Smartening up Ports Digitalization with Artificial Intelligence (AI): A Study of Artificial Intelligence Business Drivers of Smart Port Digitalization

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ABSTRACT

Artificial intelligence (AI) is digitalizing transportation at sea, on land, and in the air. It has the potential to cut human error and make operations faster. However, AI is one part of a broader process to digitize and improve port operations. AI digitalization and autonomous shipping are critical in the port world; AI allows human work to be shifted toward digital platforms that are currently not fully capable. Following this, the ports industry can be sketched as a natural fit for applying AI technology, known for its complicated processes and the high proportion of human work intervention. This paper aims to analyze and explore the artificial intelligence Business Drivers of Smart Port Digitalization. This study employs the exploratory Factor Analysis (EFA), Confirmatory factor analysis (CFA), and structural equation modeling (SEM) approaches using Advance Managed Outsourced Solutions (AMOS) based on a ports communities operation management view. Then propose new AI-Ports initiatives. The value-added core tasks of ports are examined to determine the possible utilization of AI technology and the AI adoption within the ports community.

KEYWORDS: *Artificial intelligence (AI); Ports community; Critical success factors.*

JEL CLASSIFICATION: *O3, O31,O32*

1. INTRODUCTION

Most companies overestimate the maturity of the AI systems, structures, and processes that help organizations ensure the maturity of the AI platforms. This fundamental lack of understanding of what constitutes maturity in AI has contributed significantly to the failures of AI systems (Cummings, 2021). However, AI is one of the most significant technological revolutions to smarten up the port community. With AI technology, smart and digital solutions in ports become a reality. The availability of big data, linked computing, and the Internet of Things (IoT) makes the power of learning behavior such as pattern recognition using AI technology much more accessible. The ports community and the container industry are very repetitive. Learning from the past helps organizations and port communities improve future decision-making within terminal operating systems or other surrounding intelligence modules. Therefore, there is great potential for using AI technology to improve decision-making in the port community. The quality of the data is also one hurdle that should be considered. Accuracy and quality are crucial to putting the data into AI algorithms. Without high-quality data, it will become challenging to make good high-quality decisions. However, today the quality is still relatively poor, such as discipline to ensure when a ship leaves and the accuracy of storage on the ships.

New-age technologies such as AI, data analytics, machine learning, and the Internet of Things reshape the growth of many industries. The ports and maritime industries that adopted AI

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technologies have had a smaller impact on their operations and more quickly will drive the disruptions in the future smoothly (Jakob, 2020). Existing studies reported that 80% of global trade goes through the sea, resulting in significant data from the ports and maritime industry (Jakob, 2020). No wonder such data provides an excellent opportunity to use AI and data analytics technology tools to improve the efficiency and productivity of the ports and logistics industry (Jović et al., 2019). AI and machine learning (ML) algorithms have great potential to play more significant roles in ports and the shipping industry by reducing transportation cost, freight cost, and transit time (Jakob, 2020; Jović et al., 2019). And it will reduce carbon emissions as a result of applying such technologies (Jakob, 2020).

AI has a significant influence on port operations. The evolved AI technologies have allowed the ports industry to collect a considerable amount of data to manage ports industries smoothly (Rajamäki et al., 2018). Using this big data and employing it to run AI algorithms allows ports to adjust to the new market trends, enhance the port's processes, understand ports customer behavior, and introduce a new essential AI-based ecosystem for the ports industry. Finally, future AI-dedicated systems and data fusion techniques for the processing port and maritime industry (Soldi et al., 2020). Ports and shipping experts reported that AI and ML could transform maritime connectivity, but the AI applications are still in the early phases (Bruun, 2020). Therefore, big data is crucial to feed AI algorithms to produce more AI technologies inside automated equipment that is centrally controlled. However, with AI's existence, it is expected to have more intelligence inside the loading and stacking carinas to operate without central guidance for longer periods during operations without getting a continuous feed of instructions from the controlled center. You can think of wrongly placed containers and how the new technology can solve them without getting this sorted out from the central system. To explore these issues, this research develops and validates a new model and tests the effect of the factors discovered through research in the establishment of new intelligence systems in ports. It addresses the following research question: What are the building blocks and business drivers of AI adoption in Ports community competitiveness?

2. LITRATURE REVIEW

2.1 What is Artificial Intelligence (AI)?

AI is the new electricity; it is anything a computer can do that formerly was considered a job for a human and making intelligent machines work like human beings in different areas such as speech recognition, planning, problem-solving, and learning. AI involves programming intelligence to make computers behave like humans (Greenwald, 2018). AI can help in different fields to boost crop productivity. For example, in the healthcare sectors, the deployment of AI will cause a paradigm shift in the delivery of healthcare services. AI can analyze using sophisticated machine algorithms to provide actionable real-time analytics in healthcare. The reason is that this healthcare industry is highly regulated and allows clinicians to focus on the patient instead of focusing only on voluminous data (Ganapathy etal., 2018). In the education field, AI also refers to the computerized system that resembles human mental processes of decision-making in teaching and learning. Therefore, AI can assist educational leaders in making data-driven decisions, and human judgment can always be used to guide and drive the shortcomings of AI-assisted data-driven decisions (Wang, 2021).

