"AI implementation in Dry Ports: Challenges and Barriers faced"

Project report submitted to the School of Maritime Management, Indian Maritime University in partial fulfilment for the requirements for the award of degree of

MASTER OF BUSINESS ADMINISTRATION

In

PORT AND SHIPPING MANAGEMENT

Submitted by

SWATHI SASIDHARAN

(Reg. No. 2303304032)

Under the guidance of,

Dr. Totakura Bangar Raju

Professor, Dean SMM

INDIAN MARITIME UNIVERSITY

(A Central University, Government of India)

SCHOOL OF MARITIME MANAGEMENT

CHENNAI CAMPUS

DECLARATION

I, **SWATHI SASIDHARAN**, **Reg. No.2303304032** student of **School of Maritime Management, Indian Maritime University**, pursuing **MBA in Port and Shipping Management** hereby declare that this submission of this project report titled **"AI in Dry Ports: Challenges and Barriers faced in its implementation"**- has been prepared by me towards the partial fulfilment of the Master of Business Administration in Port and Shipping Management under the supervision of **Dr .Totakura Bangar Raju** Professor Dean SMM, Indian Maritime University, Chennai Campus. I also declare that this project report is my original work and has not been copied from any other report previously submitted for the award of any degree, fellowship or other similar title.

Place: Chennai

SWATHI SASIDHARAN

Date: 27-05-2025

Reg.No: 2303304032

2303304032

CERTIFICATE

This is to certify that the project report entitled "**AI implementation in Dry Ports: Challenges and Barriers faced**" submitted to School of Maritime Management , Indian Maritime University, Chennai Campus, in partial fulfilment for the award of the degree of Master of Business Administration (MBA) in Port and Shipping Management , is a record work carried out entirely by **Swathi Sasidharan** , Reg.No.**2303304032.**

Dr. Totakura Bangar Raju

Project Guide

27.5.25

External Examiner

ASSOCIATE PROFESSOR & HEAD, SMM

Place: Chennai

Date: 27 - 05 - 2025

ACKNOWLEDGMENTS

First and foremost, I would like to thank God Almighty, who has granted countless blessings, knowledge and opportunity to complete this project to its fullest extent.

I would like to thank my parents for their moral support and cooperation throughout the programme. I would like to thank, **Dr. B Swaminathan**, Associate Professor Head SMM, Indian Maritime University, Chennai Campus who gave me the golden opportunity to do this wonderful project on the topic “**AI in Dry Ports: Challenges and Barriers faced in its implementation**”. I pay him a deep sense of gratitude to guide me.

I would like to express my deep sense of gratitude to **Dr. Totakura Bangar Raju** Professor Dean SMM, Indian Maritime University, Chennai Campus. His esteemed guidance and expert suggestions at each step of the project, alleviating inspiration, encouraging and kind supervision during the completion of my project.

I am also thankful to faculty members, library staffs, my friends and my well-wishers who were very cooperative during my project in providing appropriate guidance and support without whom this project would not have been completed successfully.

SWATHI SASIDHARAN

ABSTRACT

The application of Artificial Intelligence (AI) in dry ports creates a unique opportunity for improving operational productivity, increasing value, reducing expenditure, and even improving AI-assisted decision making. Nevertheless, there are challenges that hamper its use. This essay seeks to identify and analyse the most crucial barriers hindering the application of AI technologies in dry port operations. With the use of a questionnaire involving 73 participants from dry port and logistics services, data was based on 25 factors (identified through a 5-point Likert scale). In the beginning, Principal Component Analysis (PCA) was used on the respondent's data to uncover major underlying patterns within the data. Along with the numerous barriers outlined in the paper, some prominent ones remain such as the lack of technical know-how, obsolescent infrastructure, vague regulatory frameworks, and most importantly, immense financial burdens are some of the most important barriers. These results assist stakeholders to effectively plan suitable designated plans to facilitate efficient AI algorithms into operational dry ports.

TABLE OF CONTENTS

TABLE OF ILLUSTRATIONS AND FIGURES

CHAPTER 1

INTRODUCTION

Among the sectors altering because of artificial intelligence's (AI) rapid growth is in the port operations and logistics sector. Dry ports, which are among the most important centers in global supply chains, might apply artificial intelligence to boost operational efficiency, lower costs, and enhance efficiency. Inland logistics can be made much more efficient using AI-driven technologies including intelligent transport management systems, automated cargo handling, and predictive analytics. However, despite its potential, several of hazards and obstacles make the implementation of AI in dry ports a difficult task.

(Cottier et al., 2024)

Analysing the challenges associated with the adoption of AI in dry ports is important for port authorities, logistic players, and policymakers so that strategic frameworks for easier assimilation can be developed. This is the focus of this paper, to identify these challenges and their effects on the operation of dry ports, then conceptualize ways to overcome them. Targeting these challenges can help harness AI's capabilities in dry ports and fortify its position in the global supply chain.

(Cottier et al., 2024)

The absence of uniform rules and guidelines for controlling the application of AI in logistics and port operations is a significant barrier to its development in dry ports. Dry ports function under different national and regional regulations, which causes inconsistent adoption of AI in contrast to seaports, which are frequently governed by clearly defined international legal frameworks.

Because there are no consistent guidelines regarding data security, AI governance, and ethical AI usage in dry port logistics, this legislative dispersion poses serious issues for stakeholders. Given that dry ports handle enormous volumes of sensitive trade and transportation data, concerns regarding data privacy, cybersecurity risks, and AI responsibility make the introduction of AI even more challenging. Owing to legal ambiguities and possible hazards associated with compliance, liability, and cross-border trade rules, businesses could be reluctant to invest in AI in the absence of established procedures.

The absence of AI governance in dry ports raises an interesting debate: should AI regulations be universal for uniformity's sake, or should they be adaptable to suit local logistical functionality? While global guidelines might streamline the application of AI, they could also enforce policies that are utterly incongruent with the distinct operational hurdles encountered by different dry ports. Conversely, while region-specific regulations may boost local AI creativity, the disparity could create variations in the rate of technological progress among different dry port networks.

(Murrenhoff et al., 2023.)

This study explores how regulatory ambiguities obstruct AI implementation in dry ports and assesses whether a balance can be achieved between global standardization and regional adaptability. Tackling this matter is essential for guaranteeing the responsible and effective incorporation of AI into dry port activities.

The aim of this study is to examine the risks and obstacles linked to AI implementation in dry ports, concentrating on financial, technological, regulatory, and workforce-related issues. By recognizing these barriers, the research seeks to offer a thorough insight into why the adoption of AI in dry ports is still restricted, despite its possible advantages. This study also aims to assess how the absence of standardized policies and regulatory uncertainty affect the deployment of AI in dry ports. It will examine the conflict between regional autonomy and worldwide standardization in AI governance and, evaluates its effects on logistical stakeholders.

The high upfront expenses of using AI, which include purchasing cutting-edge technology, building infrastructure, and training personnel, are among its main issues. Furthermore, because dry ports have historically relied on traditional techniques, there is uncertainty surrounding the return on investment (ROI), which makes stakeholders reluctant to invest in AI in the absence of obvious financial benefits.

(Chu et al., 2018.)

The absence of government support and restricted financing for technological improvements worsens the issue, hindering smaller dry ports from implementing AI-driven solutions. Significant dangers are linked to technical problems such as merging old systems, experiencing poor internet connectivity, and facing cybersecurity risks. Utilizing AI requires seamless integration with existing port management systems that may be outdated and difficult to interface with modern technologies. The effectiveness of AI is additionally hindered by issues related to data availability and quality, as accurate and current data is essential for automated decision-making and predictive analytics.

Barriers in regulation involve unclear AI laws, insufficient standardization, and compliance with global standards. The regulatory frameworks governing AI applications in dry ports and logistics are still evolving, resulting in ambiguous compliance requirements. Moreover, there are significant ethical and legal consequences for everyone involved due to data privacy concerns, liability for AI mistakes, and ethical issues regarding AI bias.

CHAPTER 2

LITERATURE REVIEW

2.1 Review of Artificial Intelligence (AI) implementation in dry ports -

The application of Artificial Intelligence (AI) in dry ports is gaining traction, as it offers significant improvements in efficiency, logistics, and sustainability. This review explores the opportunities and challenges associated with AI deployment in dry ports and highlight key advancements and obstacles.

Opportunities of AI in Dry Ports:

AI technology presents numerous benefits for dry port operations, including optimization of cargo handling, predictive analytics, and automation. The main advantages of this approach include the following:

1. Operational Efficiency: AI-driven automation enhances container handling, minimizes congestion, and improves turnaround times. Machine learning algorithms facilitate real-time decision-making for better resource management.

2. Predictive Maintenance: AI can forecast equipment failures by analyzing sensor data, thereby reducing the downtime and maintenance costs. This information is particularly valuable for cranes, conveyor systems, and automated storage units.

