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FACTORS INFLUENCING EMPLOYEES' INTENTION TO PARTICIPATE IN A BRING YOUR OWN DEVICE IN THE PORT SUPPLY CHAIN NETWORK: A CORRELATIONAL STUDY USING UTAUT2 THEORETICAL

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ABSTRACT

The study aimed to assess the factors that influenced port users' willingness to participate in BYOD programs in Ghana's Maritime and Port sector. The extended Unified Theory of Acceptance and Use of Technology (UTAUT2) was used as the theoretical framework for the quasi-quantitative study. The study examined whether eight factors were predictors of the intention of Ghanaian employees to participate in a BYOD program, moderated by social influence. The study used principal component analysis (PCA) in SPSS and structural equation modeling in Stata to analyze and report the data. The results showed that only three factors, namely Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and HT, significantly influenced employees' behavioral intention (BI) to participate in a BYOD program, while Social Influence (SI), Hedonic Motivation (HM), and Price Value (PV) had no effect on Behavioral Intention (BI). Age did not moderate the influence of any factor on BI. The study provides insights into the port supply chain network's usage of BYOD and will aid academics in explaining the discrepancies between the UTAUT2 theoretical framework's predictions for different industries and specialties. The study's findings will also be useful for researchers who aim to implement the UTAUT2 theoretical framework to understand employees' BI to join the BYOD program in any industry. From a practical perspective, the study will assist managers in the port business in Ghana and the sub-region in focusing on the important structures that constitute the initial steps to introducing BYOD in the port supply chain industry.

Keywords: *BOYD, Maritime Ports, Ghana, Supply Chain Network, UTAUT2*

1. INTRODUCTION

To reduce the danger of viral exposure and maintain business continuity during the COVID-19 pandemic, most businesses closed their locations and let employees to work from home using personal devices [1]–[3]. In order to retain the built-in cost savings and continue the elevated employee productivity gains, businesses are making BYOD a normal practice in the workplace while nations recover from the COVID-19 epidemic [4]–[6]. BYOD is a setting where employees are permitted to use their own personal devices to access organizational resources to complete their tasks [7]. There are several issues with BYOD programs that have a detrimental impact on employees' intentions to sign up for them [8]. Workers complained about unrealistic management demands for immediate responses to questions from clients, coworkers, and management regardless of the time or place [8]. Concerns regarding the privacy and security settings that businesses demanded before allowing employees to connect their mobile devices to the corporate network existed among the workforces. Employees were not allowed to fully utilize the capabilities of their own devices for personal activities due to the privacy and security settings [9]. When investigations uncovered private information that employees were not yet willing to discuss, workers lost faith in management's ability to maintain control in the case of a company-wide probe[10]. Worries regarding BYOD are becoming more prevalent among employees, which has a negative impact on their decision to use BYOD [11].

The maritime and port economy seaports are an essential component of the economies of the countries that they are in [12]. Eighty percent of the world's trade takes place on the sea, while more than seventy percent of it takes place on land [13]. Growing globalization has led to increased rivalry in the transportation of goods between seaports, which in turn has resulted in a sharp increase in the number of vessels moving through many seaports using a variety of transport modalities [14]. Because of this, the maritime and port industries play a significant role in the facilitation of trade as well as the generation of value and prosperity. Previous research that examined bring-your-own-device (BYOD) adoption focused on companies, employees, and consumer markets, respectively [15], [16]. From the perspective of businesses, the research concentrated on control frameworks and the advantages of bring-your-own-device policies for businesses. These governance frameworks manage how devices used by workers connect to the company network, as well as the risks and cyber security assaults that are caused by workers' personal devices [10], [17]–[19]. The research done on bring-your-own-device (BYOD) adoption analyzed how employees felt about the practice in relation to the potential dangers it posed. Given the immense contribution that the maritime and port sector makes to the economies of most countries around the world, there was a paucity of empirical research on the factors that influenced employees' intention to participate in BYOD specifically in the maritime and ports sector [20], [21]. The literature provides ample evidence to support the claim that BYOD adoption is a real problem, particularly in the context of the COVID-19 pandemic. [1]–[3], all highlight how the pandemic has led to an increase in remote work, which in turn has led to a greater reliance on personal devices for work-related tasks. This has raised concerns regarding privacy and security settings, as well as restrictions on the full utilization of personal devices for personal activities [9]. [22] note how unrealistic management demands for immediate responses to questions from clients, coworkers, and management regardless of the time or place have also emerged as a major issue in the context of BYOD adoption. Such issues can negatively impact employee satisfaction and trust in management, which can in turn lead to decreased willingness to use BYOD [23]. The literature also highlights the importance of understanding the factors that influence employees' intention to participate in BYOD specifically in the maritime and port sector. [21] and [24], emphasize the essential role that seaports play in the economies of many countries and the need for empirical research to understand the factors that influence BYOD adoption in this context. The use of UTAUT2 as a theoretical framework to understand the specific characteristics that affect port users' willingness to engage in a BYOD program is supported by [25], who reports that UTAUT2 has a prediction accuracy of 70%, which is significantly higher than the accuracy of other technology adoption theories. The extension of UTAUT2 to the maritime and port industry and the empirical research on the six predictors of UTAUT2 and their contributions to BYOD adoption in Ghana, notably in the maritime and port domain, will help generate dialogue among industry players on the key predictors of BYOD adoption and contribute to the UTAUT2 theoretical framework from a maritime and port perspective [26]. The remainder of the paper is broken down into the following sections: In Section 2, a review of the relevant literature and a theoretical underpinning are presented. The research methodology, data gathering procedures, and analysis processes are broken down in greater detail in Section 3. In the fourth portion, the findings will be presented, and the fifth section will examine and detail the recommendations, as well as the practical and policy consequences. The final section summarizes the findings of the paper, discusses the limits of the study, and outlines potential paths for further research.