2.2 Theoretical framework and hypotheses development

The digital transformation process of the ports community is now unstoppable. AI technologies with the support of the Internet of Things, blockchain, 5G, and Big Data are essential for port facilities. (González-Cancelas etal., 2020). There is considerable theoretical literature on the impact of digital transformation and AI on the Ports community. However, there is very little empirical study on its effectiveness in the ports community using AI. This paper empirically investigates how artificial port community intelligence can influence customer port community competitiveness. The findings reveal that digital transformation using AI technology in the ports community can affect the Ports community's competitiveness. This paper is based on the wide-scale adoption of AI reported by Rahman etal. (2021). The AI should reassure consumers that the new AI technology will function as expected, without failures. The assurance is reported in several areas related to data, including reliability, dependability, and explainability. These matured elements will provide the tools to enable AI adoption into implementation and applications. In this paper, we discuss how the explored business driver will help in the adaptation process of AI in the ports community and present a general framework that addresses the business driver's rules in AI adoption.

2.2.1 Boost Productivity

Sea currents and winds influence maritime operations. Therefore, providing decision support for these maritime operations based on historical real-time data of the ship status is considered a significant concern in ship safety. However, collecting and analyzing a large amount of ship data in fundamental operations is challenging. (Li et al., 2020). Therefore, AI can boost productivity and speed up the ship docking (Van Thiel et al., 2019). defines AI technology as a tool to correctly interpret data, learn from such data, and achieve specific goals through flexible adaptation of those learnings.

The loading times at the port are another factor that addresses the changing ships and the port's ability to ensure efficient cargo transfers. The average time a vessel needs to stay in a port or the average loading time illustrates the capability of the port to handle cargo efficiently. It can also be defined as (the difference between the time of port entrance and time of departure) (Ducruet et al., 2014). Therefore, the port and terminal authorities can modify the container loading time to increase the capacity of storage yards and gain more space considering that there are challenges considering that there are different regulations in terms of hours of operation. Therefore, AI based on historical data and machine learning can be used to boost productivity and reduce load times. By having new innovative AI platforms, humans will be able to perform more complex tasks, and AI can perform repetitive tasks. Therefore, AI will provide more flexibility to reduce the wait and lead times for receiving goods from stakeholders, suppliers, and customers. Noting that current AI platforms offer services, such as real-time transportation route predictive maintenance (Foster and Rhoden, 2020), new AI initiatives can serve the ongoing demand of reducing the load time in the ports community.

Other technologies, such as big data and the Internet of Things (IoT), have provided the business industry with new interactions that have reset business understanding. For example, AI and Big Data (BD) are used to construct new digital platforms and structures to consider human and non-human interactions in the educational sector. In light of this kind of interaction, previous studies on AI and Big Data suggested that AI and Big Data can be used to build a very analytical tool (Bonami et al., 2020). Al is expected to be able to develop a new digital dashboard to replace the current traditional radio and radar interactions between harbor pilots, captains, and terminal operators as a result of the rapid rise of the new Internet of Things (IoT) and Big Data (Huang et al., 2018).

AI customer service chats could be automated chatbots to answer in a realistic and natural manner. In addition, achieving customer satisfaction is one of the fundamental objectives of any organization today; companies should focus their efforts on improving the relationship

with customers, stakeholders, suppliers, investors, and legislators. Therefore, engagement with all these entities is the key to achieving these goals and an essential component of good corporate governance (Andres-Jimenez et al., 2020). One example is one of the largest marine terminal operators, "DP World"; DP world is a dedicated professional and experienced team that serves customers and effectively manages containers to enhance customers' supply chain efficiency. The company constantly invests in technology related to terminal infrastructure and works closely with business partners to provide quality services and establish solid relationships to enhance customer interactions satisfaction (Al Bawaba, 2009). The customers' and stakeholders' satisfaction in the ports industry is not an option in the ports industry; it is a divinity to boost productivity. For example, the Banks industry benefits from virtual agents by delivering round-the-clock services and automating bank services to reduce inbound calls and enhance customer satisfaction. According to Adroit Market Research, over the past few years, banks have been adopting voice recognition technology, and it is expected to grow at a compound annual growth rate CAGR of 40% from 2020 to 202. Therefore, AI solutions can automate customer service and make it possible, and it will allow ports communities to resolve issues as soon as they arise. This means that agents, customers, and stakeholders can have their inquiries resolved 24 hours a day and increase customer satisfaction. This will make the community more productive by freeing up more time, while allowing customers to still have a personal and accurate interaction. Furthermore, this enables companies to spend less money on customer service employees and invest more in other areas, such as sales, marketing, or engineering. Consequently, the following hypothesis was developed:
H1. Boosting productivity is significantly driving the AI adoption of Port Digitalization.

2.2.2 Predicting the future

Cox et al. (2019) defines AI as a predicting tool for the future due to its ability to make flexible rational decisions in response to unpredictable conditions in different business industries, considering the recent technologies such as big data, analytics tools, machine learning, and natural language processing (NLP). Chatbots have been developed to answer predictable inquiries. However, the existing literature is still flooded with arguments that chatbots have advantages in consistency and patience in answering customer queries, but with less attention to customer queries (Cox et al., 2019). Other researchers have extensively explored the possibility of using big data to build predictive models. For instance, work has been done on predicting a future personal life event based on social media interactions (Maryam et al., 2021). Therefore, in a port environment, the data can be collected, organized, and processed; after that, AI can predict patterns in the logistics chain and offer prediction times when lorries, vessels, and containers will reach terminals, resulting in more excellent planning in the logistic chain. For example, an AI technology in the port community can predict an alternative route that can be found for the container and recommend a new route within minutes if there is any risk to the container based on the historical data.

