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Digital transitions at the port: human capital, technology adoption and operational efficiency among independent truckers

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Abstract

Purpose – In this study we seek to understand the relationship between a trucker's level of human capital, their ease of use of new technology innovations and how this translates into overall port efficiency at the Port of Tema.
Design/methodology/approach – To perform this inquiry, we develop a five-construct framework with trucker's self-efficacy and mentorship moderating relationship between human capital, perceived ease of use (PEOU) of new technology innovations and port efficiency. We utilize a structural equation model (SEM) to analyze data retrieved from 174 independent truckers at the Tema Port.
Findings – We find significant relationships between a trucker's human capital variables such as education, skills and training and PEOU, which in turn had effects on efficiency. We also interestingly found that truckers with a higher self-efficacy did not necessarily transition faster with use of the new technologies and those that received mentoring support had varying effects on ease of use of new technology.
Originality/value – We present new and interesting evidence on the new technology innovations at the port, their perceived assimilation into the relatively lowly-educated workforce and how these antecedents affect perceived operational efficiency in a unique African and port context.

Keywords Human capital, Innovation adoption, Port efficiency, Mentoring, Self-efficacy, Africa
Paper type Research article

1. Introduction

In recent times, issues of innovation management have become essential to workforce development and operational efficiency literature (see De Vincenzi & da Cunha, 2021; Vieira, Bonfim, & da Cruz, 2021). Understanding the operationalization of institutional technology innovations and consequently the assimilation of these innovations by a widespread of stakeholders to drive productivity, has been a growing area of interest for business scholars

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(Silva & Di Serio, 2021). Li (2025) shows that even within R&D-intensive environments, performance effects are shaped by contextual and institutional variables. This heterogeneity validates our focus on independent truckers in a port setting with varied human capital levels. Theories of technology and innovation adoption suggest that adoption depends on the perceived usefulness (PU), ease of use and external factors like mentorship and self-efficacy (Ma, Mamun, Masukujjaman, & Ja'afar, 2025). In 2015, the Ghana Ports and Harbours Authority (GPHA) and some private sector actors (APM Terminals and Bollore Transport Logistics) entered into an agreement to develop a new port Terminal that could handle the growing container numbers at the Port of Tema (http://mps-gh.com/about/). The development of the new Terminal resulted in the emergence of new technologies such as the Truck Appointment System (TAS) that ensures efficient allocation of pick-up and exit times for truck drivers at the terminal. New technology and innovation have good returns for individuals and organizations (Oliveira & Fraga, 2011). However, prior research shows that the usefulness of new technology or innovation depends on the adaptability to user skill levels (Venkatesh, Thong, & Xu, 2023). Danquah and Amankwah-Amoah (2017) have also noted that while new technology is advantageous, it needs to be integrated within the specific context of the users. In this paper, we seek to address the question of: how human capital of independent truckers influences their perceived ease of use (PEOU) of new port technology and its ultimate impact on port efficiency? We also examine the roles of mentorship and driver self-efficacy in this relationship.

We frame our thesis within the technology adoption model (TAM) literature (Norzaidi, Chong, Murali, & Salwani, 2007) and argue that technology adoption presents positive outcomes for organizations and individuals (Oliveira & Fraga, 2011). However, for these benefits to be realized, one of the essential elements is the ease of use of the new technology. We define PEOU as the extent to which a truck driver perceives the TAS as requiring minimal effort to engage and use (Patwardhan, Pandey, & Dhume, 2014). The key benefit of the TAS is to improve efficiency at Terminal 3. While the literature of the impact of technology adoption is not lacking, few studies have focused on the linkages between technology adoption and efficiency of use especially within the port context and within a sub-Saharan setting (Wiafe, Koranteng, Tettey, Kastriku, & Abdulai, 2019). Theoretically, there is also a dearth in scholarly works investigating prerequisite antecedents to the TAM. For instance, Kamal, Shafiq, and Kakria (2020) express concerns with TAM constructs explaining relevant pre-conditions of end users of the intended technology. These issues expose the ability of TAM to adequately infer constructs such as PEOU where there may be differences in levels of comprehension to the target technology to be adopted (Kamal *et al.*, 2020; Korkmaz, Fidanoglu, Ozcelik, & Okumus, 2022) We therefore step back and question the role of human capital in the form of education, experience, port training and extra driving skills on the new technologies adoption at the new Terminal in the Port of Tema. Because driving is a skill that focuses on ability and mental states, we also explore the moderating role of self-efficacy and mentorship on the above relationship. Mentorship references the informal guidance that truck drivers receive from experienced drivers (Ramalho, 2014) and other agents on the use of this new technology while self-efficacy is about the driver's belief in his or her own abilities (Lyons & Bandura, 2019) to use the new technologies.