2. LITERATURE REVIEW

2.1 Empirical Review

The daily lives of employees now include using mobile devices and other network-capable equipment [27]. These gadgets are constantly present in the workplace, homes, and social settings of employees [28] Businesses lacked a BYOD strategy that permitted their employees to accomplish work-related tasks using their personal devices during the global COVID-19 epidemic [1], [29]. The perspectives of companies and employees were included in earlier research on BYOD adoption in the workplace [15], [30]. The literature concentrated on governance frameworks and the

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advantages of BYOD for businesses. These governance frameworks control how employees connect their own devices to the company network and protect against data breaches and cyber security threats [10], [17], [19], [31] . Additionally, independent constructions show that there is some link based on the predictability of the UTAUT2. In the investigations of [32] PE was identified as the most potent predictor of BI . The researchers also discovered that EE was the second-best indicator of BI. Again, [33] found that Americans and Germans had different levels of SI's impact on BI. The shows that because they are emotionally bonded to the group, members of collective cultures place a higher importance on their own brand within the community. It was determined that BI was considerably impacted by FC and that it had a direct impact on employees' sentiments [34], [35] . In Ontario, Canada, HM and HT predicted employees' behavioral intention to adopt technology [34]. Additionally, PV was less significant for workers whose everyday tasks were well-aligned with technology [32]. Contrary results were observed for the moderating effect of age, as earlier research revealed that citizens' ages significantly influenced their behavioral intention to use e-government services [36]. However, [37] found no statistical difference in the adoption of personal mobile devices in the educational setting between age groups.

The literature suggests that the widespread use of mobile devices in employees' daily lives has led to a lack of Bring-Your-Own-Device (BYOD) strategies that permit employees to use their personal devices for work-related tasks during the COVID-19 pandemic [1], [38]. Previous research on BYOD adoption in the workplace has primarily focused on governance frameworks and the advantages of BYOD for businesses [17], [19], [31] [19]. While the literature has identified various factors that influence employees' behavioral intention to adopt BYOD, such as performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT), there is no consensus on which factors are the most influential (Tamilmani et al., 2020; Weeger et al., 2018; Ouattara, 2017; Dwivedi et al., 2017). Additionally, there is conflicting evidence on the moderating effect of age on employees' willingness to adopt personal mobile devices for work-related tasks (Munyoka and Maharaj, 2017; Nikolopoulou et al., 2020). Therefore, the purpose of this study is to identify the most influential factors that affect employees' behavioral intention to adopt BYOD in the workplace during and after the COVID-19 pandemic and to explore the moderating effect of age on this relationship. The justification of the study stems from the fact that the lack of BYOD strategies in businesses during and after the COVID-19 pandemic has created a need for further research on the factors that influence employees' willingness to adopt BYOD in the workplace. While previous studies have identified various factors that affect employees' behavioral intention to adopt BYOD, there is no consensus on which factors are the most influential. Additionally, conflicting evidence exists on the moderating effect of age on this relationship. Therefore, this study aims to contribute to the literature by identifying the most influential factors and exploring the moderating effect of age, which will provide valuable insights to businesses seeking to adopt BYOD strategies post pandemic in the maritime and port industry.

2.2 Theoretical Frameworks

Technology adaptation studies have developed several ideas and models over the last few decades to clarify and determine the factors that drive new technology adoption. Theories of Reasoned Actions, Innovation Diffusion Theory, Planned Behavior, Decomposed Theory of Planned Behavior, Theory of Innovation Resistance, Perceived Characteristics of Innovation (PCI), Theory of Perceived Risk, and Unified Theory of Acceptance and Usage of Technology are all included in this collection of theories (UTAUT).