Changing the future of the logistics and shipping sector is one of the benefits of AI. Ports community, shipping, and logistics have used the same legacy systems for years; subsequently, AI and transformation in these sectors help the sectors become increasingly dynamic. According to studies, those in the port and logistics industries who implemented AI platforms early in their operations saw a 5% increase in profitability compared to those who did not. This was achieved by providing new solutions to shorten the time without delaying the movement of goods and services (Foster and Rhoden, 2020). For example, according to Foster and Rhoden (2020), the Yara Birkeland, a fully electric container ship, is expected to perform entire operations by 2020 to reduce the intralogistics costs and maximize resources. The AI platforms can assist with analyzing data and assist with the decision-making process and Predictive Decision Making by providing real-time data, forecasting, and analyzing existing problems, such as redundancies, incidents, and duplication of effort (Foster and Rhoden, 2020). Therefore, AI platforms can optimize the operation of the logistics and supply chain sector and reduce costs by providing faster deliveries of goods and services to customers and making intelligent choices. Data collection will help make better decisions, improve decision-making and problem-solving, and enhance predictive planning.

One of the most challenging decision problems in the ports community is optimizing vessel schedule predictions using AI and machine learning (Dulebenets et al., 2019). Most of the shipping companies in the ports community aim to determine vessel sailing speeds of a given shipping route, port times, and vessel handling rates at ports. Therefore. AI can provide modern predictive analytics, which will improve the quality of vessel scheduling data. Some international ports, such as those in China, Indonesia, and Brazil, have been noted to use AI and automation for their port operations in action, claiming that these ports are more efficient in terms of labor, yard space, and general function, whereas some other ports, such as those in Jamaica, are entirely manual. For example, Jamaica's current terminal operating system (TOS) dictates every part of the operation, which is manual (Foster and Rhoden, 2020). AI will play a significant role in automating and integrating customs data, starting from all process automation using TOS. The AI and TOS integration will reveal inefficiencies and make the necessary actions and adjustments before the activities occur.

AI has been increasingly adopted in the automotive industry, developing systems that perform better than humans and replicate them. AI technology was incorporated into the vehicles industry to collect data, processes data, and choose an exact action; All collected information is analyzed by AI techniques using deep learning, machine learning, and natural language processing. AI has provided applications like advanced communication with the drivers and passengers, directing the vehicle to the gas station, analyzing and predicting the route to reach the destination based on the traffic conditions, and following the shortest path (Wankhede etal., 2021). Likewise, AI can be used in the ports community to drive and affect the overall performance, predicting and optimizing any given target destination.

In the same way, AI can analyze the primary steps associated with predicting the ongoing voyage, including classifying the vessel's current destination and predicting the route the vessel will travel to the destination. Therefore, AI can predict the effective speed for the remainder of the voyage by understanding the port-specific pilotage processes to the final destination, limitations, and schedules, such as tide windows. Consequently, the following hypothesis was developed:
H2. Predicting the future is significantly driving AI adoption of Port Digitalization.

2.2.3 Improve Port Competitiveness

The business stakeholders and academics have historically been watchful of efficiency trends in this shipping industry related to the ports community; the reason is that operation efficiency refers to creating and delivering services and goods faster, cheaper, better, more efficient, and more accurate. It means catering to the customer's expectations by improving internal operations to meet rising demands and gaining a competitive edge in the industry (Venkadasalam etal., 2020). Wahyuni etal. (2020) discussed and developed a port competitiveness model for Indonesian Port, comprising government support, operational performance, and business support. The study discussed the ports' effectiveness factors and reported the late adoption of recent technology.

Big data is one of the critical components that can be used with AI analysis to improve business performance and produce higher revenues in the port community (Wahyuni etal., 2020). Previous studies on AI and Big Data suggested that AI and Big data can be used to construct a very analytical tool that will improve operational efficiency (Bonami et al., 2020). So it is expected that the rapid development of the new Internet of things (IoT) and big data will empower Al with further communications between harbor pilots, captains, and terminal operators (Huang et al., 2018). Therefore, by building on this conclusion, organizations can enhance their transformed projects' business value, performance, and revenue.

Previous studies about deploying AI as part of the intelligent ports have been shown to reduce Operation costs and increase the port's competitiveness, such as having advanced robotics AI-based, AI solutions (Lesniewska et al., 2019). Therefore, having AI technologies in port will have a global impact by optimizing manual and time-intensive processes using different data analytics and robotics (Foster and Rhoden, 2020). The maritime industry is one of the most competitive industries in the ports community. However, the profit margins of shipping companies are the primary concern today, and the significant challenges are to optimize shipping routs due to the increase in fuel prices (Alexiou et al., 2021). AI can be used to improve maritime transport by applying new information that will improve the shipping industry by understanding and utilizing the shipping routes properly by identifying the best route at the best speed.

One of the primary indicators of port performance is port efficiency. AI will also make the task more efficient, effective, and less time-consuming. Port efficiency has been reported as one of the main benefits of AI in ports and terminals due to bringing supply chain stakeholders together (Schwerdtfeger, 2021). More efficient ports considering lower transportation costs and enhancing the process of imports and exports are primary keys to port efficiency (Foster and Rhoden, 2020). Transparency in information using the recent AI technology and knowledge sharing will improve the operational efficiency of the supply chain in the port community. Therefore, a knowledge port community with high efficiency in managing big data resulting from AI can be established to provide high-efficiency knowledge services for the port supply chain (Yang and Yang, 2021).