By answering these questions, we make some contributions first to the port management literature. Secondly, we are able to link human capital theory and technology adoption theory in one study with the former being an investigative theoretical antecedent. We then explore the impact of these two constructs on the efficiency of the Port of Tema. Thirdly, we present new evidence on the technology adoption issues and how they affect perceived port efficiency in the African context. This is essential, because different environments present different conditions, with which organizational actors have to contend. Finally, we provide evidence on the variations in the relationship between human capital, PEOU and port efficiency with respect to the varying driver self-efficacy and availability of mentorship opportunities.

The rest of the manuscript reviews the literature, presents the study methodology and findings. The final sections discuss the findings and make conclusions.

2. Literature review

2.1 Theoretical background: technology acceptance model

The Technology Acceptance Model is a framework that describes how individuals accept and use new technology. The TAM is fundamentally an information systems theory that has permeated social science and organizational management literature (Chirchir & Simiyu, 2016). Several researchers have utilized the TAM throughout the years to describe an individual's adoption of an information system. Another variant of TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT) that integrates multiple adoption theories, making these set of theories effective at predicting technology innovation adoption across multiple industries (Gupta & Ahmad, 2023), especially the two primary components of the TAM are PU and PEOU. This study uses PEOU as proxy for the framework (Venkatesh & Davis, 1996; Pillai & Sivathanu, 2020). PEOU is "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989 p. 5). Assuming all other factors remain constant, the likelihood that people will embrace a technology increases with ease of use. From the perspective of theoretical advancement, Straub (2009) asserts that TAM examines the individual and the decisions an individual makes to accept or reject a specific innovation. Recent empirical work by Amboage, Monteiro, and Bortoluzzo (2024) supports the practical application of UTAUT in logistics-oriented technology adoption, showing how behavioral intention and usage duration both predict effective uptake. This aligns with our emphasis on PEOU as a mediating mechanism. Research suggests adding human capital considerations to UTAUT to better explain adoption disparities (Ma *et al*., 2025). Adoption is not only the choice to accept an innovation, but also the degree to which that innovation is integrated into the appropriate context. In underpinning the study, the framework is explained such that in a new context, new technology depends on some prerequisite human capital possession which in turn infers "organizational" efficiency.

2.2 Human capital, perceived ease of use and port efficiency

Various scholars have proven the relationship between technology and human capital. Findings by Zuo, Wheeler, and Sun (2021) revealed the positive relationship between human capital and drone technology adoption in Australia. Technology adoption success depends on workforce skill alignment with digital tools and structured training (Weinberg, 2004; Fonseca, Lagdami, & Schröder-Hinrichs, 2021). Ballestar, García-Lazaro, Sainz, and Sanz (2022) also maintain that a combination of human capital and technology is critical to increasing the efficiency of the technology transformation process. Che and Zhang (2018) assert that a country's ability to be efficient in adopting high-end technology greatly rests on the level of skill of its labor force to handle this technology. The scholars show that increases in skilled labor force in a developing country facilitate the adoption of frontier technology and hence raise productivity (Che & Zhang, 2018). Pardim, Contreras Pinochet, Viana, and Souza (2024) emphasize the importance of unlearning in fostering innovation uptake, particularly in organizational contexts where legacy routines dominate. This provides a useful lens for understanding why experience may not directly correlate with technology adoption among independent truckers. Weinberg (2004) also shows this, that technological progress is generally biased toward skill, and so the skill and experience of the labor force is a fundamental determinant of their ease of technological adoption or use. Concurrently, Fonseca *et al*. (2021) stressed the need for promoting scientific standards of education and training on technological applications that are emerging in order to develop the appropriate human capital to ensure efficiency of use. These authors maintained that more specialized human capital is needed to match the advancements in technology. Jaiswal, Arun, and Varma (2022) finds that with the

development of AI technologies, demand for high levels of human capital will continue to rise. Education enhances digital literacy, yet some studies suggest it may hinder adaptation to simpler systems (Uematsu & Mishra, 2010). From our review, it is evident that the level of human capital is relevant for technological adoption, which leads to enhanced productivity hence it can be posited that:

H1. Human capital (education, experience, driving skill and port training) has a positive and significant effect on ease of use of new port technologies.