It was decided to employ the UTAUT theoretical framework since it explains 70% of the difference in BI and about 50% of the usage difference [39].

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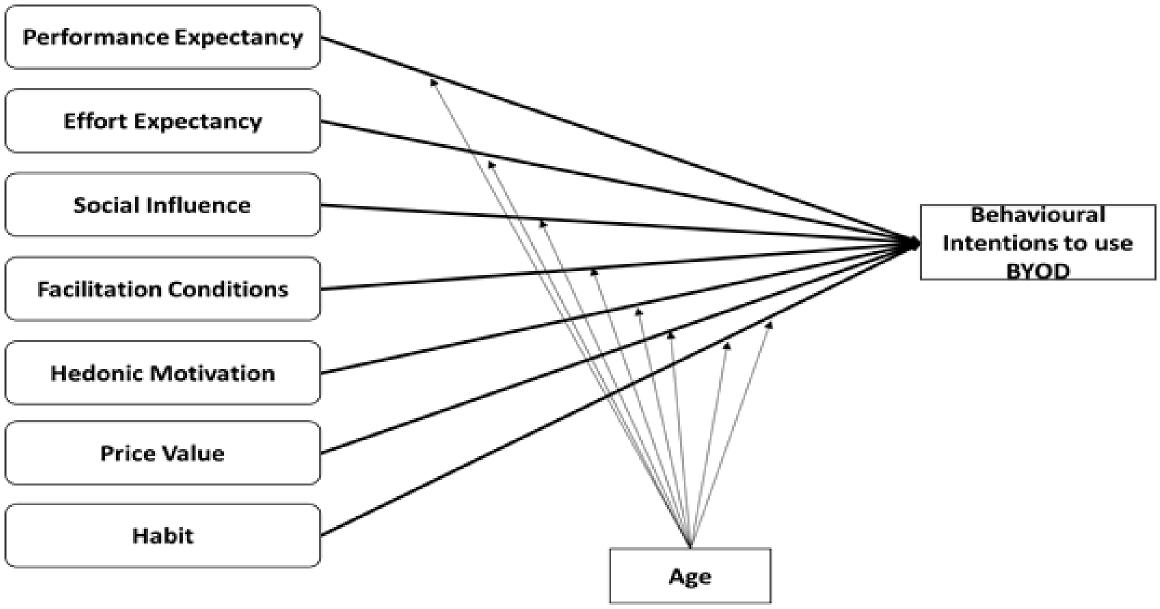

Figure 1: Authors Own Construct (2022) Adapted From [40], UTAUT2 Theoretical Framework

2.2.1 Unified Theory of Acceptance and Use of Technology

The UTAUT2 theoretical framework was used as the basis for this research. As an extension of the original UTAUT theoretical framework, UTAUT2 incorporates eight additional overlapping ideas about technology adoption. the Theory of Reasoned Action, (b) Theory of Planned Behavior, (c) Theory of Technology Acceptance Model, (d) Model of Personal Computer Use, (e) Motivational Model, (f) Innovation Diffusion Theory, and (h) the Combined Theory of Planned Behavior and Technology Acceptance Model [40]. Extension of UTAUT2 to consider the impact of social impact, hedonic advantages, end-user experience as well as age on people's technology adoption behavior in businesses was done by [40]. When it comes to technology adoption theories, [32] claim that UTAUT2 is the most comprehensive. Predictors included the following: PE, EE SI; FC; HM; PV; (HT); Age; and BI participation in BYOD as the dependent variable.

Performance Expectancy (PE): According to [41], Performance Expectancy (PE) refers to the perceived benefits of technology that drives individuals to use new technology. In the context of the maritime and port industry, PE measures how much port or marine users anticipate to benefit from using technology in terms of job performance [40]. Empirical studies, such as those conducted by [42] , have shown that PE is a strong predictor of Business Intelligence (BI) adoption. Based on this, we propose the following hypothesis: Ha_1, PE has a positive impact on the participation of marine and port users in BYOD programs.

Effort Expectancy (EE): Effort Expectancy (EE) refers to the degree of ease of use of a technology system, according to [40]. Studies have found that EE is one of the best predictors of Business Intelligence (BI) adoption [43], [44]. Furthermore, the more effort required to complete tasks, the more EE becomes a limiting factor [23]. Based on this literature, we hypothesize that EE has an impact on the willingness of maritime and port users to participate in the BYOD program. Specifically, our hypothesis is Ha_2: EE influences the willingness of maritime and port users to participate in the BYOD program.