Collaboration has become mission-critical for the ports community. However, without visibility for all kinds of business interactions, the business leaders are blind to the barriers that disrupt the port's productivity. An AI-enabled port community system could increase collaboration between stakeholders, including port authorities, third-party logistics providers, and cargo owners. It will align all digital roadmaps across all stakeholders (Schwerdtfeger, 2021). This could allow for mutually beneficial opportunities to improve collaboration by sharing data and providing AI-enabled insights for future predictions and developments. AI has great potential for use in port and terminal communities, but there are questions about how AI technology can be utilized. AI could change business processes and workflows to improve the interaction's effectiveness and efficiency between the ports units. As a result, intelligent AI applications that allow users to interact and collaborate with other entities in real-time can be implemented, resulting in increased efficiency, competitiveness, sustainability, and cost savings for all port stakeholders, including terminal operators, port authorities, and cargo owners. Consequently, the following hypothesis was developed:
H3. Improving Working Environment is significantly driving the AI adoption of Port Digitalization.

2.2.4 Safer Working Environment and Safer Shipping

The challenge of handling cargo safely and efficiently is the most significant concern facing the ports community and the maritime industry. Safety is one of the significant benefits of AI in ports and terminals (Schwerdtfeger, 2021). AI and Port transformation using AI can mean a safer working environment. Therefore, accidents will become less common with automation using AI. Therefore, AI can analyze data to provide a risk-free environment by having real-time information, which will result in a safer working environment. AI also creates a safer working environment, reducing driver mistakes and accidents and helping with overall work safety security. For example, AI in the construction field is used to increase the safety of the workers and raise work efficiency. AI is used primarily to get information and make decisions for the future. Most construction companies use AI for safety, estimation, quality measurement, maintenance, planning, and monitoring (Liu et al., 2021).

The "Artificial Intelligence Market in Homeland Security, Public Safety & National Security: 2020-2025" reports that AI technologies can increase the investigative capabilities in many relevant fields, including public safety analytics, disaster and mass incident management, and the development of predictive capabilities (HSRC, 2021). AI also has the potential to manage all maintenance activities on ships and predict when spare parts may break down. Using AI technologies will allow real-time data sharing about operating conditions, enabling ports management to proactively identify needed maintenance or repairs for the ships and avoid unexpected issues or downtime for the entire operation. Polese et al. (2021) discussed the importance of the investment in predictive maintenance using AI technology in their study. Investing in AI predictive maintenance allows companies to enhance the sustainable value indexes and profitability ratios, assuming that improved quality of any provided services will increase revenues and reduce maintenance costs. As per the study, there are numerous implications of using AI technologies for preventative maintenance on enhancing decision support systems and sustainable competitive advantage.

You cannot provide 100% security, but companies predict when terrorists will attempt to strike a target through AI. Using AI in ports will make the ports community unpredictable by providing more intelligent, adaptive solutions (Tadjdeh, 2016). Therefore, AI helps improve the ports community with security checks to control port access for security reasons. According to Starke and Lünich (2020), AI technologies have the potential to identify pressing societal issues, evaluate policy effectiveness, and forecast potential policy outcomes. On that basis, it seems likely that demands to embed AI in the port processes will increase, and AI technology, with the support of machine learning, can deliver a better job of optimizing the port. AI is expected to play a major role in digitalizing terminals in two areas. First: optimizing yard processes. Second: optimizing the vessel processes. Therefore, it can be used as a decision-making system in port for operation predictions such as what will happen in the future supply chain system.

It is clear that AI has great potential for use in the port community, but there are questions about how it can be used. Central to this is how AI predicts the future, boosts productivity, and speeds up ship docking and reduce load times, improve operational efficiency, and provides a safer working environment and safer shipping. And these areas will be most relevant to the ports community in the future. Consequently, the following hypothesis was developed:

H4. Improving Port Competitiveness is significantly driving the AI adoption of Port Digitalization.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

To develop a research model to propose and measure the AI business drivers of Smart Port Digitalization, this study began by investigating cited factors that influence AI capabilities in the port community. The literature review identified four major factors that drive the ports community to invest in AI (Figure 1): Predicting the future, Boost Productivity, Improving Port Competitiveness, and improving the working environment. The theoretical framework and hypotheses of this study are identified from the literature.

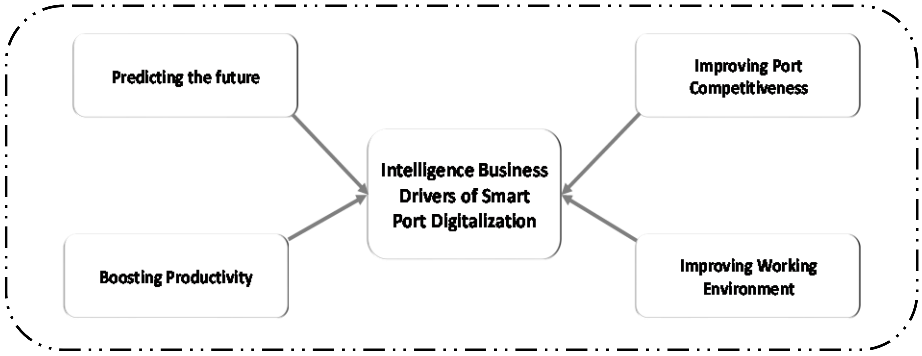


Figure 1. Conceptual framework.
Source: Mohamad et al., (2019)

- **H1**. Boosting productivity is significantly driving the AI adoption of Port Digitalization.
- **H2**. Predicting the future is significantly driving AI adoption of Port Digitalization.
- **H3**. Improving Working Environment is significantly driving the AI adoption of Port Digitalization.
- **H4**. Improving Port Competitiveness is significantly driving the AI adoption of Port Digitalization.