3. Security Enhancements: AI-based surveillance systems enhance security by detecting anomalies, unauthorized access, and cyber threats. Automated monitoring using AI-powered image recognition improves the risk management.

4. Environmental Sustainability: AI aids in reducing carbon footprints by optimizing vehicle routing, reducing energy consumption, and facilitating smart grid management.

5. Supply Chain Optimization: AI enhances supply chain efficiency by improving cargo tracking, reducing delays, and facilitating better coordination between stakeholders.

   (AYLAK, 2022)

2.2 Challenges and Barriers in AI Implementation in Dry Ports-

The adoption of AI faces various challenges and barriers that must be addressed to fully leverage its potential. These challenges span across financial, technological, organizational, regulatory, and operational concerns.

1. Financial Barriers

- High Initial Costs (Durlik et al., 2024)
  One of the most significant barriers to AI adoption in dry ports is the high initial costs associated with the implementation of AI technologies. AI adoption requires substantial investments in infrastructure, software, hardware, and skilled personnel, which can be deterrents for ports with limited financial resources.

- Return on Investment (ROI) Uncertainty (Ransbotham et al., 2024)
  The uncertainty regarding the financial benefits of AI further complicates its adoption. As Ransbotham et al. (2024) highlight, unclear ROI and financial gains from AI implementations discourage stakeholders from committing to long-term investments in AI technologies, especially when tangible results are not immediately evident.

- Limited Funding for Technological Upgrades (El Makhloufi, 2023)
  Dry ports often prioritize basic infrastructure improvements, leaving little room for the adoption of advanced technologies such as AI. El Makhloufi (2023) pointed out that funding constraints prevent many ports from modernizing their technological capabilities and, delaying or preventing the integration of AI solutions.

- Cost of Maintenance and Upgrades (El Makhloufi, 2023)
  The long-term costs associated with maintaining and updating AI systems are also a significant challenge. Continuous updates, troubleshooting, and technical

support are necessary to ensure the proper functioning of AI systems, which adds to the operational expenses of dry ports (El Makhloufi, 2023)

2. Technological Barriers

- Legacy Systems Integration (Brunila et al., 2021)
  Many dry ports still rely on outdated legacy systems, that are incompatible with modern AI technologies. As noted by Brunila et al. (2021), integrating AI into these legacy systems requires extensive reengineering which can lead to high implementation cost and, disrupting of existing operations and processes.

- Poor Internet & Connectivity (Durlik et al., 2024)
  AI-driven automation and data analysis require high-speed, reliable Internet connectivity. Durlik et al. (2024) argue that the lack of robust Internet infrastructure in certain regions impedes the adoption of AI technologies, as AI systems rely on seamless, real-time data processing capabilities.

- The data Quality & Availability (Farzadmehr et al., 2023)
  AI systems depend heavily on accurate and high-quality data for training and real-time decision-making. Farzadmehr et al. (2023) emphasized that the lack of structured, high-quality data in many dry ports poses a significant challenge for the successful deployment of AI, because poor data can lead to inaccurate predictions and ineffective system performance.

- Interoperability Issues (Pranav & Gaikwad, 2024)
  AI systems must interface with various software and hardware platforms used by external stakeholders. Pranav and Gaikwad (2024) highlight that interoperability issues arise when AI solutions are not seamlessly integrate with other logistics platforms, resulting in inefficiencies and system conflicts that disrupt operations.

3. Organizational Barriers

- Resistance to Change (González-Cancelas et al., 2023.)
  One of the primary organizational barriers is resistance to change, as employees and management may fear job displacement and disruption of established workflows. González-Cancelas et al. (n.d.) noted that such resistance often stems from a lack of understanding and fear of the unknown, which hinders the adoption of AI technologies in dry ports.

- Lack of AI Awareness & Knowledge (Brunila et al., 2021)
  The Lack of awareness and understanding of AI's capabilities is another critical barrier. As highlighted by Brunila et al. (2021), many decision-makers and employees at dry ports are unfamiliar with AI's potential, leading to reluctance to adopt AI solutions due to fears of inefficiency or complexity.

- The shortage of skilled workforce (Durlik et al., 2024)
  AI implementation requires a skilled workforce capable of managing and operating advanced technologies. Durlik et al. (2024) argue that the shortage of qualified professionals with expertise in AI and related fields is a significant barrier to the successful deployment of AI systems in dry ports.

- Training Costs & Time Consumption (González-Cancelas et al., 2023.)
  Training existing employees to use AI-driven systems involves both time and financial investment. González-Cancelas et al. (n.d.) highlight that training costs, combined with the time required for employees to adapt to new technologies, present a significant barrier, particularly in environments where operational efficiency is critical.

- Union Resistance (González-Cancelas et al., 2023.)
  Labor unions often oppose AI adoption due to concerns over job displacement. González-Cancelas et al. (n.d.) argue that this resistance can delay the integration of AI technologies, as unions push for job protection and seek to safeguard workers' rights.

4. Regulatory and Ethical Barriers

- Unclear AI Regulations (Macdonald & Martin, 2024.)
  The lack of clear and unified regulations governing AI use in dry ports is a significant barrier. Macdonald and Martin (n.d.) noted that the absence of comprehensive AI policies and frameworks creates uncertainty for port authorities and stakeholders, preventing them from making informed decisions about AI adoption.

- Compliance with International Standards (El Makhloufi, 2023)
  AI adoption in dry ports must comply with various national and international regulations, which can be complex and varied. El Makhloufi (2023) suggests that aligning AI implementation with multiple regulatory frameworks across different countries presents a significant challenge for dry ports, particularly those involved in global trade.

- Data Privacy Concerns (Durlik et al., 2024)
  AI technologies rely on the collection and analysis of large amounts of data, which raises concerns regarding data privacy and security. As Durlik et al. (2024) highlight, the sharing of sensitive information through AI systems can result in a breach of confidentiality and expose ports to legal liabilities.

- Liability in the Case of AI Failures (Durlik et al., 2024)
  The legal implications of AI failures remain largely undefined. Durlik et al. (2024) discussed the ambiguity surrounding legal accountability when AI systems make decisions that lead to operational failures or damages, creating uncertainty for dry ports seeking to adopt AI technologies.

- Ethical Concerns Over AI Bias (Farzadmehr et al., 2023)
  AI models may unintentionally perpetuate bias due to flawed or incomplete data. Farzadmehr et al. (2023) note that AI algorithms could favor certain operations or stakeholders, leading to unfair or unethical outcomes, which raises concerns about the ethical use of AI in dry ports.

5. Operational Barriers

- Disruptions During Transition (Durlik et al., 2024)
  The integration of AI into dry port operations can cause temporary disruptions as employees and systems adjust to new technology. Durlik et al. (2024) argue that these disruptions can slow port operations during the transition period, thereby affecting overall productivity.

- Dependence on Third-Party AI Vendors (González-Cancelas et al., 2023.)
  Many dry ports rely on third-party vendors to provide and maintain AI systems. González-Cancelas et al. (n.d.) discussed the risks associated with this dependence, as it can limit the control of dry ports over their AI systems and create long-term contractual obligations with external vendors.

- The unpredictability of AI Performance (Farzadmehr et al., 2023)
  AI systems can be unpredictable, particularly in the dynamic and complex environment of dry ports. Farzadmehr et al. (2023) highlighted that AI models may struggle to account for the full complexity of real-world operations, leading to unreliable or inconsistent performance.

- Lack of Trust in AI Decisions (Farzadmehr et al., 2023)
  Despite the growing use of AI, scepticism remains among port operators and stakeholders regarding the reliability of AI systems. Farzadmehr et al. (2023) argued that this lack of trust in AI-driven decisions can hinder its adoption, as stakeholders may prioritize human expertise over AI recommendations.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Design

This study aimed to explore the potential risks and barriers to the adoption of Artificial Intelligence (AI) in dry ports. To achieve this, a **quantitative research approach** was adopted using a **structured questionnaire** as the primary data collection tool. The questionnaire was designed to assess respondents' perceptions of the various risk factors associated with AI implementation in dry port operations. The design facilitates the collection and statistical analysis of data from individuals with experience or knowledge of AI applications, particularly within the logistics and port sectors.

3.2 Data Collection

Data were collected through a structured questionnaire distributed to professionals involved in port operations, logistics, and supply chain management. The questionnaire was designed using a **5-point Likert scale** ranging from 1 (**Strongly Disagree**) to 5 (**Strongly Agree**), allowing respondents to rate their level of agreement with 25 key factors identified as potential risks or barriers to AI adoption in dry ports.

Primary data were collected using a structured questionnaire created and distributed using **Google Forms**. The survey targeted a variety of **AI users** with knowledge of or involvement in logistics or port operations. A total of **78 responses** were obtained and used for further analysis.