Social Influence (SI): Social Influence (SI) refers to the extent to which individuals believe that others in their social circle expect them to use a new technology [45]. While SI may not have a significant impact on technology adoption in voluntary situations, it can still play a role in shaping individuals' intentions to use the technology. For instance, SI has been found to be a significant predictor of technology adoption in organizational contexts [42]. Therefore, we hypothesize that Ha_3, SI significantly influences the participation of maritime and port users in the BYOD program.

Facilitating Conditions (FC): FC is defined by [46] as the degree to which individuals perceive the presence of organizational and technical infrastructure to facilitate utilization of the technology system. The supporting infrastructure, according to [34], includes training programs and technical support employees, among others. FC has a direct impact on staff attitudes and has significantly influenced BI's adoption of technology [34], [47]. We expected that Ha_4, FC promotes maritime and port user participation in the BYOD program positively.

Hedonic Motivation (HM. Price Value (PV), Habit (HT): HM is the degree of pleasure or enjoyment caused using technology and is essential for determining the pace of technology adoption [40]. PV is the perceived tradeoff between new technology and the cost of adopting that technology, according to Blut et al. HT is behavior thought to be repetitive because of repeated activities over time [48], [49]. [40] modeled HM's direct and indirect effects on BI. In Ontario, Canada, HM and price value predicted employees' behavioral desire to use technology. The influence of HT and EE on employees' intentions to embrace consumer IT solutions was greater. Also, HM and PV value had less of an impact on the adoption of technology by employees due to BI [34]. HT was deemed to have the highest correlation with BI [32], [50]. The impact of PV was less significant for personnel who had the most up-to-date gadgets, such as early adopters. We hypothesized that the three constructs of HM, PV, and HT would predict the BI of employees in the maritime and ports sector to participate in a BYOD program as follows: Ha_5, HM positively influences BI of maritime and port users to participate on BYOD Program; Ha_6, PV positively influences BI of maritime and port users to participate on BYOD Program; and HT (Ha_7), positively influences BI of maritime and port users to participate on BYOD Program.

Moderating effect of Age: UTAUT2 has been frequently used to explain the adoption of technologies by company employees. Several research utilized only a subset of model constructs without moderators [44], [51]–[53]. Among the few studies that accounted for the moderating effect of Age, the literature reveals a minor detrimental influence of BI on the adoption of new technology [54]. [36] demonstrate that the age of citizens has a significant beneficial impact on their propensity to use e-government services. [55] shown that Age moderates the relationship between EE, SI, HM, and BI. [54] demonstrate that Age has no influence on behavioral intention to adopt new technologies. The variable results of the moderating influence of Age on the propensity of BI to accept technology indicate that while investigating technology adoption, researchers must account for generational disparities. We hypothesized the moderating influence of "Age" in predicting the BI of employees in the maritime and port sector who engage in the BYOD program. The age range of Ghanaian maritime and port personnel is between 18 and 64 years old [56]. We hypothesized that the independent constructs (PE, EE, SI, FC, HM, PV and HT) strongly influence BI of maritime and port users to join in BYOD Program, mediated by Age (Ha_8:).

Behavioral Intention (BI): Factors that can explain or predict a person's behavior are shown in BI (Raman, A., & Don, 2013). BI can be explained or predicted by PE, EE, SI, FC, HM, PV, and HT with an accuracy of 70% [40], [50], [56], [44]. In Ghana's marine and ports industry, it was proposed that participation in the BYOD initiative could forecast BI.

3. METHODOLOGY

This study aimed to investigate the factors that influence maritime and port users' intention to enroll in BYOD (Bring Your Own Device) programs. A correlational research design was utilized for this study. The survey instrument developed by [40], which employs a 7-point Likert scale, was used to collect data from the participants. For Structural Equation Modeling, a seven-point Likert scale was required [58]. The survey instrument was accessible to the participants through a third-party data collection platform, Google Forms. Respondents who did not meet the inclusion criteria based on their responses to specific questions were automatically terminated from the survey using Google Forms. The study's target population comprised maritime and port users aged between 18 and 64. Based on [59] report that 80% of the adult population owns at least one mobile device, the study assumed that 80% of the 2,584,625 adults would serve as the population for this study. A sample size of 510 was drawn from the target population at a significance level of 5% [60]. The researchers developed a questionnaire using the survey builder tool in Google Forms, based on the survey instrument developed and validated by [40]. The questionnaire contained 32 questions organized into nine sections. The first section consisted of four questions on demographics, while the remaining eight sections contained 28 statements with Likert-type responses ranging from 1 (strongly disagree) to 7 (strongly agree). The Likert-type scale was used to measure the respondents' value judgment based on their attitudes, opinions, and perspectives toward the statements in each section, following the method used by [61]. The collected data was analyzed using Principal Component Analysis (PCA) in Statistical Package for the Social Sciences (SPSS) version 22 and Structural Equation Modeling (SEM) in Stata version 16. PCA was used to reduce the data dimensionality and identify underlying factors in the data. SEM was used to test the hypothesized relationships among the variables and to validate the proposed model. The analysis aimed to identify the factors that significantly influence maritime and port users' intention to enroll in BYOD programs. The results of the analysis were used to provide recommendations for improving the adoption and implementation of BYOD programs in the maritime and port industry.