The research model used conceptualizes the Intelligence Business Drivers factors of Smart Port Digitalization presented in Figure 1. This conceptual frame presents Intelligence Business Drivers of Smart Port Digitalization as a core for that model; the model illustrates and addresses the main business drivers of implementation and adoption of AI in Smart Port Digitalization.

4. RESEARCH METHODOLOGY

A structural equation modeling method was used to analyze the hypothesis. The first step was conducting the EFA followed by a confirmatory factor analysis. Then the Path model analyzes the hypothesis using regression coefficients. A comprehensive literature review has been conducted to better understand the AI Business Drivers of Smart Port Digitalization. In total, 62 sources have been identified as relevant for this research. Initially, the search was carried out using the Web of ProQuest database, as it represents one of the world's leading scientific citation searches.

Table 1 shows the number of hits after applying the reduction criteria for each search term found in the Web of Proquest database and the number of sources after manually screening.

Table 1. Literature Summary: Intelligence Business Drivers of Smart Port Digitalization.

Keywords	Articles after Applying Formal Criteria	Articles after Screening Manually
Artificial intelligence.	110	31
Port authority AND port artificial intelligence.	37	7
Port Community System.	48	15
Digital Transformation in Port Community.	14	9

Source: Temesgen et al., (2022)

5.1 Measurement:

To analyze the proposed hypothesis, the structural equation modeling method was implemented using EFA followed by confirmatory factor analysis. The proposed model was conceptualized based on the influential variables (Predicting the future, Boosting Productivity, Improving Port Competitiveness, and Improving Working Environment). The study utilizes a five-point Likert scale for all six proposed variables using the same scale with options ranging from (strongly disagree) to (strongly agree). The draft version of the measurement scale has been pretested and reviewed by three academics and five members of the top-level management in the ports community. The proposed questionnaire was revised to use a pilot study to check understandability based on their input. The Cronbach's alpha for all variables was more than 0.7 showing relatively good construct reliability, as Qu (2007) suggested.

5.2 Sampling and data collection:

The respondents involved employees from different levels of ports community management, administrative, managerial, top level of management, and other stakeholders involved within the maritime environment. Such as port authority, importers and exports, freight forwarders, and customs, considering the concept of a port community system reported by (Tsiulin et al., 2020); All these sectors are working closely to solve any communicational issue to enhance the ports community. The sampling frame consisted of 12 terminals listed in the Gulf region, and all employees involved in the port operation were targeted for the questionnaire survey. The top-level management, the decision-makers for AI adoption, were part of the targeted employees. It was presumed that middle-level and top-level management possess complete information on AI adaptation. The survey responses were collected through email and online survey platforms. Common Method Bias (CMB) using Harman's single-factor test was used to determine the validity and reliability of the constructed model. The first part of the data analysis involves descriptive analysis showing the respondent profiles. The UAE has one of the fastest growing economies in the Middle East, which is quickly growing in different industries such as logistics, Ports, and finance. To support and promote these industries, a noticeable ports and maritime activities have occurred in the UAE. A thumb rule of using quantitative analysis, as it works better to confirm or test (a theory or hypothesis) and to understand new concepts, thoughts, or experiences (Mehrabi et al., 2022).

6. DATA ANALYSIS AND FINDING

The second part of the analysis examines the business drivers of adopting AI Port Digitalization. These drivers are: Predicting the future, Boosting Productivity, Improving Port Competitiveness, and Improving Working Environment using EFA, descriptive statistics, and CFA.

6.1 EFA, Results, and Discussion:

EFA is considered one of the most powerful tools for investigating the underlying variable structure (Osborne and Fitzpatrick, 2012). EFA was also reported to be one of the very popular statistical techniques used in communication research, and the core of the AI model in the port community is communication (Hee et al., 2002). Therefore, EFA was used to explore business drivers' factors that might influence the adoption of AI in Port Digitalization. The factor loadings are presented in a rotated component matrix (Table 2). The next step is to look at the content of the questions that load highly and on each factor to identify common themes.

The questions that load on the first factor seem to relate to different aspects of productivity and represent 4 items and account for 19.087%. Therefore, of the variance, we label this factor ***Boosting Productivity***. The questions that load highly on the second factor are 5 questions, and all seem to relate to Predicting the future; therefore, we label this factor **as *Predicting the future***. It accounts for 18.089%. The Third factor is related to questions that load highly in areas related to Port Competitiveness, representing 5 items; therefore, we label this factor as ***Improving Port Competitiveness.*** It accounts for 16.476%. The fourth factor seems to relate to different questions load highly in areas associated with Safer Working Environment and Safer Shipping, security checks, processes monitoring, and resource management; therefore labeled as ***Improving Working Environment***. It accounts for 9.2016%. The last factor is related to questions that load highly in areas associated with business drivers of adopting AI technology in the ports community; therefore, they were labeled as ***Business drivers of adopting AI in the ports community***, and it accounts for 8.452%.