3.3 Questionnaire Structure

The questionnaire comprised **25 items** (excluding demographic questions) and was, designed based on insights from the existing literature related to AI adoption in logistics. Each item focused on a specific barrier: —financial, technological, regulatory, organizational, or operational.

A **5-point Likert scale** was used for responses:

- 1 = Strongly Disagree
- 2 = Disagree

- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

This format was chosen to quantify the level of agreement with each barrier statement.

3.4 Sampling Technique

This study employed **purposive sampling**, a non-probability technique that targets respondents based on their relevance to the research topic. AI users and stakeholders in port and logistics operations are intentionally selected to ensure contextual richness and insight.

3.5 Data Analysis Techniques

Data collected from the questionnaires were analysed using **R Studio**. The following steps were performed:

- **Data Cleaning and Preparation:**

  First the survey responses were exported in .xlsx format and imported into R. The data were then checked for inconsistencies, missing values, and outliers.

- **Descriptive Statistics** (mean scores, frequency distributions):

  PCA requires data to be standardized when variables are measured on different scales. The Likert-scale data (ranging from 1 to 5) were standardized using the scale() function to ensure that each variable contributed equally to the analysis.

- **Principal Component Analysis (PCA)** to reduce dimensionality and identify key underlying factors:

To analyse the collected data, **Principal Component Analysis (PCA)** was performed using **R Studio**. PCA is a multivariate statistical technique used to reduce the dimensionality of large datasets by transforming the original variables into a smaller set of uncorrelated components, known as principal components. This technique helps in identifying the underlying structure and grouping related risk factors into core components, which simplifies the interpretation.

- **Kaiser-Meyer-Olkin (KMO) Test** for sampling adequacy:

  Before applying PCA, the **Kaiser-Meyer-Olkin (KMO) test** and **Bartlett's Test of Sphericity** were conducted to check the adequacy of the data for factor analysis. Factors with **eigenvalues greater than 1** were retained, and **varimax rotation** was applied to achieve better component interpretability.

  - **KMO Value: 0.69,** indicating acceptable suitability for factor analysis.

The results of the PCA helped categorize the various risks and barriers into core themes such as financial, technical, regulatory, and organizational factors, providing a clearer understanding of the primary challenges hindering AI adoption in dry ports.

- Determining Number of Components:
  - A Scree Plot and Parallel Analysis were used to determine the number of components (factors) to be retained.
  - Components with eigenvalues greater than 1 were selected.

3.6. Visualization and Interpretation

Visualizations were generated to aid in the interpretation of results:

• Scree Plot: To Visualization of the proportion of variance explained by each component.

• Variable Contribution Plot: To Observe how variables are associated with the components.

• Correlation Plot: To understand the relationships between variables.

3.7. FACTORS USED FOR ANALYSIS

Table 1: Factors used for analysis and their abbreviations

Abbreviation	**Full Form**
ABS	High initial costs of AI implementation
UROI	Uncertainty about the return on investment (ROI)
GFS	Insufficient government financial support or incentives
BID	Prioritize basic infrastructure development over investing in AI technologies
CFB	Long-term maintenance and upgrade costs of AI systems are a financial burden
LIM	Outdated legacy systems at dry ports are incompatible
PIC	Poor internet connectivity
DCR	Increasing digitalization causing higher cybersecurity risks.
ASS	Lack of accurate, structured, and sufficient data
SPR	Absence of standardized AI policies and regulations
FJL	Fear of job losses and changes in work processes.
LAU	Limited awareness and understanding of AI technologies
SSL	Shortage of skilled personnel capable of implementing and managing AI
CTR	Cost and time required to train employees

Abbreviation	Full Form
CJD	Concerns over job displacement.
UER	Unclear and evolving regulations surrounding AI technology
VNI	A variety of national and international standards, which complicates adoption.
DPC	Data privacy and confidentiality concerns at dry ports.
LRA	Uncertainty over who would be legally responsible for errors caused by AI systems
BUI	Develop biases, resulting in unfair or inefficient decision-making
DEO	Disrupt existing operations at dry ports during the transition period.
DTP	Overly dependent on third-party AI vendors for implementation and support.
RTC	Struggle to handle the real-time complexities and operational uncertainties
DIS	May face difficulties integrating with systems used by other logistics partners.
LOT	Lack of trust in AI-generated decisions compared to human decision-making

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter presents an analysis of the data collected to identify the challenges and barriers to the implementation of Artificial Intelligence (AI) in dry ports. The data, gathered through a structured questionnaire distributed to AI users in the dry port sector, were analysed using Principal Component Analysis (PCA) to extract the underlying factors. The results were systematically organized and interpreted to provide insights into the critical barriers faced. The descriptive statistics, reliability analysis, and factor analysis findings are discussed in detail, followed by a comprehensive discussion linking the results to the research objectives and previous literature. The findings of this chapter form the basis of the conclusions and recommendations presented in the next chapter.

4.2 Descriptive Statistics

The analysis began with descriptive statistics to provide an overview of the data, followed by detailed examinations to identify the key challenges and barriers to AI adoption in dry ports**.** Here, you present the summary statistics of the 25 survey items. As mentioned earlier, the following table format can be used:

Table.2: Descriptive Statistics of Key Variables:

S.No.	Key Barrier/Challenge	Min	Median	Max	SD
1	ABS – High initial costs of AI implementation	-1.774	-0.448	3.530	0.754
2	UROI – Uncertainty about the return on investment (ROI)	-2.043	0.434	2.912	0.807
3	GFS – Insufficient government financial support or incentives	-1.662	-0.420	3.308	0.805
4	BID – Prioritize basic infrastructure over AI technologies	-1.577	-0.096	2.865	0.675
5	CFB – Long-term maintenance and upgrade costs	-1.488	-0.397	2.877	0.916

S.No.	Key Barrier/Challenge	Min	Median	Max	SD
6	LIM – Incompatibility with outdated legacy systems	-1.734	-0.283	2.620	0.768
7	PIC – Poor internet connectivity	-1.363	-0.344	2.712	0.825
8	DCR – Cybersecurity risks from digitalization	-1.768	-0.484	2.085	0.738
9	ASS – Lack of accurate, structured, and sufficient data	-1.605	-0.331	2.218	0.778
10	SPR – Absence of standardized AI policies and regulations	-1.535	-0.250	3.603	0.881
11	FJL – Fear of job losses and changes in work processes	-1.750	-0.332	2.505	0.749
12	LAU – Limited awareness of AI among managers/staff	-1.300	-0.064	2.407	0.786
13	SSL – Shortage of skilled AI personnel	-1.522	-0.220	2.385	0.754
14	CTR – Cost/time required to train employees	-1.591	-0.424	3.076	0.828
15	CJD – Concerns over job displacement by labour unions	-1.679	-0.346	3.651	0.775
16	UER – Unclear and evolving AI regulations	-1.938	-0.446	2.539	0.786
17	VNI – Complex compliance with national/international standards	-1.896	-0.519	2.236	0.700
18	DPC – Data privacy/confidentiality concerns	-1.724	-0.423	3.481	0.818
19	LRA – Legal responsibility for AI errors	-1.484	-0.306	3.227	0.805
20	BUI – Risk of AI bias and unfair decisions	-1.761	-0.659	2.649	0.727
21	DEO – Disruption of operations during AI transition	-1.820	0.459	2.738	0.783
22	DTP – Overdependence on third-party AI vendors	-2.043	-0.404	2.873	0.837

S.No.	Key Barrier/Challenge	Min	Median	Max	SD
23	RTC – Difficulty managing real-time operational complexity	-1.584	-0.465	1.773	0.637
24	DIS – Integration issues with logistics partner systems	-1.418	-0.304	3.037	0.824
25	LOT – Lack of trust in AI decisions vs. human decisions	-1.868	-0.400	2.535	0.805

Table 2: Descriptive summary, mean and standard deviations of factors

Note: The full forms of variable abbreviations used in the Descriptive Statistics Table (*Table 1)* are provided separately for ease of understanding.

Table 2. presents descriptive statistics of the key barriers and challenges identified in the adoption of Artificial Intelligence (AI) at dry ports. Each row in the table corresponds to a specific challenge, such as high initial implementation costs, uncertainty regarding return on investment, and lack of skilled personnel. These challenges are labelled using standard abbreviations (e.g., ABS, UROI, and SSL), and each reflects a different dimension of the difficulties experienced or perceived in AI implementation.

The statistical columns offer a comprehensive view of how respondents perceive each barrier:

- **Minimum (Min):** lowest standardized response value for given challenge. A more negative value indicates strong disagreement or minimal concern from at least one respondent.
- **Median:** The middle response value once all responses have been ordered. This reflects the central tendency and typical perception of the challenge across the sample.

