (2)- There is no significant influence of robotics on warehouse performance
H1(2)- There is a significant influence of robotics on warehouse performance
H0(3)- There is no significant influence of IoT on warehouse performance
H1(3)- There is a significant influence of IoT on warehouse performance
H0(4)- There is no significant influence of fuzzy logic on warehouse performance
H1(4)- There is a significant influence of fuzzy logic on warehouse performance

Research strategy

This study aims to determine the influence of artificial intelligence on warehouse performance, considering five warehouses in the Colombo area with an employment rate of more than 350. If explained further, the objective is to establish a relationship between the independent and dependent variables. Therefore, the investigation type can be mentioned as analytical.

Population

The accessible study population was the 05 warehouses in the Colombo area. The table illustrates the total number of workers from the 05 warehouses.

Table 1: Total number of workers

Warehouse	No of workers
Warehouse A	400
Warehouse B	500
Warehouse C	450
Warehouse D	550
Warehouse E	400

Distribution is spread within the selected five warehouses in the Colombo area. Moreover, all the facts for the survey were chosen through these five warehouses to get the information from warehouses. Each warehouse is considered a stratum. A proportionate percentage of workers will be selected for the sample. Therefore, the sampling population will be the workers from the selected warehouses.

Sampling method

In order to achieve the objectives and increase the precision of the research convenience sampling method will be used to select the sampling units for the sample. The researcher is searching for the most convenient respondent to find out the data for the research. Further, the research should analyze the data to identify whether the considerations are the same as other literature or are different from the previous literature sources.

Sampling Plan

Accordingly, the population is 2300 registered workers in the warehouse. A random sample of 329 will be taken out of the population (according to Krejcie and Morgan's table). In the Krejcie Morgan table, for a population of 2000, the sample size is given as 322. Therefore, for the population of 2300, the sample size will be 329. (a= 0.05)

N = Total number of registered workers = 2300

n = Sample size = 329

As the selection is based on the proportion of the workers, the allocation to cover the sample representation from each warehouse will be calculated as follow

$n_i = (N_i \div N) \times n$

n_i = Allocated proportion

N_i = number of registered employees

N = Total number of employees

n = Sample size

Warehouse A

$n_i = (N_i \div N) \times n = (400 \div 2300) \times 329 = 57$

Warehouse B

$n_i = (N_i \div N) \times n = (500 \div 2300) \times 329 = 72$

Warehouse C

$n_i = (N_i \div N) \times n = (450 \div 2300) \times 329 = 64$

Warehouse D

$n_i = (N_i \div N) \times n = (550 \div 2300) \times 329 = 78$

Warehouse E

$n_i = (N_i \div N) \times n = (400 \div 2300) \times 329 = 57$

Table 2: Proportion allocation of workers defined by warehouses

Warehouse	Number of registered workers	Sample Size	Sample Size: Rounded Value
A	400	57.2173	57
B	500	71.5212	72
C	450	64.3695	64
D	550	78.6739	79
E	400	57.2173	57
Total	2300	329	329

Source: Sample survey, 2022

3.1. Method of data collection

The data will be collected through a self-administered questionnaire to identify whether artificial intelligence influences warehouse performance. The research instrument will be distributed as a Google form and given as hard copies to warehouse workers due to the lack of infrastructure to access the questionnaire through a google sheet. The questionnaire will consist of 3 sections. The prepared questionnaire will be distributed via Gmail and hard copies. Therefore, this study is based on primary data.

Method of analysis

The results of the analysis need to be correct to obtain accurate results. In this regard, it can be said that the analysis method played an essential role in the study. Using Microsoft Excel, the data collected from the respondents were analyzed and summarized. Furthermore, the researcher consulted IBM SPSS, Minitab, and EViews software packages for advanced analysis. This study used different statistics depending on which objectives were examined and the type of data collected, either continuous or categorical. When the conditions for normality and homogeneity of variance were violated, the researcher used Mann-Whitney U tests where the y-variable was continuous and the x-variable was categorical. The correlation matrix provided insight into the direction and strength of the relationships between the continuous variables and the primary dependent variable, "Warehouse Performance." Based on the standard regression equation obtained with EViews, it was possible to determine the independent variables contributing to the variance in the dependent variable. Moreover, a multicollinearity analysis for the whole sample and its subsamples indicated that it was not a problem.

Analysis of reliability and validity

In order to achieve the study's objectives, indexes will be developed based on the collected data. These indices were constructed using the Likert scale statements presented in the questionnaire concerning the influence of artificial intelligence on warehouse performance, and the data should be checked for accuracy and validity before being used to build an index. If those two conditions are not met, index building will not be possible. Consequently, the accuracy of the data was gauged by Cronbach's alpha value or reliability. KMO values and Bartlett tests were used to check for validity (consistency). For data to be considered reliable, Cronbach's alpha value must be greater than 0.7. For validity, the KMO must be more significant than 0.6, and Bartlett's test must be unique. If Bartlett's test is unique, the sample correlation matrix for the data may be considered to deviate from the unit matrix with 95% confidence. This research reviewed the data's reliability and consistency and the essential summary information before being used for data analysis. The Cronbach's Alpha values, KMO measures, Chi-square values, and corresponding p-values of the constructs are shown in Table 3.

Table 3: Results of data reliability testing and Bartlett's testing

Variable	Cronbach's Alpha	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Bartlett's Test of Sphericity	
			Chi-Square	P-value
Warehouse Performance	0.901	0.894	2607.587	0.000
Machine Learning	0.758	0.761	311.343	0.000
Robotics	0.790	0.789	370.240	0.000
IOT	0.790	0.757	384.171	0.000
Fuzzy Logic	0.775	0.668	268.543	0.000

Source: Sample Survey, 2022

As shown in Table 3, the reliability coefficients of the five variables ranged from 0.758 to 0.901, all of which are greater than the acceptance level (0.7). Therefore, it can be concluded that the data are reliable. The KMO index was more significant than 0.6, indicating that the sample sufficiency for the analysis was confirmed; all KMO values for individual items were >0.668, which is higher than the acceptable threshold of 0.60. According to table 3.3, all KMO values are between 0.668 and 0.894, and they are higher than the acceptability limit (0.6). A significant partial correlation shows that the degree of information among the variables overlaps substantially. Hence, it is plausible to conduct factor analysis.