4. RESULTS

The results of the study are presented below. All 501 participants who participated in the survey provided feedback for the study, indicating a 100% response rate. Among the 501 participants, 28.7% were female, and 71.3% were male. This indicates that males are more predominant than females in the maritime and ports industry. The age group between 25 and 34 years old recorded the highest percentage of participants (61.9%). This finding indicates the predominance of youth in the maritime and port sample population. Based on the respondents' educational attainment, the study found that 14.3% of the participants had a high school diploma, 13.5% had no certificate, 12.8% had a bachelor's degree, 12.3% had a master's degree, 11.3% had a doctorate, and 9.5% had a professional certificate. These results suggest that despite the technical nature of the industry, which necessitates expert knowledge, the maritime and port sector has experienced a significant increase in education. The responses were evaluated based on the extent to which participants agreed or disagreed with the statement using a 5-point Likert scale (1-Strongly Disagree, 2-Disagree, 3-Neutral, 4-Agree, and Strongly Agree-5). All constructs received a weighted mean score of 4, indicating that all participants were satisfied with their performance. The standard deviation indicates the degree of dispersion among the participants' responses. The findings indicate that there were a variety of responses. Overall, most responses demonstrate some degree of precision in the measuring constructs, which is a positive indicator for the data description (see table 1).

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Table 1: Descriptive Statistics

Descriptive Statistics							
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
PE1	510	1	7	5.06	1.352	-.548	.264
PE2	510	1	7	4.96	1.264	-.407	.158
PE3	510	1	7	5.00	1.267	-.386	.212
PE4	510	1	7	4.66	1.238	-.177	.254
Weighted Average				4.92	1.28	-0.38	0.22
EE1	510	1	7	4.70	1.315	-.201	.023
EE2	510	1	7	4.68	1.320	-.188	-.165
EE3	510	1	7	4.74	1.361	-.352	.023
EE4	510	1	7	4.58	1.359	-.147	-.175
Weighted Average				4.68	1.34	-0.22	-0.07
SI1	510	1 1	7	4.11	2.009	-.102	-1.206
SI2	510	1 1	7	3.86	2.021	.073	-1.288
SI3	510	1 1	7	3.94	2.012	.055	-1.245
Weighted Average				3.97	2.01	0.01	-1.25
FC1	510	1	7	3.93	1.957	.041	-1.228
FC2	510	1	7	4.16	1.435	-.068	-.061
FC3	510	1	7	4.16	1.380	-.241	.113
FC4	510	1	7	4.19	1.449	-.163	-.087
Weighted Average				4.11	1.56	-0.11	-0.32
HM1	510	1	7	4.27	1.288	-.094	.287
HM2	510	1	7	4.33	1.297	-.139	.219
Weighted Average				4.225	1.292	-0.116	0.253
PV1	510	1	7	4.01	1.989	.004	-1.255
PV2	510	1	7	4.00	2.010	-.001	-1.259
PV3	510	1	7	4.11	1.949	-.064	-1.179
Weighted Average				4.086	1.983	-0.020	-1.231
HT1	510	1	7	4.40	1.413	-.213	.029
HT2	510	1	7	4.02	1.461	-.118	-.221
HT3	510	1	7	4.32	1.409	-.175	-.124
HT4	510	1	7	4.27	1.548	-.219	-.323
Weighted Average				4.250	1.458	-0.181	-0.160
BI1	510	1	7	4.39	1.516	-.262	-.330

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BI2	510	1	7	4.22	1.441	-.195	-.182
BI3	510	1	7	4.38	1.583	-.251	-.452
Weighted Average				4.330	1.51	-0.24	-0.32
Valid N (listwise)	510						

Source: Field Data (2022)