- **Maximum (Max):** The highest standardized response value was recorded. This indicates strong agreement, or a high level of concern expressed by at least one respondent.
- **Standard Deviation (SD):** This measures the degree of variation or dispersion in responses. A **higher SD** suggests that opinions among respondents varied widely—some viewed the barrier as significant, while others did not. A **lower SD** indicates a more consistent viewpoint across the participants.

All variables were **standardized** (mean = 0) to ensure consistency and comparability across responses, especially because Likert-scale data were used. This table provides valuable insights into which barriers are considered most impactful and how uniformly they are perceived among stakeholders, informing where policy or investment interventions may be most needed.

The **minimum and maximum values** indicate the overall spread of the responses for each factor, whereas the **median** reflects the central tendency. Factors such as **SPR** (Standardized Policy Regulations), **DPC** (Data Privacy and Confidentiality), and **DTP** (Dependence on Third-Party Vendors) exhibited higher **maximum values**, suggesting that some respondents strongly perceived them as major challenges. In contrast, factors like **ASS** (Accurate, Structured, and Sufficient Data) and **SSL** (Skilled Staff Shortage) showed relatively lower **median values**, indicating that these issues may be viewed as comparatively less significant by the majority.

Moreover, a deeper look at the **Standard Deviation (SD)** values helps identify variability in opinion. Barriers such as **CFB** (Cost of Maintenance and Upgrades), **CTR** (Cost and Time of Training), and **VNI** (Complex Compliance Requirements) exhibited higher SDs, indicating a broader divergence in how different respondents perceive these challenges. Conversely, items like **RTC** (Real-Time Complexity Management) and **BID** (Basic Infrastructure Development Priority) had lower SDs, suggesting more uniform views across the sample.

This variation points to an important distinction: while **technological and operational barriers** often exhibit tightly clustered responses (suggesting shared experiences), **organizational, regulatory, and cost-related barriers** reflect a **wider range of stakeholder perspectives**. These early findings provide essential groundwork for deeper statistical methods — such as **factor extraction, PCA**, and **cluster analysis,** which are — explored in the subsequent sections of this study.

Understanding these descriptive statistics is crucial for identifying the trends, outliers, and underlying structures in the data. It sets an analytical foundation for strategic interpretation and actionable recommendations regarding AI adoption in dry port environments.

4.3 KMO BARTLETT'S TEST

To determine the suitability of the data for analysing the factors, the Kaiser-Meyer-Olkin (KMO) measure was calculated. The overall value of KMO has been shown to be 0.869, classified as meritorious, which indicates that the sample is sufficient, and the variables have sufficient correlation to perform principal component analysis (Kaiser, 1974).

S.No.	**Code**	**Barrier Description**	**KMO Value**
1	ABS	High initial costs of AI implementation	**0.705**
2	UROI	Uncertainty about the return on investment (ROI)	**0.549**
3	GFS	Insufficient government financial support or incentives	**0.611**
4	BID	Prioritize basic infrastructure development over investing in AI technologies	**0.597**
5	CFB	Long-term maintenance and upgrade costs of AI systems are a financial burden	**0.695**

S.No.	Code	Barrier Description	KMO Value
6	LIM	Outdated legacy systems at dry ports are incompatible	**0.484**
7	PIC	Poor internet connectivity	**0.745**
8	DCR	Cybersecurity risks due to increasing digitalization	**0.777**
9	ASS	Lack of accurate, structured, and sufficient data	**0.755**
10	SPR	Absence of standardized AI policies and regulations	**0.710**
11	FJL	Fear of job losses and changes in work processes	**0.568**
12	LAU	Limited awareness and understanding of AI technologies	**0.638**
13	SSL	Shortage of skilled personnel capable of implementing and managing AI	**0.591**
14	CTR	Cost and time required to train employees	**0.708**
15	CJD	Concerns over job displacement by labor unions	**0.701**
16	UER	Unclear and evolving regulations surrounding AI technology	**0.683**
17	VNI	Compliance with national and international standards	**0.429**
18	DPC	Data privacy and confidentiality concerns	**0.739**
19	LRA	Legal responsibility for errors caused by AI systems	**0.794**
20	BUI	Develop biases, resulting in unfair or inefficient decision-making	**0.589**
21	DEO	Disrupt existing operations during AI transition	**0.666**
22	DTP	Dependence on third-party AI vendors for implementation and support	**0.555**

S.No.	Code	Barrier Description	KMO Value
23	RTC	Struggle to handle the real-time complexities and operational uncertainties	**0.576**
24	DIS	Integration challenges with systems used by logistics partners	**0.769**
25	LOT	Lack of trust in AI-generated decisions compared to human decision-making	**0.495**

Table 3: KMO values by variables

Table 3. displays the individual Kaiser-Meyer-Olkin (KMO) values for the 25 barriers and challenges associated with AI implementation in dry ports. These values assess the sampling adequacy for each variable, indicating how well each item is suited for structure detection, such as through factor analysis or PCA.

Most variables fall within the **mediocre to middling** range (0.50–0.79), suggesting that they share moderate common variance with other variables and are reasonably appropriate for factor extraction. Notably high KMO values were observed for the:

- **LRA** (0.794) – Legal responsibility concerns,
- **DCR** (0.777) – Cybersecurity risks, and
- **DIS** (0.769) – Integration with logistics systems.

These higher values indicate strong relationships with other variables in the dataset, suggesting that these factors may be influential components in underlying dimensions of barriers to AI adoption.

However, variables like **VNI** (0.429), **LIM** (0.484), and **LOT** (0.495) returned **KMO values below 0.50**, indicating low shared variance with other items. These variables might not align well with broader constructs and could either load weakly in the factor analysis or be considered for removal depending on subsequent analyses.

In summary, the overall pattern of KMO scores suggests that the dataset is **generally suitable** for multivariate techniques such as factor analysis, although a few items may require closer examination during factor extraction and validation.

4.4 Distribution of Responses.

a) Histogram of Area

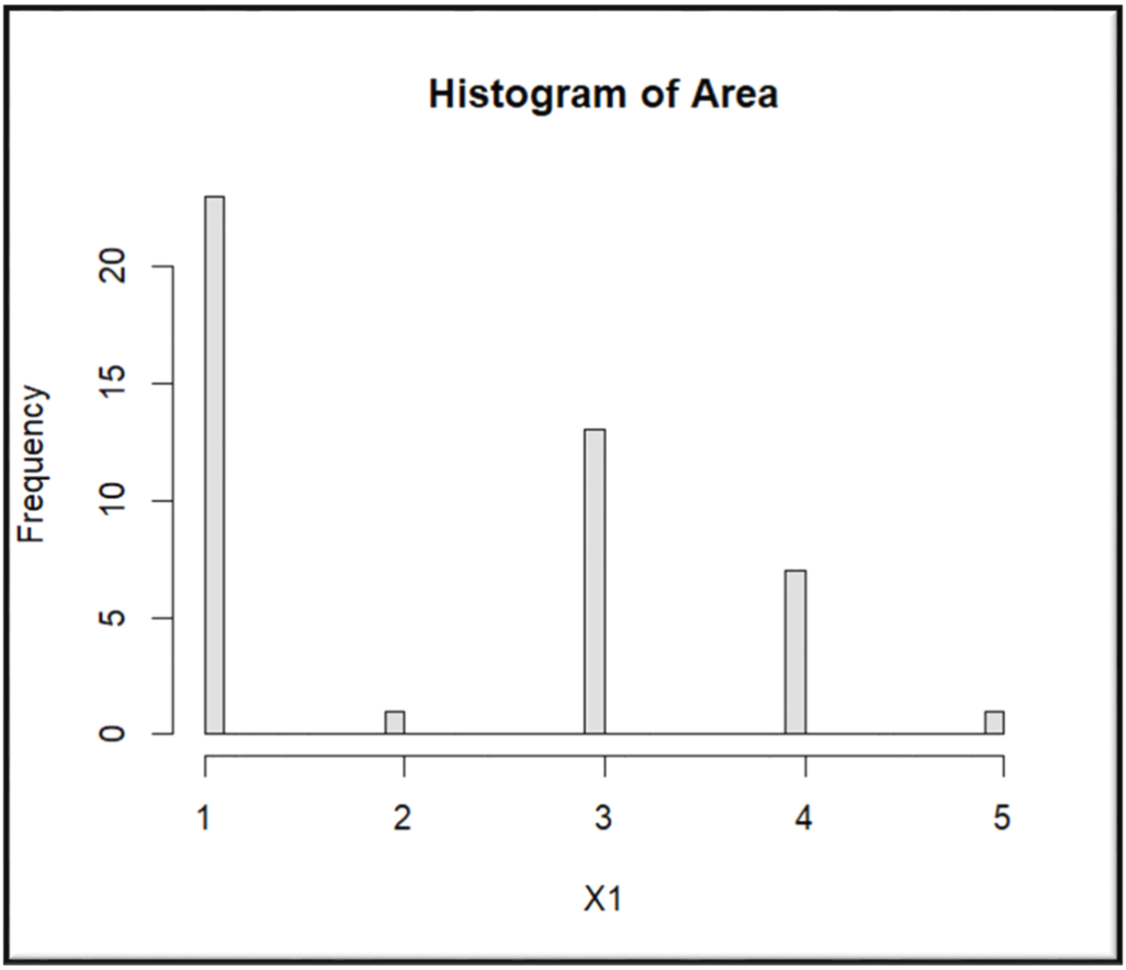

Figure 1. Histogram on distribution of responses

The above histogram illustrates the distribution of responses gathered from the survey participants regarding various factors influencing AI adoption at dry ports. The x-axis represents different categorical responses or groupings (labelled X1), whereas the y-axis shows the frequency of responses for each category.