The fact that Bartlett's test of sphericity was statistically significant ($p < 0.05$) construct revealed that correlations between items were substantial enough for Principal Component Analysis (PCA). The null hypothesis that the correlation matrix is an identity matrix is rejected based on the findings of

Bartlett's test, as indicated in the table. As a result, all offered variables are correlated and acceptable for factor analysis with a 95% confidence level.

Descriptive analysis

The numerical and graphical approaches used to organize, represent, and analyze data are descriptive statistics. The sort of descriptive statistics used to describe a variable in a sample is determined by the measurement level used (Fisher & Marshall, 2009). This is also known as the univariate analysis approach. The research implemented bar charts, pie charts, histograms, and tables to organize and present data. Furthermore, measurements of central tendencies, such as mean and median, and measures of dispersion, such as standard deviation, were used to examine the data. The skewness of the data set has also been calculated. As a result, the descriptive analysis was conducted using the demographic Variables, independent variables, and dependent variables.

Multiple regression analysis

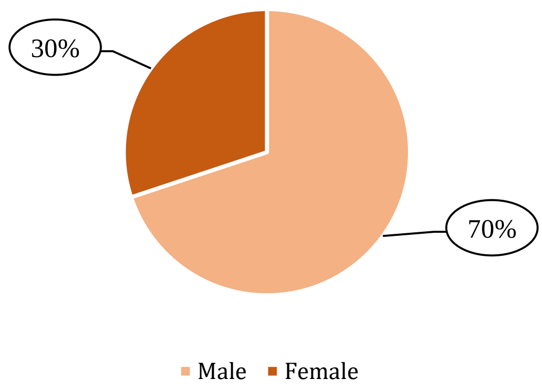
A prediction based on several values of a given variable is called a multiplicative linear model. Here, a model is developed to identify the relationship between the dependent and independent variables. Similarly, the determining coefficient shows how much of the total variance of the dependent variable of that model is described by the independent variable. It is also possible to check the specificity of the constructed regression model's existing parameters and its specificity.

4. Discussion and results

Gender composition of the respondents

Evaluating the information, the following Figure 2 illustrates the overall gender composition of the employees of the selected warehouses for the study.

Figure 2: Composition of respondents' Gender

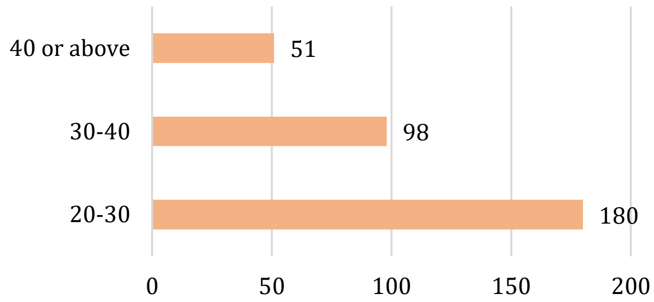


Source: Sample Survey, 2022

According to Figure 2, the sample data set represents 30% of female employees. Most of the study participants were male employees, which was 70%.

Composition of respondent's age

Figure 3: Composition of respondents' age

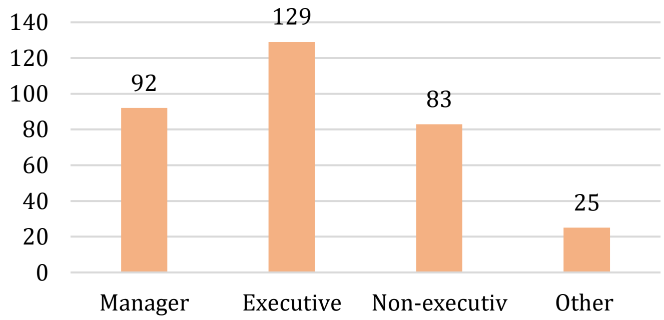


Source: Sample Survey, 2022

Figure 3, it shows the composition of respondents according to their age. The majority number of respondents were from the age range 20 -30, which was 180 respondents. There were 98 respondents from the age range 30-40, and 51 respondents from the age range 40 or above.

Composition of the respondents' level of employment

Figure 4: Composition of respondents' level of employment



Source: Sample Survey, 2022

As illustrated in Figure 4, the highest number of respondents are from the executive level, which is 129, 92 and 83 respondents from the managerial level and non-executive level, respectively. There are 25 respondents from the other category, including trainees, material handlers, forklift operators, warehouse supervisors, warehouse pickers, and shipping and receiving clerks.

Composition of use of artificial intelligence in workplace

Figure 5: Composition of use of AI in the workplace

Source: Sample Survey, 2022

Figure 5 indicates where artificial intelligence is currently used in the workplace. The highest process is inventory management which 104 respondents' have mentioned. Moreover, 90 respondents' have mentioned that AI is currently used in the shipping process of the workplace, and 85 respondents have mentioned that they use AI in the order picking and packing process. Also, 36 respondents' has mentioned that they are using AI in the safety and security process of the workplace, and 14 Respondents' have also mentioned other processes, such as documentation and research. Some have mentioned that they are not currently using AI in their workplaces.

4.1. Measuring the construct of dependent and independent variables

4.1.1. Measuring the machine learning

Table 4: Results of Eigen analysis of covariance matrix of the machine learning variables

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	2.326	58.147	58.147
2	.658	16.461	74.608
3	.590	14.751	89.359
4	.426	10.641	100.000

Source: Sample Survey, 2022

Table 4 indicates that only one eigenvalue is greater than the average variance of an indicator. Therefore, the four-dimension system can reduce to one dimension. Also, a first principal component can explain 58.147% of the total variability of the initial indicators. Table 5 gives the corresponding four scores of the first principal component.