4.1 MEASUREMENT OF CONSTRUCTS

Table 2 in the current study presents various measures of reliability and validity of the constructs. These measures are essential for assessing the quality of the data and the accuracy of the constructs being measured. The KMO statistic is used to determine whether a dataset is suitable for factor analysis. According to [62], a KMO value of 0.5 or higher is generally considered acceptable. In the current study, all constructs had KMO scores within this range, indicating that the data is suitable for factor analysis. Bartlett's Test of Sphericity is another test used to determine the suitability of data for factor analysis. A significant p-value ($p<0.05$) indicates that the data is suitable for factor analysis. In the current study, all constructs had significant Bartlett's Test of Sphericity, with a p-value of 0.001. Total Variance Explained is the percentage of variance in the data that can be explained by the factors extracted. According to [63], the total variance explained should be at least 60% to be considered satisfactory. In the current study, the total variance explained ranged from 66.233% to 92.848%, indicating that the factors extracted accounted for a significant proportion of the variance in the data. AVE, or Average Variance Extracted, is a measure of convergent validity that assesses the degree to which the items in a construct are related to each other. According to [64], an AVE value of 0.5 or higher is considered acceptable. In the current study, all constructs had an AVE value greater than the threshold, ranging from 0.619 to 0.935, indicating that the items in each construct are highly related to each other. Composite Reliability is a measure of the internal consistency of a construct. A value of 0.7 or higher is generally considered acceptable. In the current study, all constructs had a composite reliability score greater than 0.7, ranging from 0.661 to 0.920, indicating that the items in each construct are highly consistent with each other. Cronbach's Alpha is another measure of internal consistency. A value of 0.7 or higher is generally considered acceptable. In the current study, all constructs had a Cronbach's Alpha score greater than 0.7, ranging from 0.813 to 0.964, indicating that the items in each construct are highly consistent with each other. Factor Loadings are used to determine the strength of the relationship between each item and its corresponding construct. A factor loading score of 0.7 or higher is generally considered acceptable. In the current study, all constructs had factor loading scores greater than the threshold, except for the SI and PV constructs. The factor loading scores ranged from 0.787 to 0.910, indicating that the items in each construct are highly related to each other.

4.2 MEASUREMENT OF CONSTRUCTS

There are several indices used to assess the goodness of fit of a model, and this table presents three such indices along with their respective levels of fitness and thresholds. The first index presented is the Root Mean Square Error of Approximation (RMSEA). This index measures the difference between the observed data and the model's predicted data, and a lower value of RMSEA indicates a better fit. The level of fitness for RMSEA is presented as 0.082, which indicates the actual value of RMSEA for the model. The threshold for RMSEA is presented as less than 0.05, which means that if the value of RMSEA is less than 0.05, then the model is considered to be a good fit based on the criteria suggested by [65] and [66]. The second index presented is the Comparative Fit Index (CFI). This index measures the degree of similarity between the model and the observed data, and a higher value of CFI indicates a better fit. The level of fitness for CFI is presented as 0.959, which indicates the actual value of CFI for the model. The threshold for CFI is presented as greater than 0.95, which means that if the value of CFI is greater than 0.95, then the model is considered to be a good fit based on the criteria suggested by [67] and [68]. The third index presented is the [69]. This index measures the degree of similarity between the model and the observed data, and a higher value of TLI indicates a better fit. The level of fitness for TLI is presented as 0.949, which indicates the actual value of TLI for the model. The threshold for TLI is presented as greater than 0.8, which means that if the value of TLI is greater than 0.8, then the model is considered to be a good fit based on the criteria suggested by [65], [70],and [71].

Table 2: Measurement Of Constructs

Constructs	KMO	Bartletts Test of Sphericity	Total Variance Explained	AVE	Composite Reliability	Cronbach Alpha	Factor Loadings
PE	0.839	0.001	78.708	0.624	0.868	0.909	0.787
EE	0.858	0.001	86.099	0.741	0.920	0.946	0.861
FC	0.762	0.001	66.233	0.778	0.913	0.933	0.882
HM	0.500	0.001	92.848	0.619	0.765	0.923	0.964
HT	0.815	0.001	81.259	0.886	0.661	0.923	0.813
BI	0.774	0.001	90.966	0.935	0.828	0.950	0.910
Weighted Average	**0.758**	**0.001**	**82.686**	**0.764**	**0.826**	**0.931**	**0.870**

Source: Field Data (2022)

Table 3: Goodness Of Fit

Fit Indices	Level of Fitness	Threshold
Root Mean Square Error of Approximation (RMSEA)	0.082	<0.05 (Hair et al., 2010; Schumacker, R. E., & Lomax, 2010);
Comparative Fit Index (CFI)	0.959	>0.95 [67], [68]
Tucker-Lewis Index (TLI)	0.949	>0.8 [65], [70], [71]

Source: Field Data (2022)

4.3 HYPOTHESIZED MODEL TEST RESULTS

The table presented above provides the results of a structural equation model that examines the relationship between several constructs and the behavioral intention of employees to enroll in a BYOD (Bring Your Own Device) program. The results indicate that four of the hypothesized constructs, including PE, EE, FC, and HT, have a significant positive effect on the employees' behavioral intention to enroll in the BYOD program. The coefficient (β) for PE is 0.20, which means that a one-unit increase in PE is associated with a 0.20-unit increase in the employees' behavioral intention to enroll in the BYOD program. The p-value associated with this coefficient is less than 0.001, indicating that the relationship is statistically significant. Similarly, the coefficient for EE is 0.24, indicating that a one-unit increase in EE is associated with a 0.24-unit increase in the employees' behavioral intention to enroll in the BYOD program. The p-value associated with this coefficient is less than 0.001, indicating that the relationship is statistically significant. The coefficient for FC is 0.10, indicating that a one-unit increase in FC is associated with a 0.10-unit increase in the employees' behavioral intention to enroll in the BYOD program. The p-value associated with this coefficient is 0.021, which is less than the significance level of 0.05, indicating that the relationship is statistically significant. The coefficient for HT is 0.61, indicating that a one-unit increase in HT is associated with a 0.61-unit increase in the employees' behavioral intention to enroll in the BYOD program. The p-value associated with this coefficient is less than 0.001, indicating that the relationship is statistically significant. However, the other constructs tested, including SI, HM, and PV, failed to explain and

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predict the behavioral intention of employees to enroll in the BYOD program. Age also did not moderate the prediction as initially hypothesized, as there was no impact of age on the relationship between the predictors and the endogenous variable (BI). The results suggest that PE, EE, FC, and HT are important factors in predicting employees' behavioral intention to enroll in the BYOD program. These results are consistent with previous research that has found that perceived ease of use, perceived usefulness, facilitating conditions, and habit are important factors in determining technology adoption and usage [45], [73], [74].

Table 4: Hypotheses Test Results

Hypothesis	Coef. (β)	Std. Error	z	P> |z|
PE=>BI	0.20	0.52	3.90	0.001
EE=>BI	0.24	0.56	4.29	0.00
FC=>BI	0.10	0.44	0.58	0.021
HT=>BI	0.61	0.58	10.46	0.001

Source: Field Data (2022)

5. DISCUSSIONS

The finding that PE is a significant predictor of the behavioral intention of employees to enroll in a BYOD program in the maritime and port industry is consistent with previous research in other industries. For instance, [44] found that PE was a significant predictor of the behavioral intention to use mobile payment systems in the retail industry. Similarly, [42] and [44] found that PE was a strong predictor of BI in the context of business intelligence adoption. These findings suggest that the perceived benefits of using new technology play a crucial role in employees' decision to adopt and use it. Moreover, the importance of perceived ease of use (EE) as a predictor of BI in the maritime and port industry is consistent with previous studies. [46] posits that individuals are more likely to use a technology if they perceive it as easy to use. [42] and [44] also found EE to be a significant predictor of BI in the context of business intelligence adoption. This highlights the importance of designing and implementing user-friendly systems to encourage the adoption and usage of new technology in the maritime and port industry. In addition, the finding that FC and HT are significant predictors of the behavioral intention of employees to enroll in a BYOD program in the maritime and port industry is in line with previous research. FC has been found to be a significant predictor of BI in the context of mobile payment systems [44] and business intelligence adoption [42]. HT has also been found to be a significant predictor of BI in various contexts, including mobile payment systems [44] and social media[75]–[77] . This suggests that employees' trust in management and their colleagues' opinions can influence their decision to participate in a BYOD program.

The finding that EE is a significant predictor of BI in the maritime and port industry supports the notion that ease of use is crucial in predicting technology adoption and usage in this sector. This is consistent with the findings of [42] and [44], indicating that ease of use is a critical factor in determining BI. However, the study's finding that [44] found a negative impact of EE on PE and task completion efficiency raises some concerns. This discrepancy may be due to differences in the samples or methodology used in the studies. Further research is needed to determine the impact of EE on PE and task completion efficiency in the maritime and port industry. The study's finding that FC was the least predictor of BI in the maritime and port industry is consistent with the findings of [35] and [34]. These studies have also found FC to have a moderate impact on employee attitudes and behavior towards technology adoption. This suggests that FC may not be a critical factor in predicting technology adoption and usage in the maritime and port industry. The study's finding that SI, HM, PV, and Age were non-predictors of BI in the maritime and port industry is consistent with the findings of [46] who found that SI may not significantly influence intention in voluntary circumstances. It is also consistent with previous research that has found HM and PV to be significant predictors of technology adoption and usage in other sectors[34], [52]. The lack of predictive power of these factors in the maritime and port industry suggests that industry-specific factors may be more critical in determining technology adoption and usage in this sector. Finally, the study's finding that Age did not moderate the relationship between the predictors and BI in the maritime and port industry is consistent with the findings of [54]. This suggests that Age may not be a critical moderator of the relationship between the predictors and the endogenous variable (BI) in the maritime and port industry. Instead, industry-specific factors may play a more significant role in determining technology adoption and usage in this sector.

6. IMPLICATION OF THE STUDY TO THEORY AND PRATICE

The findings of this study have important implications for both theory and practice. From a theoretical standpoint, the study contributes to the existing literature on technology adoption by identifying the key predictors of behavioral intention to enroll in a BYOD program among employees in the maritime and port industry. Specifically, the study highlights the importance of perceived ease of use, habit formation, and employee attitudes towards technology adoption in predicting the likelihood of long-term technology usage. These findings are consistent with previous research (Tamilmani et al., 2020; Weeger et al., 2018; Nikolopoulou et al., 2020; Hu et al., 2020) and provide further evidence of the robustness of these predictors across different contexts. From a practical perspective, the study provides important insights for managers and policymakers in the maritime and port industry who are interested in promoting the adoption and usage of BYOD programs. Specifically, the study suggests that efforts to enhance the perceived ease of use of technology and to promote habit formation among employees are likely to be effective in promoting long-term technology adoption and usage. In addition, the study highlights the importance of employee attitudes towards technology adoption and suggests that efforts to promote positive attitudes towards technology may also be effective in promoting technology adoption and usage. However, the study also highlights the limitations of some commonly used predictors of technology adoption, such as social influence, hedonic motivation, and personal values, which were found to be non-predictors of behavioral intention in this study. This suggests that managers and policymakers in the maritime and port industry should focus their efforts on promoting the key predictors identified in this study rather than relying on predictors that may not be effective in their specific context. The findings of this study have important implications for both theory and practice and provide important insights into the factors that drive technology adoption and usage among employees in the maritime and port industry.

7. CONLUSIONS AND RECOMMENDATIONS

In conclusion, the study provides insight into the factors that influence employees' behavioral intention to enroll in a BYOD program in the maritime and port industry. The results suggest that perceived ease of use, habit formation, and effort expectancy are significant predictors of technology adoption and usage in the industry. However, social influence, hedonic motivation, performance expectancy, and age were found to have no significant impact on employees' intention to enroll in a BYOD program. These findings have important implications for both theory and practice. From a theoretical perspective, the study adds to the existing body of knowledge on the factors that influence technology adoption and usage in organizations. Specifically, it highlights the importance of perceived ease of use and habit formation in predicting technology adoption and usage in the maritime and port industry. From a practical standpoint, the findings can be used to guide the implementation of BYOD programs in the maritime and port industry. To increase the likelihood of successful adoption and usage of the technology, organizations should focus on designing systems that are easy to use and encourage habit formation among employees. They can also provide training and support to help employees overcome any barriers they may face when adopting new technology. Moreover, organizations should consider the unique characteristics of their workforce, such as age and job role, when implementing BYOD programs to ensure that the program is tailored to their specific needs. The study provides valuable insights for organizations looking to adopt new technology in the maritime and port industry. By considering the factors identified in this study, organizations can increase the likelihood of successful adoption and usage of BYOD programs, ultimately leading to improved productivity and efficiency in the workplace.

7. LIMITATION AND FUTURE RESEARCH DIRECTION

The study was conducted in a specific industry, i.e., maritime and port industry, which limits the generalizability of the findings to other industries.

Future research should explore the predictors of technology adoption in other industries to generalize the results. Also the study relied on self-reported data, which may be subject to social desirability bias, and may not reflect actual technology adoption behavior. Future research should use objective measures of technology adoption, such as usage logs or behavioral observation. Furthermore, study only focused on the predictors of the behavioral intention to enroll in a BYOD program and did not investigate actual technology adoption behavior. Future research should examine the actual adoption behavior of employees to validate the study's findings. The study did not consider other individual factors, such as personality traits or individual values, that may affect technology adoption behavior. Future research should investigate the role of these individual factors in technology adoption behavior. Researchers can also conduct comparative studies across different industries to identify differences and similarities in the predictors of technology adoption behavior. Again, a longitudinal study is required to examine the actual technology adoption behavior of employees over time and investigate how the predictors of technology adoption behavior may change over time. Also future studies may be required to investigate the role of individual factors, such as personality traits or individual values, in technology adoption behavior to provide a comprehensive understanding of technology adoption behavior.

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