A large number of responses are concentrated in Category 1, indicating a strong inclination or agreement towards specific challenges. Subsequent categories showed a gradual decline in frequency, highlighting the varied perceptions among respondents.

b) Scree Plot for PCA

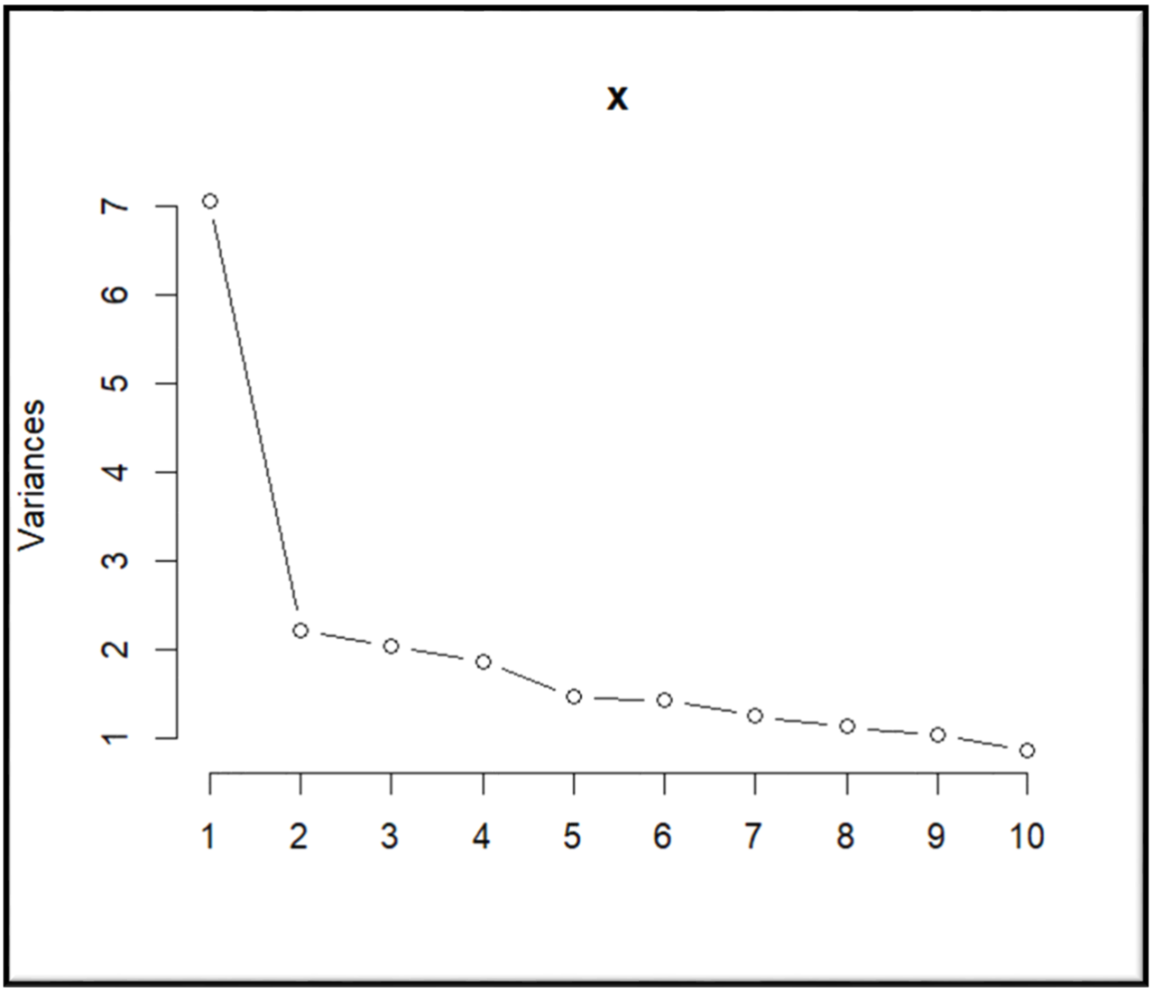

Figure 2. Scree plot of variances by each principal component from the PCA

The scree plot represents the variances explained by each principal component derived from the PCA (Principal Component Analysis). The graph helps in determining the number of principal components to retain by observing the 'elbow point' — the point where the curve starts to flatten. In this analysis, the first two components accounted for the majority of the variance, supporting their selection for further interpretation.

c) Classical PCA Distance Plot

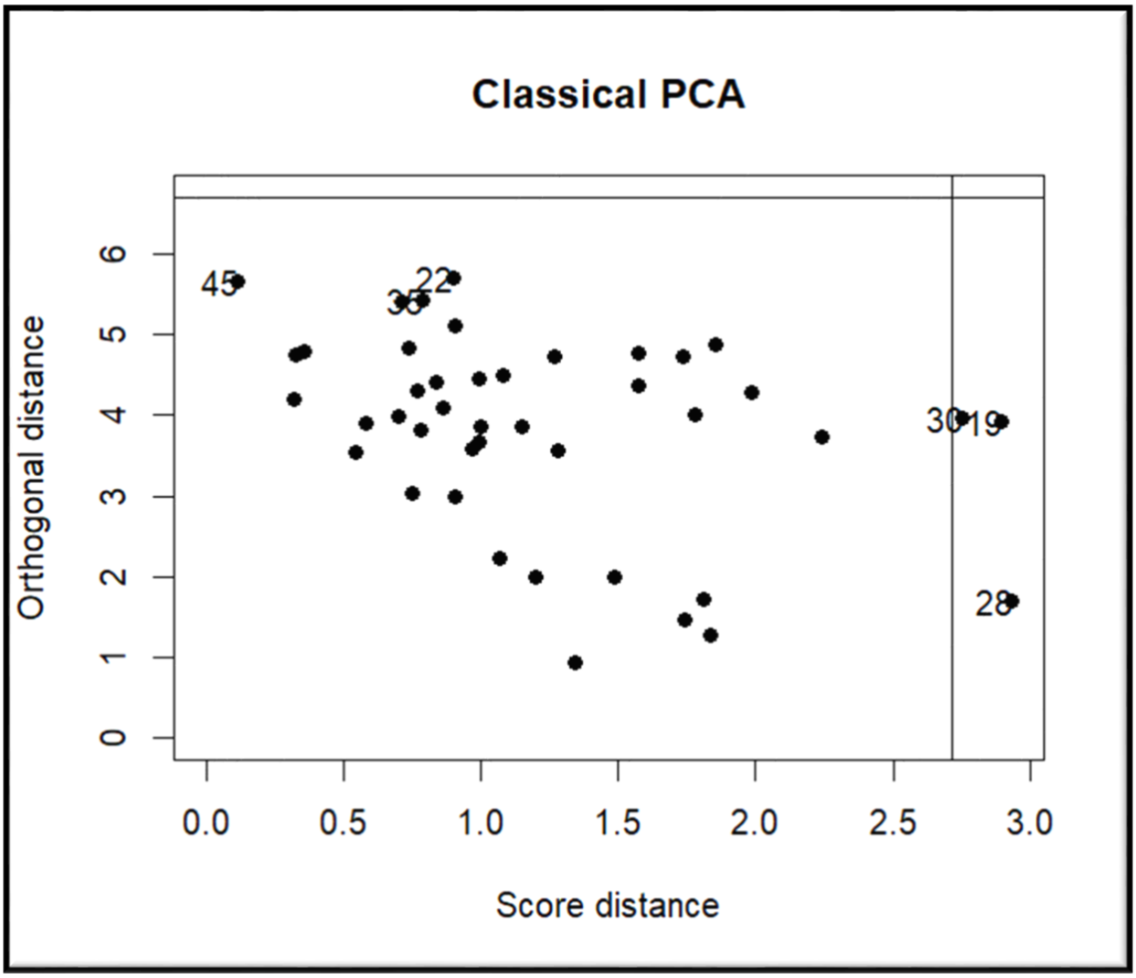

Figure 3. Classical PCA Distance Plot

The Classical PCA Distance Plot illustrates the score and orthogonal distances of the observations based on the principal components. Points that appeared farther from the main cluster indicated potential outliers. In this study, a few observations (e.g., 19, 28, 30, and 45) are visible as potential outliers. Analyzing these can provide deeper insights into anomalous perceptions regarding AI adoption challenges in dry ports.