Table 5: Eigen scores of the first principal component

Indicator	**Eigen Value**
MACHINE_LER_1	.808
MACHINE_LER_2	.805
MACHINE_LER_3	.740
MACHINE_LER_4	.691

Source: Sample Survey, 2022

Based on the above Eigen scores, the following equation calculates the overall machine learning index

Overall machine learning

X1=0.808MACHINE_LER_1+0.805 MACHINE_LER_2+0.704 MACHINE_LER_3+0.691 MACHINE_LER_4

The summary statistics of the level of sensitivity for machine learning

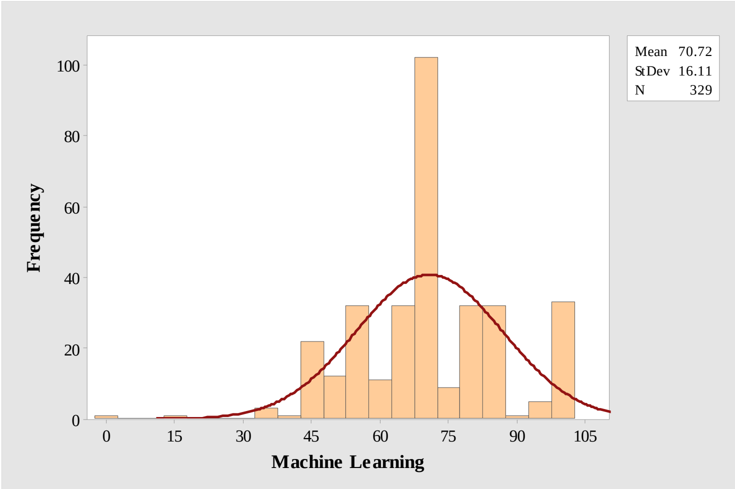
Table 6: Summary statistics of the level of sensitivity for machine learning

Summary Statistic	**Value**
Mean	70.717
Median	71.412
Std. Deviation	16.109
Skewness	-0.28
Kurtosis	0.92
Minimum	0
Maximum	100

Source: Sample Survey, 2022

According to Table 6, the respondents' machine learning Index ranges from 0% to 100%. The average machine learning index is 70.717 %, with a standard deviation of 16.109 %. The machine learning index has a skewness value of -0.28, suggesting a negatively skewed distribution. The machine learning index distribution is a positive kurtic distribution in terms of kurtosis value (0.92). Because the kurtosis value is lower than 1, the distribution is not too peaked. Furthermore, Figure 5 shows the histogram of the distribution of the level of machine learning. However, it can be noticed that the level of machine learning follows a normal distribution, as seen in Figure 6.

Figure 6: Histogram of the distribution of the level of machine learning



Source: Sample Survey, 2022

4.1.2. Measuring the robotics

Table 7: Results of Eigen analysis of covariance matrix of the Robotics Variables

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	2.470	61.754	61.754
2	.593	14.836	76.589
3	.483	12.087	88.677
4	.453	11.323	100.000

Source: Sample Survey, 2022

Table 7 indicates that only one eigenvalue is greater than the average variance of an indicator. Therefore, the four-dimension system can reduce to one dimension. Also, a first principal component can explain 61.754% of the total variability of the initial indicators. Table 8 gives the corresponding Eigen scores of the first principal component.

Table 8: Eigen scores of the first principal component

Indicator	**Eigen Value**
ROBOTICS_1	.798
ROBOTICS_2	.813
ROBOTICS_3	.743
ROBOTICS_4	.787

Source: Sample Survey, 2022

Based on the Eigen scores, the overall robotics index is calculated by the following equation.
Overall Robotics
X2=0.798 ROBOTICS_1+0.813 ROBOTICS_2+0.743 ROBOTICS_3+0.787 ROBOTICS_4

The summary statistics of the level of sensitivity for robotics

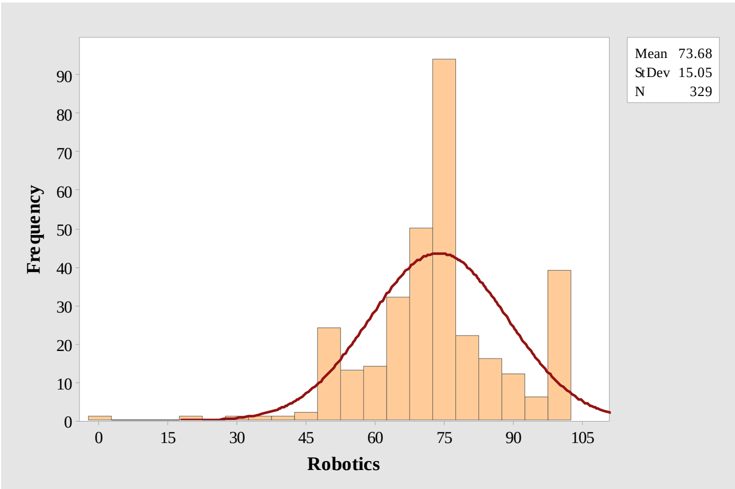
Table 9: Summary statistics of the level of sensitivity for robotics

Summary Statistic	Value
Mean	73.675
Median	75
Std. Deviation	15.049
Skewness	-0.35
Kurtosis	1.59
Minimum	0
Maximum	100

Source: Sample Survey, 2022

Table 9 represents the robotics index of the respondents, which spans from 0% to 100%. The robotics index has an average of 73.675% and a standard deviation of 15.049%. The skewness coefficient for respondents' robotics index is -0.35, indicating a somewhat negative skewed distribution. Regarding the kurtosis value, the distribution of the robotics index is a favorable kurtic distribution (1.59). The distribution is too peaked since the kurtosis value is greater than 1. However, as seen in the histogram of the sensitivity level distribution for the robotics graph (Figure 7), the robotics index of respondents does not follow a normal distribution.

Figure 7: Histogram of the distribution of the level of sensitivity for robotics



Source: Sample Survey, 2022

4.1.3. Measuring the internet of things (IOT)

Table 10: Results of Eigen analysis of covariance matrix of the IOT variables

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	2.460	61.488	61.488
2	.624	15.604	77.092
3	.556	13.898	90.990
4	.360	9.010	100.000

Source: Sample Survey, 2022

Table 10 indicates that only one eigenvalue is greater than the average variance of an indicator. Therefore, the four-dimension system can reduce to one dimension. Also, a first principal component can explain 61.488% of the total variability of the initial indicators. Table 11 gives the corresponding Eigen scores of the first principal component.

Table 11: Eigen scores of the first principal component

Indicator	Eigen Value
IOT_1	.819
IOT_2	.826
IOT_3	.723
IOT_4	.764

Source: Sample Survey, 2022

Based on the above Eigen scores overall IOT index is calculated by the following equation.
Overall IoT,

$$X3=0.819\ IOT\_1+0.826\ IOT\_2+0.723\ IOT\_3+0.764\ IOT\_4$$

The summary statistics of the level of sensitivity for the internet of things (IoT)

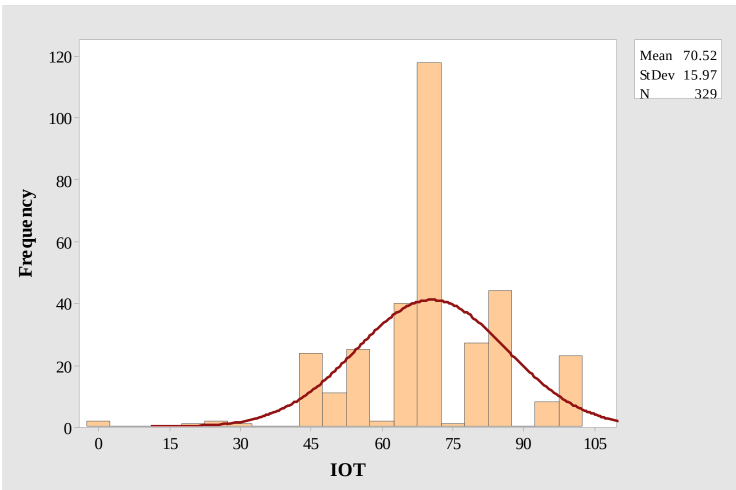
Table 12: Summary statistics of the level of sensitivity for the Internet of things (IoT)

Summary Statistic	Value
Mean	70.524
Median	71.383
Std. Deviation	15.973
Skewness	-0.67
Kurtosis	1.94
Minimum	0
Maximum	100

Source: Sample Survey, 2022

The IoT index of the respondents ranges from a minimum of 0 % to a maximum of 100 % (table 12). The IoT index has a mean of 70.524 % and a standard deviation of 15.973 %. The skewness coefficient for respondents' IoT index is -0.67, indicating a highly skewed distribution. In terms of kurtosis value, the distribution of the IoT index is a favorable kurtic distribution (1.94). The distribution is too peaked since the kurtosis value is greater than 1. Figure 4.7 shows the histogram of the distribution of the level of sensitivity for emotional characteristics. It can be observed that the IoT index of respondents does not follow a normal distribution.

Figure 8: Histogram of the distribution of IoT



Source: Sample Survey, 2022

4.1.4. Measuring the Fuzzy Logic

Table 13: Results of Eigen analysis of covariance matrix of the fuzzy logic variables

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	2.069	68.954	68.954
2	.534	17.799	86.753
3	.397	13.247	100.000

Source: Sample Survey, 2022

Table 13 indicates that only one eigenvalue is greater than the average variance of an indicator. Therefore, the three-dimension system can reduce to one dimension. Also, a first principal component can explain 68.954% of the total variability of the initial indicators. Table 14 gives the corresponding Eigen scores of the first principal component.

Table 14: Eigen scores of the first principal component

Indicator	Eigen Value
FUZZY_LOG_1	.863
FUZZY_LOG _2	.820
FUZZY_LOG _3	.807

Source: Sample Survey, 2022

Based on the above Eigen scores overall fuzzy logic index is calculated by the following equation.
Overall fuzzy logic
X4=0.863 FUZZY_LOG_1+0.820 FUZZY_LOG_2+0.807 FUZZY_LOG_3

The summary statistics of the level of sensitivity for Fuzzy Logic

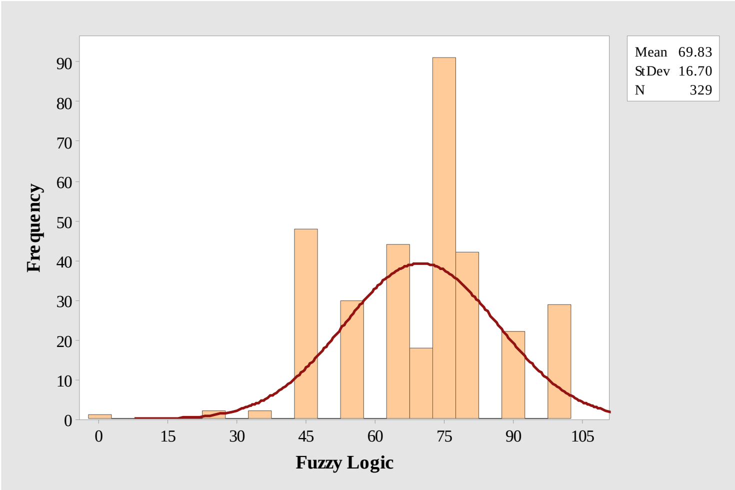
Table 15: Summary statistics of the level of sensitivity for fuzzy logic

Summary Statistic	Value
Mean	69.833
Median	72.657
Std. Deviation	16.703
Skewness	-0.22
Kurtosis	0.23
Minimum	0
Maximum	100

Source: Sample Survey, 2022

The respondents' fuzzy logic index spans from a low of 0 % to a high of 100 %, as seen in Table 15. The average music characteristics index is 69.833 %, with a 16.703% standard deviation. The skewness coefficient for respondents' fuzzy logic index is -0.22, indicating a negatively skewed distribution. Regarding the kurtosis value, the fuzzy logic index distribution is a favorable kurtic distribution (0.23). Because the kurtosis value is lower than 1, the distribution is not too peaked. However, the researcher can notice in Figure 9 that the histogram of the distribution of the level of sensitivity for fuzzy logic follows a normal distribution.

Figure 9: Histogram of the distribution of fuzzy logic



Source: Sample Survey, 2022

4.1.5. Measuring warehouse performance

Table 16: Results of Eigen analysis of covariance matrix of the warehouse performance variables

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	6.608	41.299	41.299
2	2.052	12.825	54.123
3	1.346	8.415	62.538
4	.944	5.898	68.436
5	.641	4.007	72.443
6	.619	3.868	76.311
7	.537	3.357	79.668
8	.505	3.158	82.826
9	.451	2.817	85.643
10	.418	2.615	88.258
11	.384	2.399	90.657
12	.357	2.232	92.889
13	.322	2.014	94.903
14	.303	1.895	96.798
15	.287	1.796	98.594
16	.225	1.406	100.000

Source: Sample Survey, 2022

Table 16 indicates that only one eigenvalue is greater than the average variance of an indicator. Therefore, the sixteen-dimension system can reduce to one dimension. Also, a first principal component can explain 41.299% of the total variability of the initial indicators.

Table 17: gives the corresponding Eigen scores of the first principal component

Indicator	Eigen Value
WAREHOUSE_PER_1	.706
WAREHOUSE_PER _2	.655
WAREHOUSE_PER _3	.625
WAREHOUSE_PER_4	.686
WAREHOUSE_PER_5	.756
WAREHOUSE_PER_6	.708
WAREHOUSE_PER_7	.736
WAREHOUSE_PER_8	.632
WAREHOUSE_PER_9	.616
WAREHOUSE_PER_10	.638
WAREHOUSE_PER_11	.620
WAREHOUSE_PER_12	.628
WAREHOUSE_PER_13	.616
WAREHOUSE_PER_14	.614
WAREHOUSE_PER_15	.528
WAREHOUSE_PER_16	.451

Source: Sample Survey, 2022

Based on the above Eigen scores overall warehouse performance index is calculated by the following equation.

Overall fuzzy logic

Y=0.706 WAREHOUSE_PER_1+0.655 WAREHOUSE_PER_2+ 0.625 WAREHOUSE_PER_3+ 0.686 WAREHOUSE_PER_4+ 0.756 WAREHOUSE_PER5+ 0.708 WAREHOUSE_PER_6+ 0.736 WAREHOUSE_PER_7+ 0.632WAREHOUSE_PER_8+ 0.616 WAREHOUSE_PER _9+ 0.638 WAREHOUSE_PER _10+ 0.620 WAREHOUSE_PER _11+ 0.628 WAREHOUSE_PER _12+ 0.616 WAREHOUSE_PER _13+ 0.614 WAREHOUSE_PER _14+ 0.528 WAREHOUSE_PER _15+ 0.451 WAREHOUSE_PER_16

The summary statistics of the level of sensitivity for warehouse performance

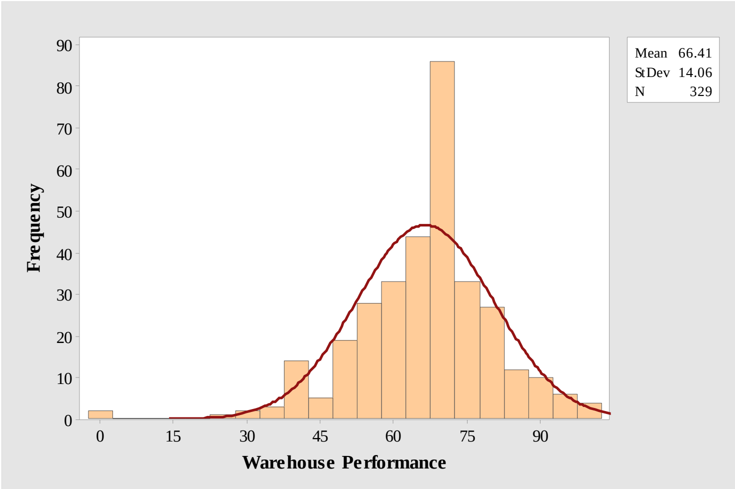
Table 18: Summary statistics of the level of sensitivity for warehouse performance

Summary Statistic	Value
Mean	66.414
Median	68.497
Std. Deviation	14.061
Skewness	-0.7
Kurtosis	2.48
Minimum	0
Maximum	100

Source: Sample Survey, 2022

The respondents' warehouse performance index varies from a minimum of 0 % to a maximum of 100 % in Table 18. The average warehouse performance index is 66.414 %, with a 14.061 % standard deviation. The respondents' warehouse performance index skewness coefficient is -0.7, indicating a strongly negative skewed distribution. Regarding kurtosis value, the music characteristics index distribution is a positive kurtic distribution (2.48). The distribution is too peaked since the kurtosis value is greater than 1. However, the histogram of the distribution of the level of sensitivity for warehouse performance, as shown in Figure 10, follows a normal distribution.

Figure 10: Histogram of the distribution of the level of sensitivity for warehouse performance



Source: Sample Survey, 2022

4.2. Comparison of warehouse performance and demographic factors

4.2.1. Warehouse performance and gender

The Mann-Whitney U test was carried out to confirm the conclusion drawn from the figure.

Table 19: Mann-Whitney U test

Mann-Whitney U	Wilcoxon W	Z	p-value
9413.500	35978.500	-2.492	.013

Source: Sample Survey, 2022

H0: The distribution of warehouse performance is the same across categories of gender.

H1: The distribution of warehouse performance has differed across categories of gender.

The Man-Whitney U test in Table 19 shows that the null hypothesis is rejected since the calculated P-value (0.013) is less than the significant value (0.05). Therefore, it can be concluded that the warehouse performance varies according to gender (male and female).

4.2.2. Warehouse performance and age

Table 20: Kruskal Wallis Test

Chi-Square	Df	p-value
0.024	2	0.988

Source: Sample Survey, 2022

H0: There are differences among the respondents age for warehouse performance

H1: There are no differences among the respondents age for warehouse performance

As per Table 20, the p-value (0.988) is not less than the critical values (0.05); thus, the null hypothesis was rejected at a 5% significance level. Therefore, it can be concluded that there are no differences among the respondents age for warehouse performance.

4.3. Association among variables

Variable Identification

Y = warehouse Performance

X1 = Machine Learning

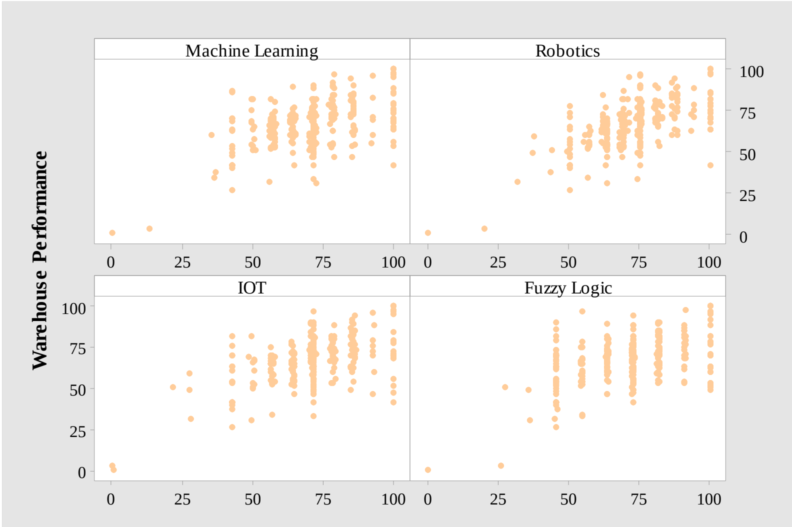
X2 = Robotics

X3 = Internet of Things (IOT)

X4 = Fuzzy Logic

Relationship between warehouse performance and other constructs

Figure 11: Relationship between warehouse performance and other constructs

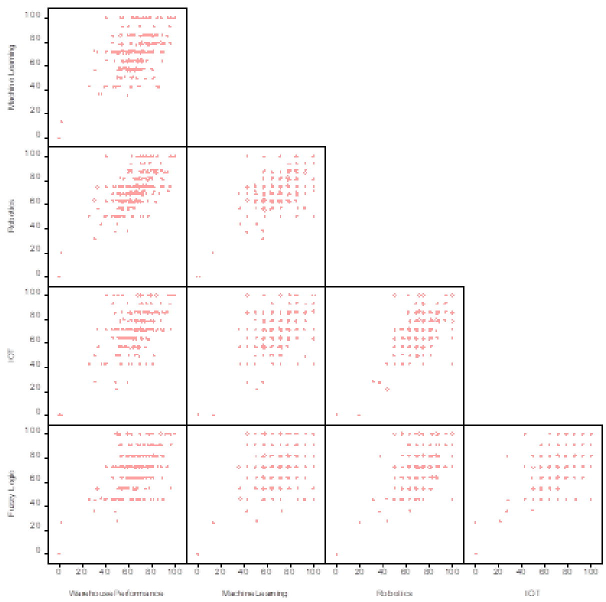


Source: Sample Survey, 2022

As per the scatter plot in Figure 11, it can be observed that there is a linear, positive relationship between all the independent variables, such as machine learning, robotics, the Internet of things, and fuzzy logic, with a dependent variable named warehouse performance.

Correlation analysis

Figure 12: Correlation Matrix between Y and X1-X4



Source: Sample survey, 2022

According to the correlation matrix in Figure 12, the independent variables, machine learning, robotics, Internet of things (IoT), and fuzzy logic, have a positive linear relationship with the dependent variable, warehouse performance.

Table 21: Correlation Matrix between Y and X1-X4

		Y	X1	X2	X3	X4
Y	Pearson Correlation	1.000				
	Sig. (2-tailed)	-------				
X1	Pearson Correlation	0.594	1.000			
	Sig. (2-tailed)	0.000	-------			
X2	Pearson Correlation	0.556	0.525	1.000		
	Sig. (2-tailed)	0.000	0.000	-------		
X3	Pearson Correlation	0.342	0.402	0.534	1.000	
	Sig. (2-tailed)	0.000	0.000	0.000	-------	
X4	Pearson Correlation	0.520	0.630	0.587	0.513	1.000
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	-------

Source: sample survey, 2022

The following hypotheses were constructed and checked to find the relationship between the dependent and explanatory variables.

H0: There is no linear correlation between Xi th and Y variable

H1: There is a significant influence on the Xi th from the Y variable (where Y = warehouse performance and Xi = machine learning, robotics, Internet of things, fuzzy logic).

According to the results of the correlation analysis in Table 21, the correlation coefficient of machine learning is 0.594. The p-value (0.000) of machine learning is greater than the alpha value (0.05); thus, the null hypothesis is not accepted. Therefore, it can be concluded that there is a positive linear correlation between machine learning and warehouse performance. The correlation coefficient of robotics is shown as 0.556, where the p-value is (0.000). Here it is greater than the alpha value (0.05); thus, the null hypothesis cannot be accepted where it concludes that there is a positive linear correlation between robotics and warehouse performance. The correlation analysis illustrates that the correlation coefficient of the Internet of things (IoT) is 0.342. Since the p-value (0.000) is greater than the significance level (0.05), the null hypothesis is accepted. Therefore, it can be concluded that there is a linear correlation between the Internet of things and warehouse performance. The correlation coefficient of fuzzy logic is 0.520 with the p-value (0.000) which is greater than the alpha value (0.05); thus, the null hypothesis cannot be accepted, and it concludes that there is a positive linear correlation between fuzzy logic and warehouse performance.

Although some linear correlations exist between independent variables, their strengths are not strong. Therefore, the multicollinearity problem might not be presented with the associated variables. Overall, the correlation analysis results showed that the selected dependent variable could be modeled with given independent variables using Multiple Linear Regression Analysis.

Regression analysis

Table 22 presents the results, including coefficients estimated, corresponding p-values, R2 value, overall significance criteria, and model evaluation criteria such as the Akaike information criterion of the regression model. Before conducting the regression analysis, the researcher transformed the dependent variable to the square of the dependent variable due to heteroskedasticity. Therefore, the researcher transforms variables by taking square, square root, and the log to overcome the issues with heteroskedasticity (Astivia & Zumbo, 2019).

Table 22: Results of the regression analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MACHINE_LEARNING	0.094035	0.044530	2.111725	0.0355
ROBOTICS	0.339807	0.047119	7.211656	0.0000
IOT	0.196403	0.046157	4.255136	0.0000
FUZZY_LOGIC	0.177582	0.038710	4.587552	0.0000
C	8.476249	3.132270	2.706104	0.0072
R-squared	0.524140	Mean dependent var		66.41380
Adjusted R-squared	0.518265	SD dependent var		14.06098
SE of regression	9.759319	Akaike info criterion		7.409403
Sum squared resid	30859.16	Schwarz criterion		7.467094
Log-likelihood	-1213.847	Hannan-Quinn criteria.		7.432418
F-statistic	89.21817	Durbin-Watson stat		1.793610
Prob(F-statistic)	0.000000			

Source: sample survey, 2022

According to the p-value (0.0000) of the F-test in Table 22, it is below the threshold level (α-value = 0.05). Therefore, the null hypothesis is rejected, and it concluded that at least one coefficient is significant in the present regression model. The regression model is statistically significant at a 5% significance level. It can be concluded that the regression model's constant is significant at a 5% significance level since the p-value (0.0072) is below the significance level (0.05). As per table 4.19, The p-value (0.0355) corresponding to the coefficient of machine learning is below the significance level (0.05). So, the investigator can reject the null hypothesis and can be concluded that the level of sensitivity for machine learning towards the regression model is significant. Therefore, machine learning has a significant influence on warehouse performance. The p-value (0.0000) corresponding to the coefficient of robotics is below the significance level (0.05). So, the investigator concluded that the level of sensitivity for robotics towards the regression model is significant. Hence, there is a significant influence of robotics on warehouse performance. The p-value (0.0000) corresponding to the coefficient of the Internet of things is below the significance level (0.05) in Table 22. So, the investigator can reject the null hypothesis and can be concluded that the level of sensitivity for the Internet of things towards the regression model is significant. Thus, the Internet of things has a significant influence on warehouse performance. Since the p-value (0.0000) corresponding to the coefficient fuzzy logic is below the significance level (0.05). So, the investigator can reject the null hypothesis, and it can be concluded that the level of sensitivity for fuzzy logic towards the regression model is significant. Therefore, there is a significant influence of fuzzy logic on warehouse performance.

The R2 value evaluates the goodness of fit of the regression model. As in table 22, the R2 value is 52.41%. Therefore, the present regression model, including all the independent variables such as machine learning, robotics, the Internet of things, and fuzzy logic explains 52.41% of the total variability of the warehouse performance. It is not a sufficient level for considering a well-fitted model.

Akaike info criterion is reported as 7.409403, the Schwarz criterion is reported as 7.467094, and the Hannan-Quinn criterion is reported as 7.432418. The model evaluation criteria are closer to 10 in the present regression model.

Residual Diagnostic Tests

Linearity

As per the scatter plot in Figure 11, a linear relationship between dependent and independent variables can be observed. Furthermore, the significant correlations reported in Table 23 are also evident for the linearity of the data.

Multicollinearity

Table 23: VIF table

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
Machine Learning	0.001983	36.02650	1.772065
Robotics	0.002220	43.36055	1.731578
Internet of Things	0.002130	38.47339	1.871853
Fuzzy Logic	0.001498	26.68124	1.439702
C	9.811118	33.89029	NA

Source: Sample Survey, 2022

Table 23 indicates no multicollinearity problem since all VIF values are less than 5. Therefore, this model's assumption of the absence of multicollinearity is satisfied.

Normality

Table 24: Normality Test: Jarque-Bera test

Measure	Value
Jarque- Bera	0.326091
Probability	0.849552

Source: Sample Survey, 2022

To check the normality assumption, the Jarque-Bera test has been performed.

The Jarque-Bera test can be used to confirm the normality further as follows:

Since the p-value (0.849552) of the Jarque-Bera is greater than the alpha-value (0.05), thus the investigator can retain the null hypothesis. Therefore, we can conclude that the residuals follow the Normal distribution at a 5% significance level. As a result, the assumption of normality is satisfied.

Homogeneity of Variances

Table 25: Heteroskedasticity Test: Breusch-Pagan-Godfrey

Measure	Value
F-statistic	0.776303
P- value	0.5412

Source: Sample survey, 2022

According to Table 25, the p-value (0.5412) is more significant than the significance level (0.05). Therefore, the above-mentioned null hypothesis is not rejected, and it can be concluded that the population variances are the same for the residuals. Hence, the assumption of homogeneity of variances is satisfied with a constructed regression model.

Absence of Autocorrelation

Table 26: Breusch-Godfrey Serial Correlation LM Test

Measure	Value
F-statistic	0.37421
P-value	0.6523

Source: Sample survey, 2022

As per Table 26, the p-value of the serial correlation test is 0.6523, which is greater than the significance level (0.05). Therefore, the investigator can accept the null hypothesis that the residuals are random. Hence, the assumption of autocorrelation is satisfied with a constructed regression model. Therefore, we can conclude that all the assumptions are satisfied with the present regression model.

Regression Equation

Y = 8.4762+0.094 X1 +0.3398* X2 +0.1964* X3 +0.1775* X4*

Y = warehouse performance

X1 = Machine learning

X2 = Robotics

X3 = Internet of things (IoT)

X4 = Fuzzy Logic

Considering the regression equation, it was concluded that machine learning, robotics, the Internet of things, and fuzzy logic influence warehouse performance. Among these factors, robotics, the Internet of things, and fuzzy logic is increasingly associated with the level of warehouse performance, so it can be concluded that these two factors influence warehouse performance. It can also be concluded that machine learning is moderately related to warehouse performance. However, regression analysis may conclude that machine learning, robotics, the Internet of things, and fuzzy logic directly affect warehouse performance.

5. Conclusion

The researcher has conducted a study to identify the influence of artificial intelligence on warehouse performance. Thus, this study was conducted to identify the influence of artificial intelligence on the warehouse performance of Sri Lanka's warehouses to gain economic profits while reducing the cost, time, and safety of the workers.

Accordingly, a sample study was conducted, including five warehouses in the Colombo area, to identify the influence of artificial intelligence on warehouse performance. A sample of 329 workers was selected 70% were male workers, and 30% were female workers. According to the analysis, 180 respondents were in the age category of 20-30, 98 respondents from 30-40, and 51 respondents were above 40. Also when it comes to the level of employment highest number, which is 129, is from the respondents who are at the executive level. The least was from the category other, which is 25 respondents, which include trainee staff, warehouse supervisors, forklift operators, material handlers, shipping and receiving clerks, and warehouse pickers. 92 and 83 respondents from managerial and non-executive levels of employment, respectively. When talking about the current process that artificial intelligence is using in the workplace, 104 respondents have mentioned that they are currently using artificial intelligence in inventory management. Moreover, also 90 respondents mentioned that they use artificial intelligence in the shipping process, and 85 respondents and 36 mentioned that they use artificial intelligence in picking and packing and safety and security management, respectively. Fourteen respondents state that they use artificial intelligence in documentation, color sorting, and printing.

The first independent variable was machine learning, where the sensitivity lest from Minitab illustrated Also,e sensitivity of robotics, the Internet of things, fuzzy logic, and warehouse performance was 73.675%, 70.524 %, 69.833 % and 66.414 %, respectively, which illustrates that there is a normal distribution in machine learning, fuzzy logic, and warehouse performance.

The relationship figure, it shows there is a positive linear relationship between the independent and dependent variables. The hypothesis was mentioned to determine whether there is an influence on warehouse performance with machine learning, robotics, the Internet of things, and fuzzy logic. The correlation matrix, it states that the null hypothesis, which shows that there is no influence of machine learning, robotics, the Internet of things, and fuzzy logic on warehouse performance, can be rejected as there is a significant influence of the independent variables on the dependent variable.

The sub-objective was to find whether demographic factors influence warehouse performance according to the Mann-Whitney tests carried out to test whether gender influence warehouse performance. The null hypothesis can be rejected as the p-value is lower than the significant level. That means that there is a significant influence of gender on warehouse performance. The second demographic factor was age. In order to test whether there is an influence of age on warehouse performance Kruskal Wallis test was carried on. According to the P- value, as it is greater than the significant level, one can conclude that there is no significant influence of age level on the warehouse performance.

The second sub-objective was to find whether warehouse efficiency could be increased by increasing warehouse performance. Here the researcher has taken three indicators time, inventory, and cost, where. These are used to increase warehouse performance. As the regression analysis showcases, artificial intelligence's significant influence on warehouse performance will increase warehouses' efficiency and effectivenessuses.

The R-squared value reveals that 52% of the data fit the regression model in the regression model. This model is purely based on human behavior or thinking of computerizing the workload. In such occurrences, lower R-Squared values could have resulted. However, this model can further develop by adding relevant variables after a thorough study.

Based on the findings of the study entitled “influence of artificial intelligence on warehouse performance,” the following commentaries from the warehouse workers can make some essential suggestions for the further development of artificial intelligence in Sri Lankan warehouses.

People are concerned about their job roles and that they would lose their jobs by initiating artificial intelligence into their processes. This was the idea of a small number of respondents, but when it comes to a whole lot of people were concerned about initiating artificial intelligence as they can reduce the workload and also the safety and security measures of workers. As the respondents mention, there is a huge workload daily, so using robotics was their main aim to reduce the workload and also to ensure the safety and security of the workers. As forklifts and different types of vehicles that are operated manually can make mistakes and even there will be human deaths, and also the goods can be damaged.

Further, they have mentioned that initiating these will not make a difference without people with the proper knowledge to maintain these and gain good profits. So, with the manual ways of accessing the process, the suggestions were to give explicit knowledge about artificial intelligence, its types, how these can be implemented, and how to work with these processes. Some respondents have stated that though they carry on a huge workload, they have not achieved the company’s targets. Some workers have been traumatized due to this situation, so it is best to implement artificial intelligence so that the work load can be reduced and they can achieve more than the given targets.

According to the study’s findings, most respondents stated that deploying drone-based AI in a warehouse for inventory management would be possible and extremely promising, as indicated by Amazon and Walmart’s recent employment of drones in their warehouse operations. As a result, the author would communicate that thought in the thesis.

Furthermore, the survey’s findings show that, while the staff is aware of AI applications and their implications for inventory management and other warehouse activities, they lack the essential knowledge and skills required to run and monitor the equipment and software. As a result, another advice for the warehouse manager is to conduct some internal on-the-job learning classes for warehouse personnel to improve the staff’s competency and facilitate the development of future Artificial Intelligence projects in the warehouse.

When the gender issue arises, it also states in the research that there is a significant influence of gender on warehouse performance, so if artificial intelligence is implemented, it would be easy to do the work stress-free and quickly, efficiently, and effectively. Furthermore, many respondents suggested using international color codes when working and maintaining their processes. Moreover, the maintenance of machines should be periodically done.

Since this model only explains 52% of the variance, it implies that additional factors might influence warehouse performance. As a result, future researchers might develop this model by including the other related variables that impact warehouse performance. Likewise, a study on the influence of artificial intelligence on the warehouse was conducted, targeting only warehouse workers in the Colombo District of Sri Lanka. Here the warehouses were selected where there are more the 350 workers. Accordingly, future researchers can conduct this study targeting warehouses in different industries and warehouses with different workers in the Colombo District and other districts.

Authors' contributions

All authors contributed to the work's conception, design, and writing.

Funding

The study did not receive any financial support

Declaration statements

No potential conflict of interest is reported by the authors.

Citation information

Angammana, J. S. K., & Jayawardena, A. M. A. (2022). Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka. *Journal of Sustainable Development of Transport and Logistics, 7*(2), 79-109. doi:10.14254/jsdtl.2022.7-2.6.

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