H2. Ease of use of new port technologies mediates the relationship between human capital and perceived port efficiency.

2.3 Moderating role of mentorship

Dugguh and Galadanchi (2014) define employee mentoring as the process of using specially selected and trained individuals to provide guidance and advice which will help to develop the careers of the subordinates allocated to them. Mentorship plays a role in the adoption of technology in the workplace. According to Torriani-Pasin (2021), mentorship could aid rehabilitation professionals to improve their skills and knowledge in relation to Health technologies. Mentorship improves technology acceptance by reducing resistance and fostering confidence among adopters (Dorner & Kumar, 2016). Dorner and Kumar (2016) describe how invaluable mentorship was in enabling a group of teachers in Hungary to integrate technology into their classroom activities. Kopcha (2010) also recognized how mentoring of teachers proved to be a valuable strategy in enhancing their ability to integrate technology into classroom activities. Similarly, Cypress (2019) concluded that inexperienced researchers needed mentors to guide them in using computerized software for both management and analysis of data as these tasks can be both time consuming and challenging. The role of mentorship in technology is essential because the absence of it can be an obstacle to the effective implementation of new technology (Almuntaser, Sanni-Anibire, & Hassanain, 2018). Amankwah-Amoah (2020) highlights the fact that mentorship programs are crucial for fostering organizational learning and improving technology acceptance among workers. In the logistics sector, experienced truckers can facilitate knowledge transfer to less experienced colleagues, reducing the resistance to new port management technologies. Without structured mentorship programs, independent truckers may struggle to navigate the complexities of digital systems, limiting efficiency improvements. We therefore hypothesize that:

H3. Mentorship moderates the mediated relationship between human capital, perceived ease of use and port efficiency.

2.4 Moderating role of self-efficacy

Self-efficacy is an individual's beliefs about their capabilities to produce at designated levels of performance that exercise influence over events that affect their lives (Lyons & Bandura, 2019). Self-efficacy influences technology adoption and ultimately leads to better performance at the workplace. Adami *et al.* (2022) assessed the adoption of technology in construction sites and found that factors such as self-efficacy help construction site workers to safely operate robots. Marikyan, Papagiannidis, Rana, and Ranjan (2022) proved that self-efficacy determined the intention to adopt block chain technology. In addition, Fischer-Preßler, Bonaretti, and Fischbach (2022) discovered that what inspires people to adopt mobile emergency technology is self-efficacy. Charness and Boot (2009) provided evidence that attitudes and abilities are among the most powerful predictors of technology use. This was proven by Ngusie, Kassie, Chereka, and Enyew (2022), who found self-efficacy to be significantly linked to health-care providers' readiness to use electronic health records. This

means that low technology adoption could be attributed to low self-efficacy as confirmed by Na and Sheu (2022). Therefore, we hypothesize that:

H4. Self-efficacy moderates the mediated relationship between human capital, perceived ease of use and port efficiency.

3. Methods

3.1 Research context

The Port of Tema was birthed out of the necessity to support the massive imports into Ghana (Hilling, 1966). As of 1951, the then existing ports were woefully inadequate to serve the dire need for ports through which consumer goods and developmental materials could be brought into the country (Hilling, 1966). By 1962, the Port of Tema had been constructed, making it the largest man-made harbor in Africa. In the late 1990s, the Government of Ghana and its global development partners sought to address this issue post the collapse of the Black Star Line in 1997 through the Ghana Trade and Investment Gateway Project (Gateway Project) established in 1998 (Aryee & Hansen, 2022). The project largely driven by a trade facilitation focus also sought to develop the port infrastructure to reduce the cost of imports and exports from Ghana, ultimately, making Ghana the entrepôt to West Africa (Chalfin, 2010). Until recently, the GPHA was solely responsible for the management of the Port of Tema overseeing its activities. In June 2015, the GPHA entered a joint venture with private company Meridian Port Holdings Limited, which was a joint venture with APM Terminals and Bolloré Transport and Logistics, to increase the capacity of the Port of Tema to a capacity that can accommodate a wider range of berthing ships and to improve work flows to make the Port of Tema the trade hub in the West African region (Lawer, 2019).The Port of Tema may not be the largest port in West Africa in terms of capacity, but it has made significant progress in recent years in terms of infrastructure development, efficiency and connectivity such that it plays a crucial role in Ghana's economy and serves as an important trade gateway for the West African sub-region with its biggest competitors being the Port of Abidjan in Ivory Coast and the Lagos Apapa Port in Nigeria (Lawer, 2019). Such arrangements are not new to sub-Saharan African ports as other ports in Africa have received similar logistics investments in their ports (Yang, He, Zhu, & Notteboom, 2020). The question then is, are these investments in technology logistics resulting in enhanced operations especially for small stakeholders in the ports' value chain?