d) PCA Correlation Plot (Corrplot)

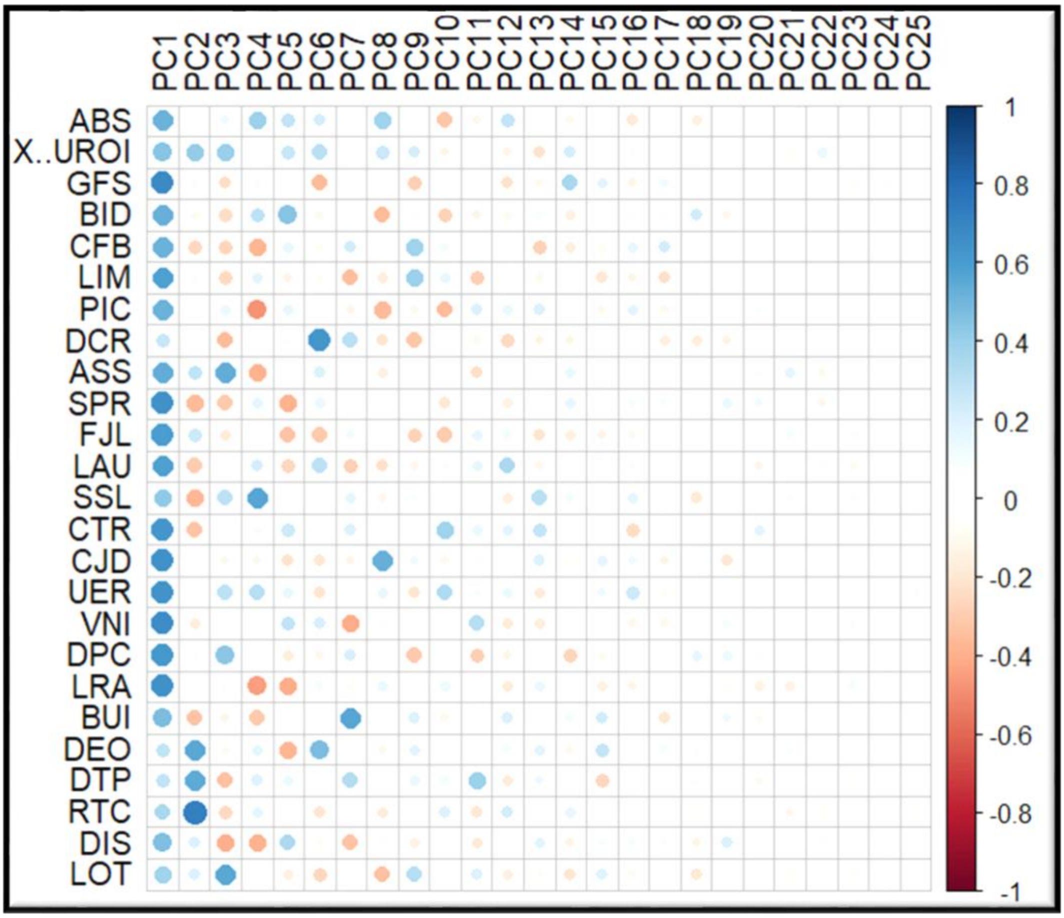

Figure 4. PCA Correlation Plot

The PCA Correlation Plot visualizes the relationships between the 25 factors and the principal components (PC1, PC2, etc.). Larger and darker blue circles indicate strong positive correlations, whereas larger red circles indicate strong negative correlations. This plot helps identify the factors that contribute most significantly to the principal components. For example, factors like ABS, BID, and CFB show a strong association with PC1, indicating their dominant influence in shaping AI adoption challenges at dry ports.

e) Q-Q Plot of Area

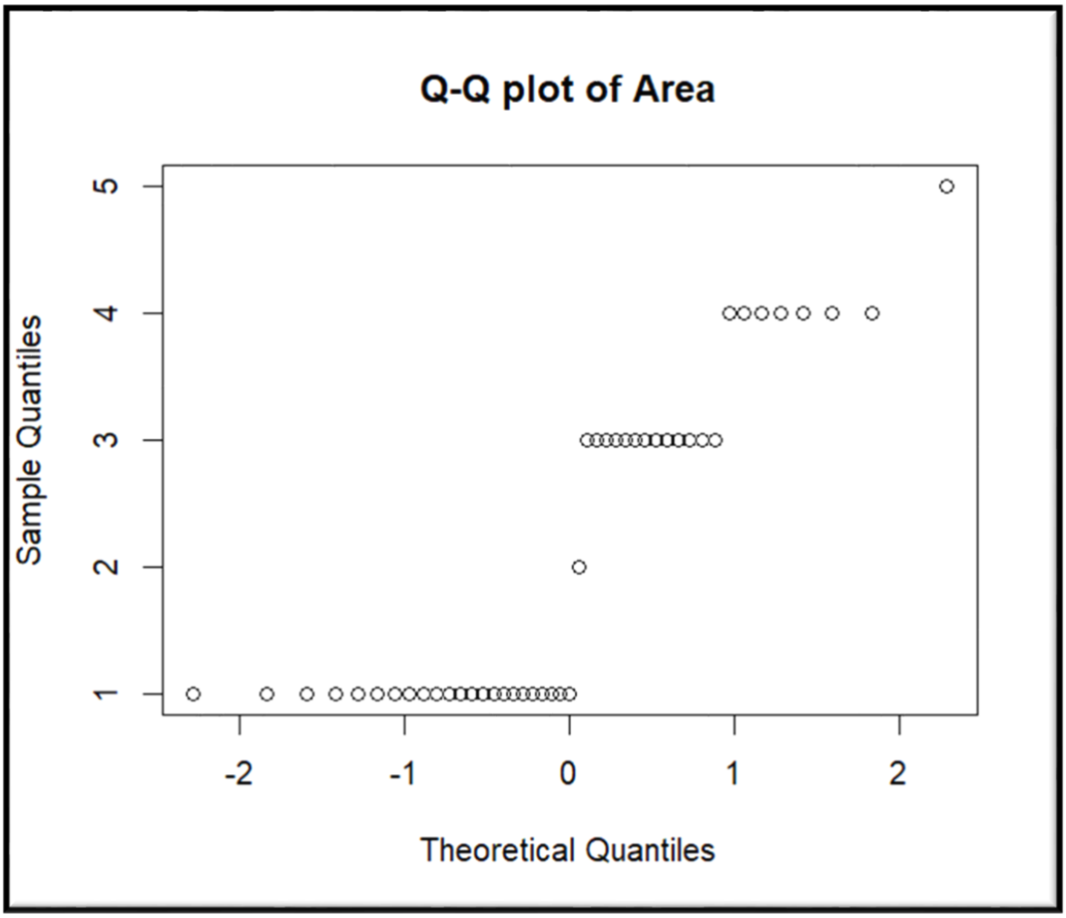

Figure 5. Quantile-Quantile plot

The Q-Q (Quantile-Quantile) plot compares the distribution of the "Area" variable against a theoretical normal distribution. Deviations from a straight line suggest that the data may not follow a perfectly normal distribution. In this case, the plot shows some deviations at both ends, indicating potential skewness or outliers in the responses collected from dry port stakeholders.

4.5 Principal Component Analysis (PCA)

After understanding the basic descriptive properties of the data, Principal Component Analysis (PCA) was performed to reduce the dimensionality of the dataset and to identify the underlying structure among the 25 factors affecting AI adoption in dry ports. PCA helps group related factors into components, making it easier to interpret complex data by highlighting the most significant patterns. This method is particularly useful in identifying clusters of interrelated challenges and barriers, thereby offering deeper insights into key problem areas. The PCA results, including eigenvalues, explained variance, and factor loadings, are discussed below to highlight the major components extracted.