To confirm the reliability of all the measurement scales, the average variance extracted (AVE) was used to measure the amount of variance that a factor captures from its items relative to measurement error. In contrast, composite reliability (CR) was used to measure the internal consistency of the factor (Akter et al., 2016). Table 2 shows that The CR and AVE closed to thresholds 0.80 and 0.50. Thus, each construct and its measures in the research model effectively distinguish themselves from other constructs. Overall, the measurement model was considered satisfactory due to the adequate reliability (AVE > 0.50, CR > 0.80) and convergent validity (loadings > 0.75). Table 4 shows the discriminant and convergent validity.

Table 2. Factor Loading from the One-Level Confirmatory Factor Analysis

Reflective Construct	Items		Loading	CR	AVE
Boost Productivity	1	Speed up ship docking	.929	.90	0.71
	2	Reduce Load Times	.927		
	3	Digital dashboards	.920		
	4	Achieving customer satisfaction	.508		
Predicting the future	5	Predict patterns in the logistics chain	.959	.91	0.67
	6	Faster Decision-making process	.959		
	7	Optimizing vessel schedule predictions	.953		
	8	Predicting and optimizing any given destination	.604		
	9	Predicting the effective speed	.493		
Improve Port Competitiveness	10	Improve business performance	.906	.85	0.54
	11	Reduce Operation costs	.815		
	12	optimize shipping routs	.698		
	13	Improve Port efficiency	.677		
	14	increase collaboration	.504		

Reflective Construct	Items		Loading	CR	AVE
AI Business Drivers	15	Data reliability	.677	.67	0.34
	16	Data dependability	.614		
	17	Data explainability	.531		
Improving Working Environment	18	Manage incidents and maintenance activities	.796	0.77	0.53
	19	Improving ports community with security checks	.687		
	20	Monitor processes and human decision- making.	.686		

Source: Mohamad et al., (2019)

The Kaiser-Meyer-Olkin Test (KMO) and Bartlett's test of sphericity were conducted to determine the business drivers of adopting AI in the ports community in the collected data. The results are shown in Table 3.

Table 3. KMO Test and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.852
Bartlett's Test of Sphericity	Approx. Chi-Square	2361.370
	Df	210
	Sig.	0.000

Source: Mohamad et al., (2019)

The KMO Test and Bartlett's Test (KMO > 0.5) show no severe issues in the data, and the correlation between the items is sufficient to run the factor analysis. EFA was used with the extraction method, and Varimax rotation on the 20 item items showed a preferable load greater than 0.40 on the relevant factor (Akter *et al.*, 2016).

The reliability results of the new model for the 5 scales are presented in Table 4 and indicate strong measures: the measures range from 0.571 to 0.947, satisfying the recommended threshold value (Akter *et al.*, 2016). Table 5 represents the correlation matrix for the five factors: reliability statistics, predicting the future, Boost Productivity, Improving Port Competitiveness, improving the working environment, and Business drivers in Adopting AI technology in the Ports community. The correlation matrix represents a perfect relationship between factors; the Port Competitiveness strongly correlates with Boost Productivity about the AI capabilities. Business Drivers of adopting AI also show a strong correlation with Boost Productivity, Port Competitiveness, and Predicting the future. No significant relationship was found between Improving Working Environment and Port Competitiveness, Predicting the future, and Boost Productivity. The next step was running the regression analyses to see which factors significantly impact the business drivers of adopting AI in the ports community. Next, discriminant analysis was conducted to test the importance of each element in distinguishing high and low levels of impact on business drivers of adopting AI in the ports community. Table 4 shows the mean and standard deviation of each factor. It can be seen that the Boost Productivity and AI Capabilities and Competitiveness scores of 3.34 and 3.21, respectively, on a scale of 1-5, represent the highest means among all the constructs. The level of Operational Efficiency and Predicting the Future is low, indicating that the people in these organizations do not think their Operational Efficiency and Predicting the Future matured enough. The Working Environment has the lowest mean among all the constructs, scoring 2.34.

Table 4. Reliability statistics and Descriptive statistics

Construct	Cronbach's Alpha	Mean	Std. Dev.
Boost Productivity	.945	3.24	0.98
Improve Port Competitiveness	.847	2.56	0.86
Predicting the future	.801	2.57	0.78
Business Drivers of adopting AI	.730	2.44	0.59
Working Environment	.711	3.29	0.79

Source: Mohamad et al., (2019)

Table 5. Descriptive statistics and correlations

	BP	PC	PF	BD	WE
Boost Productivity (BP)	1				
Port Competitiveness (PC)	.510**	1			
Predicting The Future (PF)	.431**	.621**	1		
Business Drivers of adopting AI (BD)	.271**	.464**	.542**	1	
Working Environment (WE)	-.099	-.050	-.031	.086	1
*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).					

Source: Mohamad et al., (2019)

The Bentler-Bonett's Normed Fit Index (NFI) was calculated using AMOS to check the convergent validity, which provides the degree to which the different approaches to measuring a factor generate the same result. As shown in Table 6, the items on each scale are convergent as all NFI values above 0.90, which indicates a satisfactory fit (Akter et al., 2016).

Table 6. Construct validity analysis.

Reflective construct	Convergent Validity Bentler-Bonett NFI	Discriminant Validity Factor Cronbach's *a*- Average correlation between factors
Boost Productivity	0.998	0.941
Predicting the future	0.996	0.867
Port Competitiveness	0.921	0.901
Business Drivers of adopting AI	1.00	0.741
Working environment	1.00	0.571

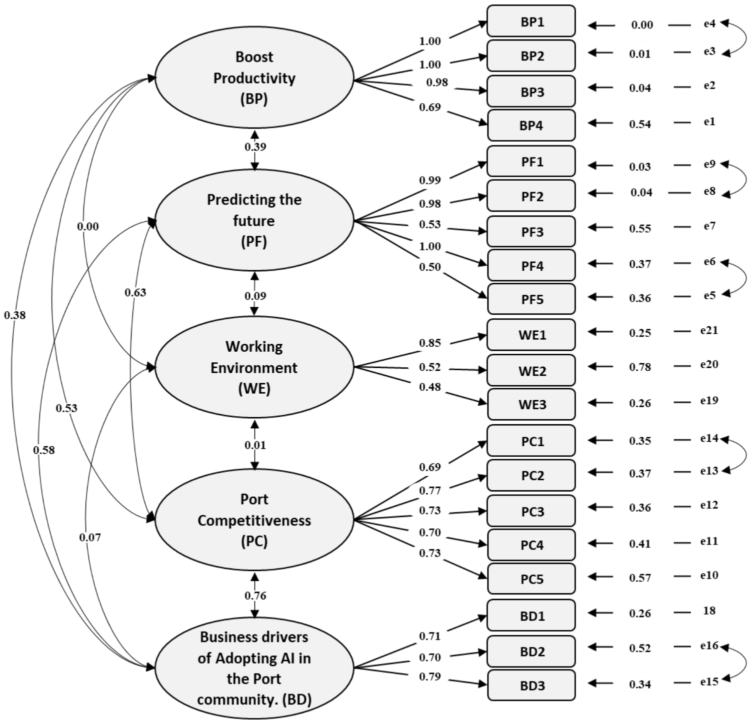
Source: Mohamad et al., (2019)

The discriminant validity was tested using SPSS by calculating Cronbach's *a* to confirm that each construct and its indicators are distinguished from the other constructs. As shown in Table 6, the five constructs are distinct, and the measures confirm the discriminant validity (Akter et al., 2016).

6.2 CFA

To assess the adequacy of the hypothesized model for all items, CFA using AMOS software was conducted in the 129 validated samples. Based on EFA analysis: Boost Productivity, Predicting the future, Port Competitiveness, Working Environment as a priori factors for business drivers of adopting AI in the ports community. Figure 2 shows the final CFA measurement model, and the measured variables represent each construct using AMOS 20.0. the same model was also used to examine convergent and discriminant validity. The model represents the final measurement model of AI capabilities factors. To reduce the value of x^2 and achieve an acceptable model fit, the two-headed arrow is used to connect the two observed variables using AMOS (Górecki et al., 2018). The figure implies that business drivers of adopting AI in the ports community, Boost Productivity, Predicting the future, Port Competitiveness, and Working environment five are correlated factors. The figure also shows that the fit indices reporting acceptable loading are statistically significant for the AI Capabilities in the ports community. The figure shows that the construct "Boost Productivities" has high positive correlations with "Predicting the Future", "Operational Efficiency", and "AI Capabilities of 0.38, 0.43, and 0.38, respectively. However, the construct "Boost productivity" does not correlate with "Working environment."

Similarly, "Predicting the future" has a positive correlation with "Working Environment," "Port Competitiveness," and "AI Capabilities" of 0.08, 0.63, and 0.58, respectively. However, the construct "Working Environment" does not correlate with "Port Competitiveness" and has a low positive correlation with "Business drivers of Adopting AI in Ports community," with 0.06. Finally, "Port Competitiveness" is correlated with "Business drivers of Adopting AI in Ports community" of 0.76.

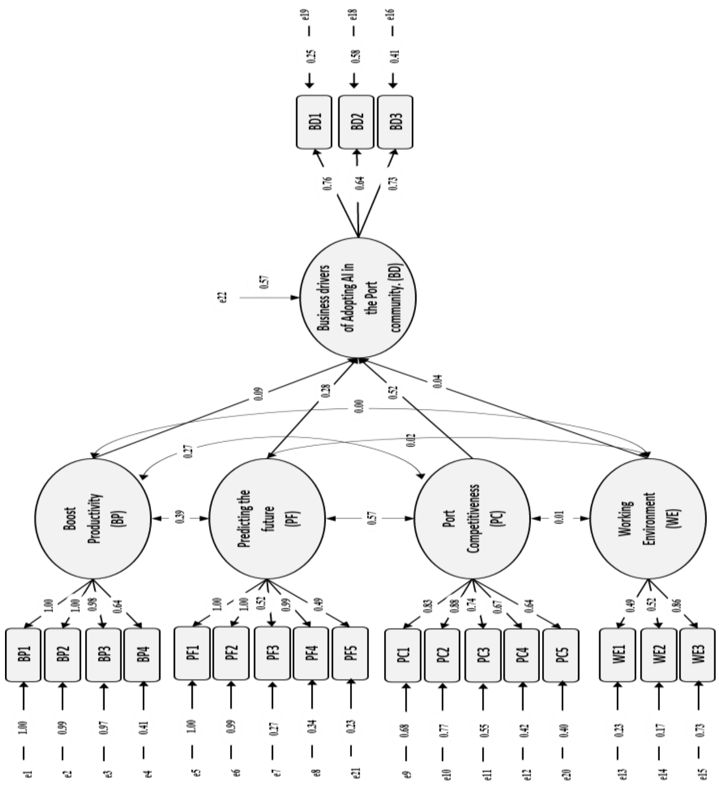


χ^2 = 1095	TLI = 0.920	CFI = 0.942
CMIN/DOF =1.69	DOF = 188	RMSEA=0.072

Figure 3. CFA measurement model for business drivers of adopting AI
Source: Mohamad et al., (2019)

To obtain acceptable Model fit indices: the comparative fit index (CFI), NFI, root mean square of error approximation (RMSEA), and Tucker–Lewis index (TLI) were selected to judge the model fit. The CFI, TLI, and NFI threshold should be greater than 0.9, and RMSEA must be lower than 0.08 (Garg and Khurana, 2017). The CFI, NFI, TLI, and RMSEA values are 0.815, 0.899, 0.947, and 0.080 respectively. The structural AI capabilities model was the next step and hypothesized relationships were constructed using the maximum likelihood estimation method and a covariance matrix with 21 measurement items. Figure 3 shows that the structural equation model implies that higher-order latent factors show overall AI capabilities correlations among Boost Productivity, Predicting the future, Operational Efficiency, and

Working environment, showing clear correlation measurement factors for AI capabilities. The model shows an acceptable goodness-of-fit and the significance of the coefficient estimates for all five. The highest impact is on operational efficiency, followed by predicting the future, and the lowest impact is on the working environment, followed by Boosting productivity.



χ^2 = 1095 TLI = 0.920 CFI = 0.791
CMIN/DOF =1.78 DOF = 199 RMSEA=0.075

Figure 4. Second-order measurement model for business drivers of adopting AI
Source: Mohamad et al. (2019)

6.3 Hypothesis testing of the structural model and discussion.
Table 7 and Figure 4 show the path coefficients analysis for Business Drivers of adopting the AI model. The study reveals the significance of the hypothesized relationships among the four influence perceptions and AI business drivers.

Table 7. Fit indices of model and validity

Relationship	**Standard path coefficients**	***P* Value and support of hypothesis**	**Support of hypothesis**
Boosting Productivity → Business Drivers of Adopting AI	0.09	0.002	[H1] Supported
Predicting the Future → Business Drivers of Adopting AI	0.28	0.014	[H2] Supported
Operational Efficiency → Business Drivers of Adopting AI	0.52	***	[H3] Supported
Working Environment → Business Drivers of Adopting AI	0.04	0.013	[H3] Supported

Source: Mohamad et al., (2019)

In H1, it was hypothesized that Boosting productivity is significantly driving AI adoption of Port Digitalization. The results show (Table 12; Figure 2) that H1 is supported with a standardized coefficient, b = 0.09 at a significance of p 0.002. In H2, it was hypothesized that Predicting the future is significantly driving AI adoption of Port Digitalization. The results show that H2 is supported with a standardized coefficient, b = 0.28 at a significance of p 0.014. This result confirms the results of the previous Abidoye et al. (2019) investigated the use of AI to predict property price indexes. The study also demonstrates the impact of Olarewaju et al. (2020) developed a framework to understand the applicability of an AI-based model in predicting stock prices in the Nigerian market. Also, the same concept was used by Jafarian-Namin et al. (2020) to forecast wind power generation in an area through different AI methods. This implies that any factors related to Predicting the Future contribute positively toward the AI adoption in the ports community. Also, H3 suggests that Improving Working Environment is significantly driving the AI adoption of Port Digitalization. It has a significant and positive impact, confirmed by the estimates of b = 0.52; *p* ***. This implies that any Operational Efficiency factors will hugely contribute to the AI adoption in the ports community. Hence, Operational Efficiency factors have a higher effect on the adoption of AI technology than the other factors, and this confirms the results of previous studies (Wankhede etal., 2021). These studies developed a technique for improving operational efficiency and reducing operating costs using AI. Finally, H4 predicts that Improving Port Competitiveness is significantly driving AI adoption of Port Digitalization by the estimates of b = 0.04; *p* =0.13.

7. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

The current research study explored and determined the intelligence business drivers of port digitalization. The analysis expressed the role of the business drivers (Boost Productivity, Predicting the future, Port Competitiveness, and Working environment) to adopt AI technology in the ports community. The critical phenomenon of AI adoption in the ports community and its applications are considered in the current study to define the relationship and role of business drivers in the ports community in adopting AI Solutions. The study is novel in explaining and empirically examining the role of Business drivers of AI adoption in the ports community. The study was conducted on the port industry and its stakeholders, including vessel owners, customs, and traders. And the study found that the business drivers significantly influence the AI adoption in the ports community.

We argue that due to the complex nature of digital transformation in the ports community and the lack of AI-based solutions, new processes combine the best of past AI practices and propose and build new applications based on the reported business drivers in this study. Therefore, AI applications will become more evident and mature, which confirms the results of previous studies (Rahman et al., 2021) that an aspect of AI adoption requires assurance. Assurances from the companies that develop AI to the user base that the new AI algorithm will perform as intended and without failure considering the three significant factors of AI application assurance: reliable, dependable, and explainable. If the business drivers behind adopting the AI technology are not developed and demonstrated, AI will surely experience another new journey of non-maturity. AI systems currently cause real-life harm, and companies repeatedly make the same mistakes in the AI solution design and development of AI systems. The failures of AI systems pose serious risks (McGregor, 2020). Therefore, we introduce a systematized collection of business drivers to drive the implementation of AI systems in the ports community.

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