3.2 Data collection, measurement and operationalization

The study uses a purposive sampling technique to survey 174 independent truck drivers at the Port of Tema and administered questionnaires to them based on their willingness and ability to complete the instrument as prescribed by literature (Malhotra & Krosnick, 2007). The sample size selection was based on Hair, Anderson, Babin, and Black (2010) SEM requirements. In the construction of the questionnaire for the study, verified constructs from literature were used. Human capital is measured based on the four items of Vidotto, Ferenhof, Selig, and Bastos (2017), (education, experience, skill and training). Apart from experience, which was measured by actual years in service, all the other human capital metrics were based on a binary measure of each item (Yes = 1, No = 0). The study also conceptualized and measured PEOU from the constructs of Patwardhan *et al.* (2014). The scale for mentorship was adopted from the study of Dalton, Davis, and Viator (2015). In conceptualizing self-efficacy, measures from the study of Jackson, Gucciardi, and Dimmock (2011) were utilized. The scales of mentorship and self-efficacy were further transformed into a binary variable to form a suitable basis for the group-based structural analysis. This was done based on the recommendation of Jones and Nagin (2013) to make constructs adequate for the structural enquiry. Lastly, the data on port efficiency were also collected and scaled through a 5-point Likert scale, the efficiency of use construct was adopted from a four-item (see Table 2) measurement factor in the work of Panero, Lane, and Napier (1997).

3.3 Data analysis procedure

After data collection, inputting of raw data, introductory coding, data cleaning and subsequent data analysis was done using STATA 15. A Confirmatory Factor Analysis (CFA) was adopted in this research to ensure constructs and factor adequacy for the study which is appropriate for the usage of structural equation modeling (Huber, 2014). Previous studies confirm CFA's role in validating UTAUT constructs across industries, including logistics (Ma *et al.*, 2025). In confirming the constructs for the study, a factor analysis was conducted to ensure that the constructs as well as the critical inspection of the loadings were in accordance with fitness thresholds. From the results, the loadings lie within the interval of 0.613 and 0.981 while the Cronbach's Alpha values also ranged from 0.883 to 0.994. The measurement model was then evaluated in accordance with Hair, Hult, Ringle, and Sarstedt's (2016) recommendations and found to be appropriate for the confirmation of the constructs. These criteria are commonly used in structural equation modeling (Hair *et al.*, 2016). The research then uses discriminant validity and a convergent validity based on Rezaei and Ghodsi's (2014) framework to determine the validity of results. The discriminant validity used a cross-loading criterion and construct correlations whereas an Average Variance Extracted (AVE) and factor loadings were adopted in convergent validity. The AVE values of the constructs which are between 0.545 and 0.943 (see Table 1) are suitable for the threshold of values above 0.5 which indicates enough discriminant validity to ensure no collinearity among variables. The CR values between 0.701 and 0.993 also indicate convergence amongst individual constructs which satisfies the adequacy threshold of values greater than 0.7.

4. Discussion of findings

The results of the study indicated in the general direct model (Model 1) that education of truck drivers has a negative significant influence on the truck drivers' PEOU of the new port systems ($\beta = -0.2137$, p-value <0.01). Studies indicate educated workers may struggle with simplified technology due to prior knowledge over-reliance (Uematsu & Mishra, 2010). Experience of truck drivers had no significant relationship with PEOU of the new port systems ($\beta = 0.0013$, p-value >0.05). However, truckers had a positive significant relationship with the PEOU of the new port system ($\beta = 0.4169$, p-value <0.001). Also, port training has a negative significant influence on port truck drivers' PEOU of the new port systems ($\beta = -0.1421$, p-value <0.01. The study further indicates through its findings that port truck drivers' PEOU of the new port system is positively and significantly linked to the efficiency of use of the port systems ($\beta = 0.7453$, p-value <0.001). Research confirms that ease of use enhances efficiency in digital operations, especially in logistics (Tetteh Anang, Alhassan, & Danso-Abbeam, 2020a).

Results from the indirect effects analysis show that PEOU of the port system significantly and negatively mediates the relationship between education and efficiency of use of port systems ($\beta = -0.1593$, p-value <0.01) has no mediation relationship between experience of drivers and the efficiency of use of port systems, significantly mediates the relationship between drivers' skill and efficiency of use of port systems ($\beta = 0.3107$, p-value <0.001) and then significantly and negatively mediates the relationship between drivers' training and efficiency of use of port systems ($\beta = -0.1059$, p-value <0.01). The findings further reveal moderations to the above results when mentorship and self-efficacy were present or not in the model (see Table 2).

The topic of port efficiency has been extensively discussed in maritime and port trade related literature. However, the issue of human capital at the port and the fastidious use of port technology to achieve efficiency lags behind in the port related discourses. This study set out to unravel the relationships between human capital, PEOU of port technologies by port truck drivers and their overall connections to port efficiency especially at the Port of Tema where new port technologies have been instituted. To do this, we examine the mediating role of PEOU on the relationships between port truck drivers' education, port

Table 1. Confirmatory factor analysis, reliability and validity analysis

Items	Loading	CR	AVE	α
Perceived ease of use		*0.850*	*0.588*	*0.906*
My interaction with new port truckers' system is clear and understandable	0.825			
I find new port truckers' system to be flexible to interact with	0.817			
I feel comfortable and convenient while using the new port truckers' system	0.777			
The new port truckers' system is easy to learn and use	0.635			
Mentoring		*0.993*	*0.943*	*0.994*
My mentor helps me attain desirable assignments, including engagements with important clients	0.969			
My mentor uses his/her influence to support advancement in my work	0.981			
My mentor uses his/her influence for my benefit	0.964			
My mentor helps me learn different responsibilities within the firm	0.981			
My mentor gives me advice on how to attain recognition in the firm	0.974			
My mentor suggests specific strategies for achieving my career aspirations	0.968			
My mentor and I frequently get together informally after work by ourselves	0.970			
My mentor and I frequently socialize one-on-one outside the work setting	0.976			
My mentor and I frequently have one-on-one, informal social interactions	0.957			
Self-efficacy		*0.701*	*0.585*	*0.947*
Able to perform all the difficult technical aspects of new port truckers' system processes	0.705			
Communicate effectively with port systems at all times	0.764			
Stay mentally strong during the new port truckers' system processes	0.860			
Put in all your effort when working with the new port truckers' system	0.747			
Play an effective role in resolving conflict that arises between me and port authorities during the process	0.617			
Stay in optimal physical condition as trucker at the Newport	0.857			
Play a role in devising effective goals as a trucker at the Newport	0.663			
Carry out the tasks the freight forwarders and port authorities set	0.877			
Play an effective role in maintaining a good relationship with freight forwarders and port authorities	0.584			
Always be well organized at port sessions	0.749			
Always carry out your freight forwarders and port authorities' instructions	0.880			
Perform all the tactical plans set by freight forwarders and port authorities	0.874			
Consistently reach freight forwarders and port authorities expectations	0.814			
Deal effectively with setbacks in your relationship with your freight forwarders and port authorities	0.617			
Efficiency of use		*0.826*	*0.545*	*0.883*
The new port truckers' system processes save time on work that would have taken me longer otherwise	0.790			
The new port truckers' system processes make our work professional-looking	0.794			
I think work by the old truckers' system was better even though it is faster on the new port truckers' system (RC)	0.741			
The new port truckers' system processes ensure higher-quality work than I could do otherwise	0.613			

Note(s): KMO = 0.894

Source(s): Authors

driving experience, possessed skills and port training which sum up their human capital and the perceived efficiency of the ports. The study hypothesizes that human capital positively and significantly influences PEOU and PEOU has similar influences on efficiency.

Table 2. Structural model estimates

Structural paths	Full Model 1 β (SE)	Mentorship = 0 Model 2 β (SE)	Mentorship = 1 Model 3 β (SE)	Self-efficacy = 0 Model 4 β (SE)	Self-efficacy = 1 Model 5 β (SE)
Direct effects					
Education → PEOU	−0.2137 (0.0688)**	−0.2364 (0.1069)**	−0.1513 (0.1200)	−0.2446 (0.0661)***	−0.0903 (0.1959)
Experience → PEOU	0.0013 (0.0031)	0.0024 (0.0059)	0.0009 (0.0048)	−0.0039 (0.0029)	0.0153 (0.0097)
Skill → PEOU	0.4169 (0.0762)***	0.5589 (0.1023)***	−0.0399 (0.1924)	0.3671 (0.0616)***	−0.7526 (0.4982)
Port training → PEOU	−0.1421 (0.0635)**	0.0885 (0.1055)	−0.4081 (0.1118)***	−0.1981 (0.0578)***	−0.0671 (0.1889)
PEOU → EU	0.7453 (0.0816)***	0.8256 (0.0656)***	0.3386 (0.0939)***	0.8232 (0.1145)***	0.4038 (0.1074)***
Indirect effects					
Education → PEOU → EU	−0.1593 (0.0528)**	−0.1952 (0.0922)**	−0.0512 (0.0438)	−0.2013 (0.0581)**	−0.0365 (0.0802)
Experience → PEOU → EU	0.0010 (0.0228)	0.0019 (0.0049)	0.0003 (0.0016)	−0.0032 (0.0025)	0.0062 (0.04232)
Skill → PEOU → EU	0.3107 (0.0621)***	0.4615 (0.0956)***	−0.0135 (0.0922)	0.3022 (0.0589)***	−0.3039 (0.00423)
Port training → PEOU → EU	−0.1059 (0.4806)**	0.0731 (0.0867)	−0.1382 (0.0544)**	−0.1631 (0.0504)**	−0.0271 (0.0761)
RMSEA	0.023	0.024	0.046	0.052	0.035
CFI	0.942	0.822	0.862	0.842	0.825
TLI	0.989	0.884	0.868	0.880	0.849
SRMR	0.080	0.060	0.060	0.040	0.050
(df)	174	91	83	120	54

Note(s): ***$p < 0.001$, **$p < 0.01$ and *$p < 0.05$

Source(s): Authors

However, the study found that truck drivers who had no formal education had a better chance at PEOU of the new port technologies than those with education. This finding, though interesting, is not common to the technology adoption literature. Prevalently, education is supposed to induce higher levels of PEOU of technology (Dharshing, 2017). However, Uematsu and Mishra (2010) show that there are instances where education may be a barrier to technology adoption. Further probing into phenomena and engagements with stakeholders at the port reveal that this situation may not be at all surprising as uneducated truck drivers rely heavily on freight forwarding agents to interface with the new technologies and hence may have a higher PEOU relative to the educated driver who engages and navigates the systems personally. The study also showed that truck drivers' experience did not influence their PEOU of new port technologies. Echoing Farida and Setiawan (2025), our findings affirm that structured managerial mechanisms – such as mentorship and targeted training – enhance the performance of decentralized agents through mediated innovation adoption pathways.

The study finds a positive and significant relationship between drivers' skill and their PEOU of new port systems. In juxtaposing this result to existing theory, we show that the possession of advanced skills by truck drivers enhances their exploitation of the new port technology and ensures PEOU. As expected, possession of the required technical skills ensures easy adoption of technology (Kumar, Engle, & Tucker, 2018). Port training on the other hand returned an inverse relationship with PEOU of new port technology. This means that truck drivers who had had some port trainings previously are associated with lesser levels of PEOU of the new port systems. Again, we rely on the logic presented by the port stakeholders that untrained port truck drivers may receive help from freight forwarders at the port hence their ability to find new systems easier to use than those who are left to navigate on their own based on their past training. Also, we reckon based on our engagements with the truck drivers and other stakeholders that exposure to training materials may be a bit scarce to the drivers which explains the enquiries return negative coefficients. Finally, the study further tests the indirect effects of PEOU on the relationships between human capital variables and port efficiency. The results show that PEOU partially mediates the relationships between education and port efficiency, skill and port efficiency and port training and port efficiency.

All these findings had similar inference directions as in the direct effects of human capital and PEOU. In all, the study finds PEOU of new port systems to be positively associated with efficiency at the port. This indicates the collectivist benefits of ease of use of new port technology on the overall work output of the port. As indicated in extant studies, higher levels of technology adoption have been found to lead to efficiency in technology operations (Tetteh Anang, Alhassan, & Danso-Abbeam, 2020b). This explains the essence of stakeholders at the port ensuring that port employees are highly conversant with the operational technologies of the port to yield higher levels of efficiency. The moderation effects of mentorship and self-efficacy of the port truck drivers on the entire structural model (see Figure 1) was tested. This was done to understand how personal characteristics and informal guidance could affect the PEOU of new port systems. The results indicate that there is a negative moderation relationship between human capital and low levels of mentorship on PEOU. The same effect was insignificant within higher levels of mentorship. This indicates that truckers are better off within higher levels of mentorship than in lower levels that have negative connotations to PEOU of new port technologies. Also, there is a similar inference when considering the moderation effect of drivers' self-efficacy on the relationship between education and PEOU. Higher levels of self-efficacy are known to ensure technology uptake (Fox & Connolly, 2018). However, there was no vivid confirmation of this in the study. Meanwhile, self-efficacy returns inconsistent levels of PEOU when paired with the human capital effect. A graphical representation of these interaction effects of mentorship and self-efficacy on the relation between human capital and PEOU is seen in Figures 2 and 3 respectively.

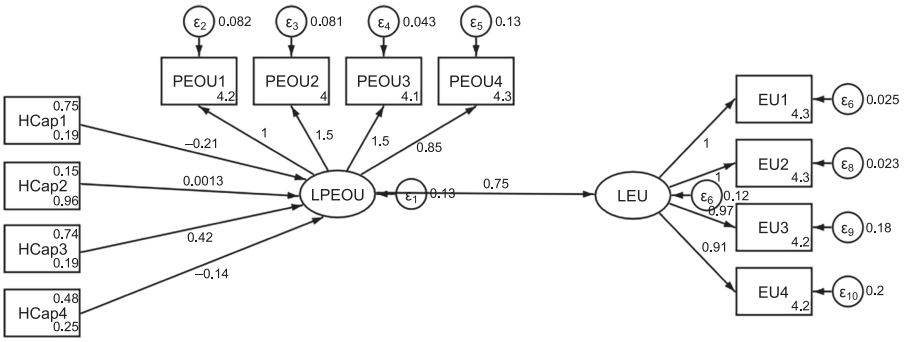

Figure 1. Full structural model. Source: Authors

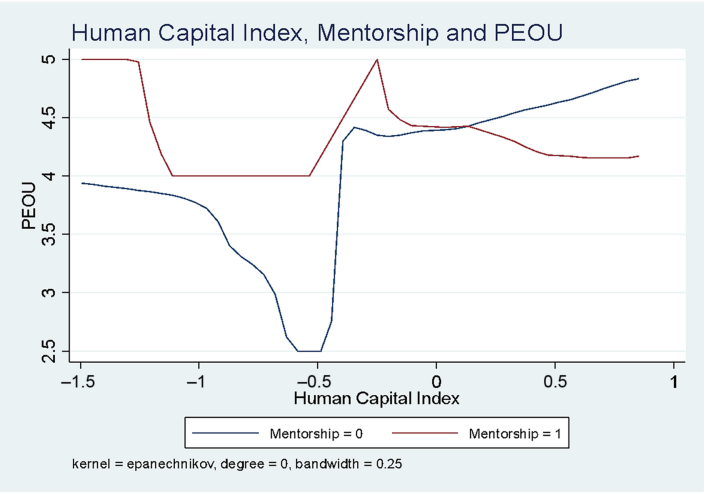

Figure 2. Interaction effect between human capital index, mentorship and perceived ease of use of new port technology. Source: Authors

5. Implications and conclusion of the study

The study presents both practical and theoretical implications for management and scholarship, respectively. From the findings, human capital (education, skills and training) largely informs PEOU of new port technologies. However, users should be aware that past experiences in terms of years at work? Do not necessarily influence the effectiveness of new port technology adoption. As Su, Wang, and Yan (2018) explain, past experiences favor exploitation rather than exploration such that since there is a new technology introduced, experience on the old port system may not be relevant to activities of the new port. Aryee and Hansen (2022) even argue that experience can have an adverse effect, because people familiar with previous systems hesitate to invest time in learning new systems, if they are not convinced that they will in fact serve them better. Also, education and port training return negative results, hence port managers need to take a second look at their training regimes to make them reflect these engagements with port truck drivers. Versiani, Abade, de Carvalho, and De Muÿlder (2024) suggest that ineffective project knowledge management can weaken organizational memory, limiting the capacity for users to

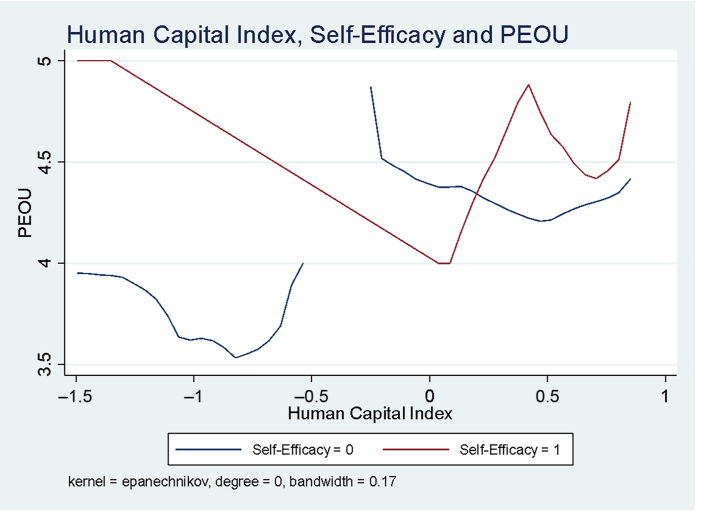

Figure 3. Interaction effect between human capital index, driver self-efficacy and perceived ease of use of new port technology. Source: Authors

internalize new systems. This may explain the inverse relationship between port training and PEOU in our study. We also observe from the results of the study that extra skills are good determinants of ease of use of new port technology and, subsequently, port efficiency. Digital literacy programs should be designed for varying education levels to ensure smooth adoption (Gupta & Ahmad, 2023). Also, managers should in their licensing regimes give some credit to drivers with these extra skills. PEOU has a positive effect on port efficiency, and this requires managers to work on the antecedents that enhance PEOU. In the line of theoretical implications, the study confirms that there are pre-conditions to PEOU of new technology adoption. Concurrently, scholars should consider probing various preconditions, especially those related to new technology users and adopters to properly explain why the TAM is inefficient in certain technology adoption settings. As indicated in the study, human capital variables such as added skills help drivers achieve PEOU. Also, Coletto, Caliari, Bernardes-de-Souza, and Callegaro-de-Menezes (2024) highlight how actor roles evolve dynamically within innovation ecosystems. This aligns with our findings that peer mentorship and external agents (e.g. freight forwarders) are critical actors in facilitating ease of use among less-educated truckers.

To conclude, the study set out to explore the nexus between human capital, PEOU and port efficiency from the context of port truckers in the Port of Tema. The findings suggest that human capital is a necessary precursor to PEOU likewise experience being an ambiguous construct to human capital that be contextually evaluated especially within industries dominated by technology-based organizations. The study findings contribute to the literature on entrepreneurship and dynamic capability issues in the maritime sector particularly in the face of disequilibria situations. The findings although robust also pave the way for future studies in the area. First, the current study adopts a survey and primary data approach; however, a quasi-experimental approach can provide another means of testing the robustness of the current findings if authors can get access to the required data sets. Second, studies on the effect of "attitudes" that may obstruct adoption of new technologies. And thirdly, the challenge of maritime blindness is Africa-wide as noted in previous studies (Ojadi, 2020; Maneno, 2019; Oruwari, 2021). Consequently, the study framework and approaches can be tested in other African ports to understand the sensitivity

of the findings to different institutional and local contexts. Finally, as Amankwah-Amoah (2021) suggests, future research should consider the role of institutional support in shaping technology adoption in developing economies. Given that independent truckers operate in highly fragmented logistics markets, understanding the interplay between workforce training, regulatory frameworks and digital literacy can offer valuable insights into enhancing efficiency at ports

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