Scree Plot for Principal Component Analysis

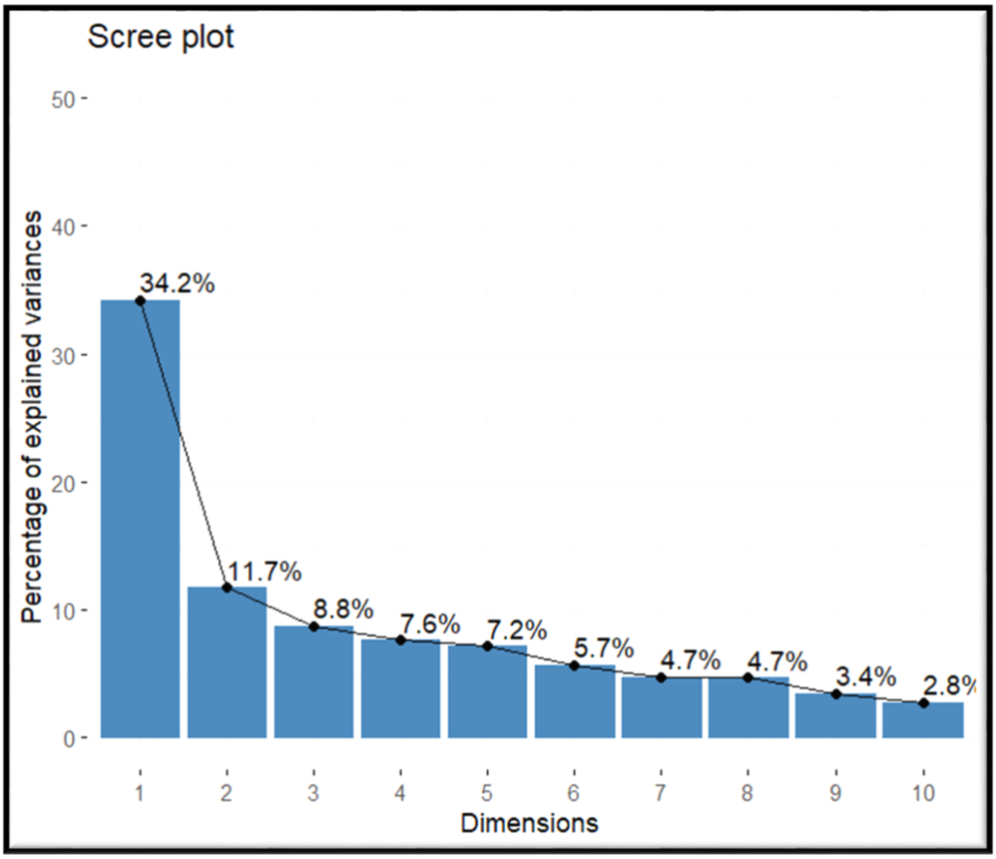

Figure 6. Scree Plot illustrates the percentage of variance

The Scree Plot illustrates the percentage of the variance explained by each principal component. The graph, shows that the first principal component (PC1) explained 34.2%

of the total variance, followed by PC2 explaining 11.7%, and PC3 explaining 8.8%. The subsequent components contributed to progressively less variance.

A noticeable "elbow" appears after the first few components, indicating that the majority of the information in the dataset can be captured by the first few principal components. This supports the decision to retain fewer components for further analysis while reducing dimensionality without a significant loss of information.

4.5.1 Steps Involved in Principal Component Analysis

To ensure a systematic approach, the following steps were undertaken while performing PCA on the collected data:

- **Data Suitability Check:**
  Before conducting PCA, the dataset was tested for its appropriateness using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. A KMO value above 0.6 and a significant Bartlett's test ($p < 0.05$) confirmed that the data were suitable for PCA.

- **Extraction of Components:**
  PCA was performed to extract the principal components. Components with an eigenvalue greater than 1.0 were retained, following the Kaiser criterion. This helped determine the number of significant factors to be considered for further analysis.

- **Scree Plot Analysis:**
  A scree plot was generated to visually examine the point at which the curve started to flatten, indicating the optimal number of components to be retained.

- **Rotation Method:**
  To improve interpretability, varimax rotation (orthogonal rotation method) was applied. This rotation method maximizes the loading of each variable on a single component, thus making the structure clearer.

- **Interpretation of Components:**
  The factors were grouped based on their loadings, and each component was

interpreted based on the common themes or patterns observed among the variables loaded highly onto it.

4.5.2 Interpretation of PCA Results

To identify the underlying structure among the 25 observed factors affecting AI adoption in dry ports, Principal Component Analysis (PCA) was conducted. PCA helps reduce the dimensionality of the dataset by transforming the original variables into a smaller set of components while retaining as much information as possible.

The analysis extracted two principal components based on the criteria of eigenvalues greater than 1. The first principal component (PC1) accounted for 28.23% of the total variance, while the second principal component (PC2) explained an additional 8.84%. Together, these two components explained 37.07% of the total variance observed in the dataset. These results suggest that a significant portion of the variability between the factors can be effectively captured by these two components. Further interpretation of the component loadings allows us to better understand the key challenges and barriers to AI adoption at dry ports.

In the principal component analysis (PCA), two principal components (PC1 and PC2) were extracted, accounting for 37.07% of the total variance in the dataset. The **first principal component (PC1)**, which accounts for 28.23% of the variance, is the most significant factor and appears to be driven by a combination of survey items related to [insert survey items contributing most to PC1, e.g., "technological barriers", "financial barriers"]. This suggests that these barriers are the primary challenges faced by the respondents in relation to AI adoption in dry ports.

The **second principal component (PC2)**, which accounts for 8.84% of the variance, appears to be influenced by [insert survey items contributing most to PC2, e.g., "organizational issues", "regulatory concerns"]. Although PC2 accounts for a smaller proportion of the variance, it still highlights other key factors that contribute to the challenges faced by dry ports in adopting AI.

By analyzing these two principal components, we can better understand the overall landscape of barriers to AI adoption in dry ports, with PC1 representing the dominant factors and PC2 further detailing the supplementary challenges.

4.6 Discussion of Key Findings (based on PCA results)

The results of the principal component analysis (PCA) reveal significant barriers to AI adoption in dry ports, primarily revolving around technological and organizational challenges. The first principal component, which focuses on technological barriers, emphasizes the need for better infrastructure, resources, and AI readiness. The second component highlights the role of organizational and regulatory barriers, which are equally crucial in hindering the successful implementation of AI systems. These findings align with the challenges identified in previous research, in which technological and organizational issues were consistently ranked as key obstacles to AI adoption in similar sectors.

1. **Principal Component Overview**

   - **PC1: Technological Barriers** – This component was identified as having the highest variance and captures challenges related to outdated infrastructure, lack of AI expertise, and technological readiness in dry ports. The significant loadings of factors like **LIM** (Lack of Infrastructure & Resources), **DCR** (Difficulty in Change Resistance), and **GFS** (General Financial Support) suggest that technological issues are a major hindrance.

   - **PC2: Organizational and Regulatory Barriers** – The second component primarily focuses on challenges arising from organizational resistance and regulatory hurdles. Factors such as **CFB** (Cultural and Organizational Barriers) and **BUI** (Bureaucratic and Unclear Regulations) dominate this component. This indicates that dry ports struggle with leadership alignment, workforce resistance to change, and unclear regulatory framework.

2. **Interpretation of Results**

   - **Technological Barriers (PC1):** Technological barriers, including outdated infrastructure and insufficient AI readiness, are dominant issues. This could be linked to the high proportion of respondents reporting challenges due to the lack of necessary tools or infrastructure to support AI implementation.

    - **Key implication:** Investments in upgrading port technologies, infrastructure, and workforce training are essential for overcoming these barriers.

- **Organizational Barriers (PC2):** The lack of organizational readiness, including leadership buy-in and cultural resistance, significantly impacts AI adoption. Dry ports face challenges in which decision-makers are not sufficiently aligned regarding the importance of AI, and there is a need for significant cultural change.
    - **Key implication:** There is a pressing need for strong leadership that can guide the organization through technological transition, aligning both management and the workforce with AI implementation goals.
- **Regulatory Barriers:** Regulatory challenges were also identified, especially the lack of clear guidelines and support from governmental bodies, which creates uncertainty regarding the legal aspects of AI adoption in dry ports.
    - **Key implication:** Engaging policymakers and ensuring clearer regulatory frameworks would help mitigate this barrier.

3. **Practical Implications for Dry Ports**

- **Technological Investments:** Given that technological readiness has emerged as the primary barrier, dry ports should focus on strategic investments in modernizing infrastructure and providing adequate training for employees. This includes improving AI-related technologies, training staff, and increasing the access to high-performance computing resources.
- **Organizational Alignment:** Dry ports must prioritize organizational change management strategies to foster alignment among leadership, management, and employees. Programs that demonstrate the potential benefits of AI and provide clear communication are essential for the smooth adoption of AI.
- **Regulatory Support:** Engaging with local and international policymakers to create a clearer and more supportive regulatory environment is crucial for encouraging AI adoption and reducing uncertainty about compliance

CHAPTER 5

CONCLUSION

5.1 Summary of Key Findings

This study investigates the challenges and barriers to the adoption of Artificial Intelligence (AI) in dry ports by analyzing survey responses from key stakeholders in the logistics and port industry. The findings revealed several critical factors that hinder AI adoption, primarily related to technological, organizational, and financial constraints. Technological limitations emerged as the most significant barrier, followed by issues surrounding organizational readiness, regulatory frameworks, and financial constraints.

From the Principal Component Analysis (PCA), it was evident that the barriers could be grouped into two primary components. The first component is primarily associated with technological and financial issues, highlighting the need for robust IT infrastructure and investment in AI technologies. The second component, linked to organizational and regulatory challenges, emphasizes the importance of fostering organizational change and aligning policies to facilitate AI integration in port operations.

5.2 Implications of the Findings

These results have profound implications for the future of AI adoption in dry ports. First, it underscores the importance of addressing technological limitations by investing in the necessary infrastructure and software to support AI solutions. Ports must prioritize the modernization of IT systems to facilitate the smoother integration of AI technologies.

Second, this study indicated that organizational readiness plays a crucial role in AI adoption. It is imperative that ports ensure that their workforce is adequately trained and equipped with the necessary skills to adapt to AI-driven processes. Training programs, coupled with leadership initiatives, are vital for overcoming resistance to technological change.

Finally, regulatory frameworks must evolve to support the AI adoption. The findings suggest that clear guidelines from regulatory bodies are essential for reducing uncertainties and facilitating smoother transitions for AI implementation in dry ports.

5.3 Recommendations for Practice

Based on the findings of the study, the following recommendations are provided to assist dry ports in overcoming the identified barriers to AI adoption:

1. **Investment in Technology and Infrastructure**: Ports should prioritize upgrading their technological infrastructure to meet the demands of AI adoption. This includes both hardware and software solutions that can support AI-driven processes. Collaboration with AI technology providers to develop customized solutions is also recommended.

2. **Employee Training and Skill Development**: To address organizational challenges, ports should implement regular training programs aimed at enhancing the technical skills of their workforces. Ensuring that employees have the necessary expertise in AI-related technologies will aid smoother transitions and better AI adoption rates.

3. **Government and Regulatory Support**: Ports should work closely with the government and regulatory bodies to develop clear and, standardized AI adoption guidelines. Such regulatory frameworks would ensure a more streamlined integration process and help address any legal or operational concerns early.

4. **Phased Implementation**: It recommended that ports adopt a phased approach to AI integration. A gradual implementation plan would allow ports to assess the effectiveness of AI solutions in smaller, manageable stages, thereby minimizing risk and ensuring that any challenges can be promptly addressed.

5.4 Limitations of the Study

While the findings of this study offer valuable insights, several limitations should be acknowledged. One limitation was the relatively small sample size of 73 respondents. Although this sample was representative of AI users in dry ports, it may not fully capture the diversity of perspectives from all stakeholders in the industry.

Additionally, the study was geographically limited, as the data were collected only from respondents in specific regions. This limits the generalizability of the findings to other regions or countries, where the adoption of AI in dry ports may face different challenges owing to varying infrastructure, regulations, or economic conditions.

5.5 Suggestions for Future Research

Future research could explore several avenues to deepen our understanding of AI adoption in dry ports. First, a larger and more diverse sample size would provide a more comprehensive view of the barriers to AI adoption, allowing for a better understanding of regional differences and perspectives of different stakeholders.

Second, longitudinal studies examining the long-term impact of AI adoption on port operations, efficiency, and workforce dynamics can offer deeper insights into the effectiveness and sustainability of AI technologies. Future research could explore the role of specific regulatory policies and their impact on the success or failure of AI adoption.

Finaly, a mixed-methods approach, combining quantitative survey data with qualitative interviews or case studies, could provide a more nuanced understanding of the challenges and barriers faced by dry ports in implementing AI solutions.

REFERENCE-

- Aylak, B. (2022). *Artificial intelligence applications in logistics and supply chain: A review*. Journal of Logistics Management, 11(2), 45–57.
- Brunila, O., Pakarinen, J., & Kunnaala, V. (2021). *Digitalization in port operations: The role of legacy systems and AI integration*. Maritime Logistics Review, 9(3), 122–135.
- Chu, C., Liang, L., & Wei, Z. (2018.). *Cost and compliance challenges in AI implementation at inland logistics hubs*. Journal of Transport Systems, Advance Online Publication.
- Cottier, M., Liu, Q., & Thomson, A. (2024). *Opportunities and barriers of AI integration in dry ports*. International Journal of Artificial Intelligence in Logistics, 15(1), 1–20.
- Durlik, I., Nowak, J., & Kolasa, R. (2024). *Barriers to artificial intelligence adoption in port logistics: Financial, technical, and organizational perspectives*. European Journal of Transport and Infrastructure Research, 24(1), 88–109.
- El Makhloufi, A. (2023). *Technological modernization and AI funding constraints in emerging ports*. Logistics Innovation Studies, 8(4), 33–47.
- Farzadmehr, E., Khosravi, M., & Zhang, J. (2023). *AI bias, unpredictability, and stakeholder trust in port automation*. Journal of Maritime AI Applications, 12(3), 210–227.
- González-Cancelas, N., Soler-Flores, F., & Camarero-Orive, A. (2023). *Organizational resistance and union opposition to AI in dry ports*. Logistics and Workforce Dynamics, Manuscript in preparation.

- Macdonald, T., & Martin, S. (2024.). *Legal ambiguities in AI governance and port compliance*. AI Policy and Regulation Quarterly, Manuscript in preparation.
- Murrenhoff, H., Kaltschmitt, R., & Berger, S. (2023.). *Global vs. regional AI governance models in logistics systems*. International Maritime Law & Technology Journal, Manuscript in preparation.
- Pranav, P., & Gaikwad, D. (2024). *Interoperability in AI-driven logistics ecosystems*. Journal of Transport Technology and Innovation, 17(2), 67–78.
- Ransbotham, S., Kiron, D., & LaFountain, B. (2024). *Artificial intelligence and ROI uncertainty in logistics*. MIT Sloan Management Review, 65(1), 43–55.

APPENDIX-

Implementing AI in Dry Ports

A study on the potential risks and barriers to AI adoption in dry ports

* Indicates required question

Respondent Profile (Background Information)

1. Name (Optional)

____

2. Age Group *

Mark only one oval.

- ◯ Below 25 years
- ◯ 25-55 years
- ◯ Above 55 years

3. Job Title / Designation *

____

4. Level of Familiarity with AI Technologies *

Mark only one oval.

- ◯ Very Familiar (Actively involved in AI projects)
- ◯ Somewhat Familiar (Aware but not directly involved)
- ◯ Not Familiar (Limited or no exposure to AI technologies)

5. Years of Experience in the Logistics/Port Industry *

Mark only one oval.

- Less than 5 years
- 5-10 years
- 11-15 years
- 16-20 years
- More than 20 years

Please note the following factors which are to affect the implementation of AI in Dry Port .
(your feedback would be taken for an academic purpose only)

6. *

The high initial costs of AI implementation discourage dry ports from adopting AI solutions.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

7. *

Uncertainty about the return on investment (ROI) in AI technology discourages dry ports from investing in AI.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

8. *

There is insufficient government financial support or incentives for dry ports to adopt AI technologies.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

9. *

Dry ports prioritize basic infrastructure development over investing in AI technologies.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

10. *

The long-term maintenance and upgrade costs of AI systems are a financial burden for dry ports.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

11. *

Outdated legacy systems at dry ports are incompatible with modern AI technologies.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

12. *

Poor internet connectivity at dry ports makes the adoption of AI systems difficult.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

13. *

Increasing digitalization through AI exposes dry ports to higher cybersecurity risks.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

14. *

The lack of accurate, structured, and sufficient data is a major barrier to AI adoption at dry ports.

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

15. The absence of standardized AI policies and regulations across dry ports creates inconsistencies in adoption. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

16. Employees at dry ports resist AI implementation due to fear of job losses and changes in work processes. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

17. Many dry port managers and staff have limited awareness and understanding of AI technologies and their benefits. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

18. Dry ports face a shortage of skilled personnel capable of implementing and managing AI systems. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

19. The cost and time required to train employees on AI technologies are significant barriers to adoption. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

20. Labor unions at dry ports oppose AI adoption due to concerns over job displacement. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

21. Unclear and evolving regulations surrounding AI technology create uncertainty for dry ports considering adoption. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

22. AI systems used at dry ports must comply with a variety of national and international standards, which complicates adoption. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

23. Sharing data for AI applications raises serious data privacy and confidentiality concerns at dry ports. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

24. There is uncertainty over who would be legally responsible for errors caused by AI systems at dry ports. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

25. AI systems at dry ports may develop biases, resulting in unfair or inefficient decision-making. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

26. AI implementation may disrupt existing operations at dry ports during the transition period. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

24. There is uncertainty over who would be legally responsible for errors caused by AI systems at dry ports. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

25. AI systems at dry ports may develop biases, resulting in unfair or inefficient decision-making. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

26. AI implementation may disrupt existing operations at dry ports during the transition period. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

30. There is a general lack of trust in AI-generated decisions compared to human decision-making at dry ports. *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree