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A TAM-Based Study on the Adoption of Digital Transformation in the Maritime Transportation Logistics Sector

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Abstract

Digital transformation is a significant global trend of the 21st-century that has substantial ramifications for various companies and sectors. It is inconceivable to envision that the maritime transport logistics industry will remain unaffected by these advancements. Digital transformation has the capacity to fundamentally revolutionize the business processes, services, and strategies of organizations working within this industry. This study examines the process of digital transformation within the maritime sector and identifies the key factors that influence its adoption. The research used structural equation modeling methodology to examine the variables and specific components indicated in the technology acceptance model. The data used in the analysis were collected via a questionnaire administered to individuals engaged in the maritime transport industry. The findings of the study indicate that the degree to which employees in the industry embraced digital transformation technologies was influenced by various factors, including their perception of how easy these technologies were to use and the perceived benefits they offered. The study's findings offer strategic suggestions for improving the successful implementation of digital transformation in the maritime logistics sector.

Keywords: Maritime transport logistics, Digitalization, Structural equation modeling (SEM), Technology acceptance model (TAM)

1. Introduction

Digital transformation refers to the use of technological innovations to revolutionize the commercial processes, organizational structures, and value propositions of various industries. Digital transformation is currently exerting a significant impact on various sectors, resulting in notable breakthroughs and advantages. The aforementioned transformation process yields significant advantages, including enhanced operational effectiveness, financial savings, and the identification of novel avenues for business growth [1]. This shift also impacts the maritime transport logistics sector. Utilization of digital technologies within the realm of maritime transportation procedure yields enhanced efficiency and reduced operational expenditures. Furthermore, the presentation of novel digital technologies within the maritime transport logistics industry offers environmental sustainability benefits through the reduction of carbon emissions, thus promoting a greener and more ecologically friendly sector [2,3].

The digital transformation process in the maritime logistics industry enabled the use of many cutting-edge technologies and applications The field of technology has witnessed notable developments in the form of the Internet of Things (IoT), artificial intelligence, big data analytics backchain autonomous ships, and drone technologies. The implementation of these technologies enhances the sustainability, safety, and efficiency of the maritime transportation sector by streamlining its logistical procedures. The implementation of IoT technology can facilitate the optimization of ship and port operations, enabling the real-time collection and analysis of data. Route optimization, energy conservation, and enhanced maintenance process management are just a few notable benefits of using big data analytics. These advantages

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are achieved through the processing and analysis of substantial volumes of data [4]. The implementation of AI in business operations, namely aboard operations and port operations, enhances efficiency through the use of automated decision-making and process optimization [5]. In the realm of shipping logistics procedures, the use of backchain technology yields expedited transaction speeds and reduced expenses. This is primarily attributed to the inherent characteristics of blockchain, which facilitate safe and transparent data sharing [6]. The use of autonomous ships and drone technologies has facilitated the advancement of safer procedures that require reduced human involvement in maritime transportation and port operations [7,8]. The digital transformation process poses considerable challenges and obstacles for the maritime transport logistics sector. The problems encompass various factors, such as the financial implications associated with investing in digital technology, the lack of interoperability between current infrastructure and digital systems, concerns over cybersecurity, the need for staff training, and the scarcity of a skilled workforce. Overcoming these hurdles and expediting the process of digital transformation will enhance the industry's capacity to respond to global competitive conditions and foster growth [9-11].

The integration of cutting-edge digital technology and processes within the sector is expected to yield improvements in efficiency, sustainability, and customer-centricity. The use of innovation is anticipated to significantly contribute to the facilitation of efficient international commerce operations. Collaboration and concerted efforts among enterprises, policymakers, and regulatory agencies within the sector are of utmost importance for facilitating and expediting the digital transformation process. It is vital for all stakeholders to prioritize the adaptation of the maritime transportation logistics sector during the digital transformation period. This study employed the technology acceptance model (TAM) to examine the adaptability of the maritime industry to digital transformation. This articlerepresents one of the initial studies in the maritime field and provides useful data for integrating technology into the maritime industry.

2. Literature Review

The concept of digitization emerged as a notable and consequential phenomenon in the 21^{st}-century, driven by rapid advancements in technology. This ongoing evolution is not just confined to institutions but also profoundly influences societal structures. The effects of these advancements extend across various industries and disciplines, reflecting the comprehensive impact of digital transformation. Scholarly literature provides an extensive investigation into the application of digital transformation in several domains, meticulously outlining the inherent advantages and associated challenges.

In contemporary technology adoption research, the integration of structural equation modeling (SEM) with TAM has proven to be highly effective. This combination allows for a detailed examination of the interplay between perceived ease of use (PEOU) and perceived usefulness (PU), along with other latent variables, thereby offering a more comprehensive understanding of the factors influencing technology acceptance. The synergy between SEM's complex variable analysis and TAM's user-centric focus has been instrumental in enhancing the robustness and applicability of research across diverse technological domains [12-15].

The evaluation of digital transformation within the maritime industry demonstrates notable progress in enhancing operational efficiency, fortifying cybersecurity measures, promoting environmental sustainability, and optimizing supply chain management. The incorporation of big data, AI technology, and machine learning significantly enhances operational practices in the domains of route optimization, fuel efficiency, and preventive maintenance. Within the domain of cybersecurity, digital technologies play an essential role in protecting critical infrastructure from cyber threats while also fulfilling environmental responsibilities and reducing carbon emissions. The adoption of backchain technology enables greater transparency in supply chain transactions and improves the entire customer experience. Therefore, this transition is expected to guide the maritime sector toward a future that is both competitive and sustainable, but it will require ongoing innovation and adaptation [16-20].

TAM is a theoretical structure that aims to provide insight into the various aspects that influence individuals' adoption of technology, as well as the underlying motivations for their acceptance. Davis [21] created the model in 1986 with the intention of analyzing computer usage patterns within an organizational context. The primary objective of this study was to determine the fundamental elements that influence the adoption of a particular technology [21].

The examination of the digital transition within the maritime industry might be conducted using TAM. Davis [21] proposed a model in which the adoption of novel technologies is contingent on individuals' perceptions of their utility and simplicity. The successful use of technologies in maritime operations necessitates the recognition of their benefits in improving operational efficiency, strengthening cybersecurity protocols, addressing environmental impacts, and optimizing supply chain management. In addition, the acceptance of technologies is more likely when they are designed to be user-friendly [22].

In conclusion, the application of TAM in evaluating digital transformation initiatives in the maritime industry offers a full understanding of the factors that impact the acceptance and successful integration of new technology.

TAM is widely used as the primary conceptual structure in academic studies concerning the adoption of information technology. Venkatesh [23] asserts that it facilitates the interpretation of individuals' dispositions toward information systems, their conduct in using these systems, and the prospective ramifications of information systems on society in forthcoming times. TAM has been subjected to comprehensive empirical examination in numerous research investigations and is widely acknowledged as a robust theoretical framework for understanding consumers' propensity to embrace technology [24,25]. Mathieson [25] found that the Theory of Planned Behavior and the TAM were equally effective at predicting user intentions. Nevertheless, TAM was seen as a more parsimonious model because of its ability to attain the same outcomes with a reduced number of components. The model is widely recognized and highly regarded in the field of information systems adoption, making it one of the most prominent and well-supported theories in the current academic literature [26].

Numerous studies have employed TAM in various technical domains and user populations. Notably, the field of e-learning has emerged as a significant area of investigation concerning the use of TAM. Al-Gahtani [27] examined the degree to which university students adopt e-learning technologies. The study's results demonstrated that TAM served as a beneficial theoretical framework for understanding the various elements that impact students' acceptance and use of e-learning systems.

The application of TAM has also been observed in the domain of electronic health (e-health) research. Kijsanayotin et al. [28] examined the connection between TAM and adoption of digital health records in healthcare services. The study found that TAM offers a useful theoretical structure for understanding the acceptability of technology within the healthcare industry.

TAM is also used in the domain of electronic commerce in relation to the literature. Gefen et al. [29] performed an analysis with the objective of investigating the application of TAM in understanding the various aspects that impact the adoption of online shopping. The study posits that TAM provides a beneficial theoretical framework for understanding the numerous elements that influence the acceptance of online purchases.

TAM is widely regarded as a prominent model used in several industries to gain comprehensive insights into the processes of technological adoption. These studies provide insights into the applicability and efficacy of TAM in understanding the factors influencing users' acceptance of technology across different technological domains. Despite the considerable amount of research conducted, the inquiry into the mechanisms and motivations underlying users' adoption of novel technologies remains unresolved in its entirety. However, empirical research has shown that the degree of user acceptance plays a key role in determining the rate at which a particular technology is adopted [23,26,30,31].

TAM has garnered extensive recognition in research on the use of information technologies, offering valuable insights into the acceptance and adoption of technology. Nevertheless, the complete extent of the model's capabilities has not been fully realized. Further investigation is warranted to explore the potential applications of TAM in diverse technological environments and among varied user demographics [32].

3. Empirical Study Design and Data Analysis

The current research focuses on the subject of digital transformation and TAMs, both of which are a noteworthy and contemporary concern within the maritime sector. In the present-day setting, which is marked by the swift displacement of traditional practices and the increasing significance of technology, the maritime sector is not immune to these global changes. Nevertheless, it is worth noting that there is an important dearth of comprehensive academic research and modeling endeavors focused on this particular form of transformation within the sector.

The primary aim of this study is to produce empirical evidence and provide practical recommendations for improving the implementation of technology within the maritime industry. TAM is a significant theoretical framework that aids in understanding the various aspects that impact the adoption of new technologies by both organizations and individuals. The application of this model to the maritime sector will provide valuable insights into the optimal integration of technology within the industry.

Following the identification of gaps and demands in the existing literature, a comprehensive plan has been devised to effectively conduct the study (Figure 1). The data of the industry that is relevant to the study have been gathered. Following the initial compilation, the dataset was thoroughly examined, where missing data, careless responses, and outlier variables were detected and then eliminated from the dataset. Normality was examined using the Statistical Package for the Social Sciences (SPSS), where the skewness and kurtosis values were assessed. Subsequently, factor analysis was conducted on the statements used in the study.

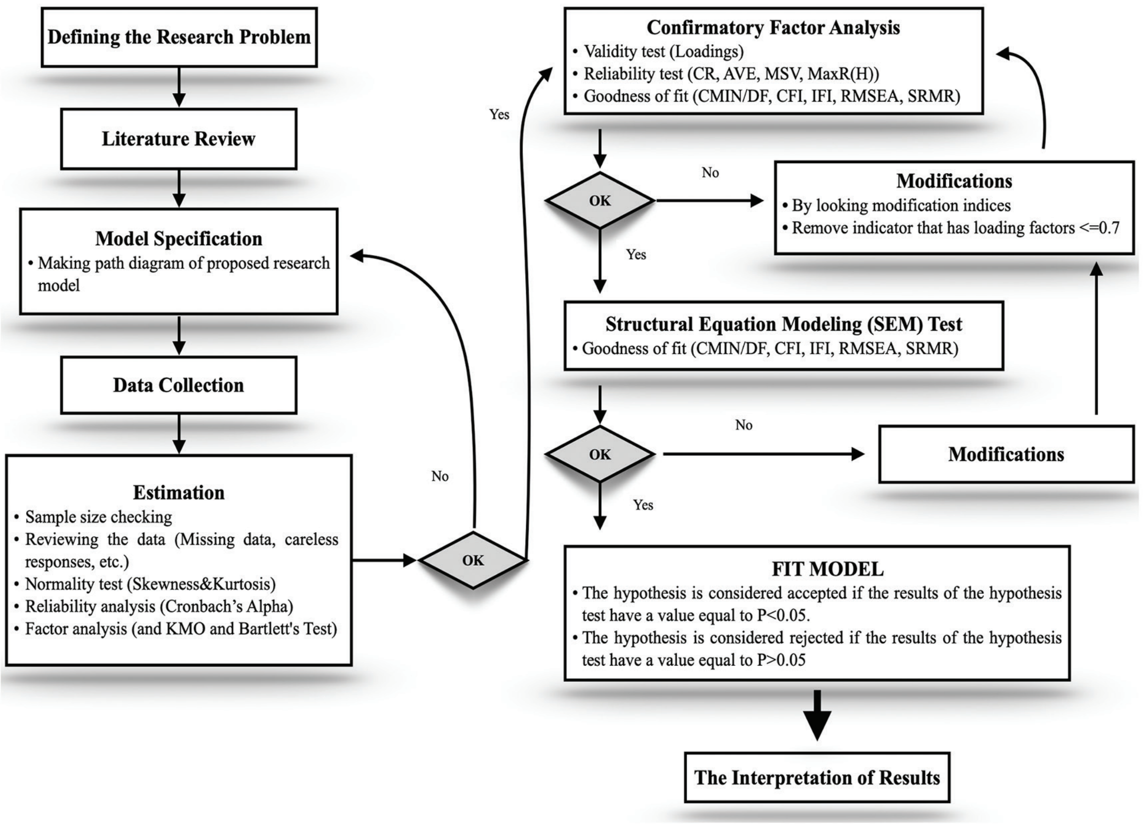

Figure 1. *Steps of the analysis*

3.1. Model Specification and Hypothesis Development

This study aims to enhance the current model by integrating insights derived from pertinent literature and concepts, with a particular focus on the maritime sector. The factors being studied in this study involve PEOU, behavioral intention (BI), PU, and use behavior (UB) as dependent variables. The independent variables in this study include subjective norms (SN), output quality (OQ), result demonstrability (RD), job relevance (JR), computer anxiety (CA), and perceptions of external control (POEC). The succeeding sections provide a detailed elaboration on the links among the variables and the hypotheses offered. The improvement of the model was based on a comprehensive evaluation of existing research. A comprehensive examination and documentation of numerous research domains' detailed analyses of studies related to TAM were conducted, with the findings being recorded in an Excel spreadsheet. The collection of data served as the fundamental basis for constructing our model in a careful and deliberate manner.

SN

SN refer to the societal influences that shape an individual's attitudes and beliefs regarding their engagement or non-engagement in a particular action [33,34]. The significance of SN is crucial within the specific environment being examined because they have a pivotal impact on the acceptance and use of new technology. Additional research on this variable is vital in both scholarly and practical contexts to enhance the implementation of TAMs and digital transformation initiatives. Hypotheses 1a and 1b have been developed for the following reasons:

Hypothesis 1a. SN exerts a substantial influence on PU.

Hypothesis 1b. SN exerts a substantial influence on PEOU.

JR

The concept of JR pertains to an individual's personal assessment of the extent to which a system or technology aligns with their job requirements and objectives [22]. The variable of JR holds significant importance in the realm of study concerning the acceptance and adoption of technology. A thorough analysis of this characteristic will aid companies and individuals in enhancing their technology selection and usage strategies with greater effectiveness. Hypotheses 2a and 2b have been developed on the basis of the aforementioned grounds.

Hypothesis 2a. JR exerts a substantial influence on PU.

Hypothesis 2b. JR exerts a substantial influence on PEOU.

OQ

The variable of OQ pertains to subjective evaluations conducted by individuals regarding the extent to which a specific technology or system enhances their work performance capabilities [18]. The variable OQ should be regarded as a crucial element in comprehending and operationalizing TAMs and strategies for digital transformation. By engaging in comprehensive studies on the quality of output, organizations and individuals can enhance their ability to effectively manage their technology choices and adaptation processes. Hypotheses 3a and 3b have been developed on the basis of the aforementioned grounds.

Hypothesis 3a. OQ exerts a substantial influence on PU.

Hypothesis 3b. OQ exerts a substantial influence on PEOU.

RD

Variable RD measures individuals' beliefs that employing a new technology will provide tangible and measurable outcomes [31]. In the present setting, it is important to conduct a thorough examination of the variable known as RD to enhance the effect of technology adoption and adaptation processes. This variable can also play a crucial role in efficient and expeditiously assessing the return on investment of a technology expenditure. Hypotheses 4a and 4b have been developed on the basis of the following rationales:

Hypothesis 4a. RD exerts a substantial influence on PU.

Hypothesis 4b. RD exerts a substantial influence on PEOU.

CA

CA is a psychological phenomenon characterized by the presence of anxiety or fear in people during their interactions with technology or computers [23,31]. It is imperative to acknowledge CA as a noteworthy factor within technology adoption models, necessitating the formulation of solutions aimed at mitigating this anxiety. The reduction of anxiety levels is associated with an increased likelihood of swift and efficient adoption of technology within the workplace, thus potentially enhancing job performance in a positive manner. Hypotheses 5a and 5b have been developed for the following reasons:

Hypothesis 5a. CA exerts a substantial influence on PU.

Hypothesis 5b. CA exerts a substantial influence on PEOU.

POEC

Individuals' perceptions of the adequacy of institutional and technological resources for the acceptance and effective utilization of new technologies constitute POEC [23,31]. It is widely recognized as a crucial factor within models of technological acceptance. Organizations must prioritize the allocation of strategies and resources to enhance their perception, as this is crucial for quickening processes of digital transformation and technology adaptation. Hypotheses 6a and 6b have been developed for the following reasons:

Hypothesis 6a. POEC exerts a substantial influence on PU.

Hypothesis 6b. POEC exerts a substantial influence on PEOU.

PEOU

The term "perceived ease of use" describes the perceived amount of work that a person thinks is necessary to use a certain system or technology, as well as their subjective evaluation of this exertion [23,24]. The notion of PEOU plays a considerable role in the acceptance and assimilation of technology within businesses. Organizations can enhance the efficiency and expediency of technology adaptation procedures by considering this factor and implementing user-friendly interfaces, effective training programs, and continuous support mechanisms. Consequently, the subsequent hypotheses, hypothesis 7 and Hypothesis 9, are posited in the following manner:

Hypothesis 7. PEOU exerts a substantial influence on PU.

Hypothesis 9. PEOU exerts a substantial influence on BI.

PU

The concept of PU is a considerable factor that influences consumers' decision-making processes regarding the acceptance and use of specific technologies or systems [21,22]. PU occupies a pivotal role within technology adoption models and tactics of digital transformation. A significant degree of this characteristic can accelerate the process of technology acceptance and have a beneficial influence on the overall work performance of an organization. To promote a perception of high usefulness, firms can execute a range of training programs, initiatives aimed at maximizing user experience, and activities designed to develop staff's technological competencies. Based on the preceding information, we propose the following proposition:

Hypothesis 8. PU exerts a substantial influence on BI.

BI

The construct of BI is a reliable indicator of the likelihood that people will engage in a particular behavior. This idea pertains to an individual's inclination to exhibit a specific behavior and incorporates the various motivational factors that impact the likelihood of the behavior being displayed [33,35,36]. With further examination, it can be shown that there is typically a positive association between BI and UB, namely the tangible use of technology [25]. A thorough understanding of these components is essential for the successful integration and implementation of an innovation in technology. Considering the factors described above, we contend that:

Hypothesis 10. BI has a significant impact on UB.

UB

Within conventional iterations of TAM, considerable attention is frequently allocated to the construct of "intention to use", which functions as a reliable indicator of an individual's inclination to interact with a specific technological innovation. Nevertheless, it is imperative to acknowledge that intentions may not always translate into tangible acts. The concept of "use behavior" becomes pertinent in this context. This dimension explores the empirical component of technology consumption, encompassing the examination of both the actual usage of technology by individuals and the specific manner in which it is employed [21,22,36]. A thorough understanding of the factors that impress "use behavior" is crucial for developing efficient training programs, enhancing system design, and ensuring ongoing support systems. These elements collectively contribute to the successful implementation of the technology under consideration.

In summary, TAM, initially introduced by Davis et al. [30], offers a significant foundational framework for comprehending the psychological and behavioral aspects that could influence an individual's decision to embrace a particular technology. However, a more detailed analysis of "use behavior" provides a more nuanced understanding of the elements that translate BIs into actual actions [37]. Figure 2 depicts the visual representation of the offered theories.

3.2. Data Collection

Prior to the initiation of the data collection process, approval was obtained from the İstanbul Technical University Social and Human Sciences Human Research Ethics Committee (approval no: 315, date: 23.02.2023), ensuring that our study adhered to the ethical standards required for research within the realm of social and human sciences.

During this study, an extensive survey was administered to professionals involved in maritime and port operations. The scientific literature that was already available served as a guide for selecting the sample size. After conducting a comprehensive investigation of the existing scholarly works, it becomes clear that determining the optimal sample size for factor analysis is a multifaceted task, dependent upon numerous variables. Consequently, it is difficult to establish a definitive number. However, the academic literature provides numerous rules and criteria of this subject matter.

A frequently accepted practice in empirical research is to use a sample size ranging from 100 to 200 when the components under investigation are robust and distinguishable and the number of variables being studied is not unduly high. According to existing literature, it is often advised that the sample size should exceed the number of observed variables by a factor of at least five, which is typically regarded as a general heuristic. In situations characterized by robust and dependable associations as

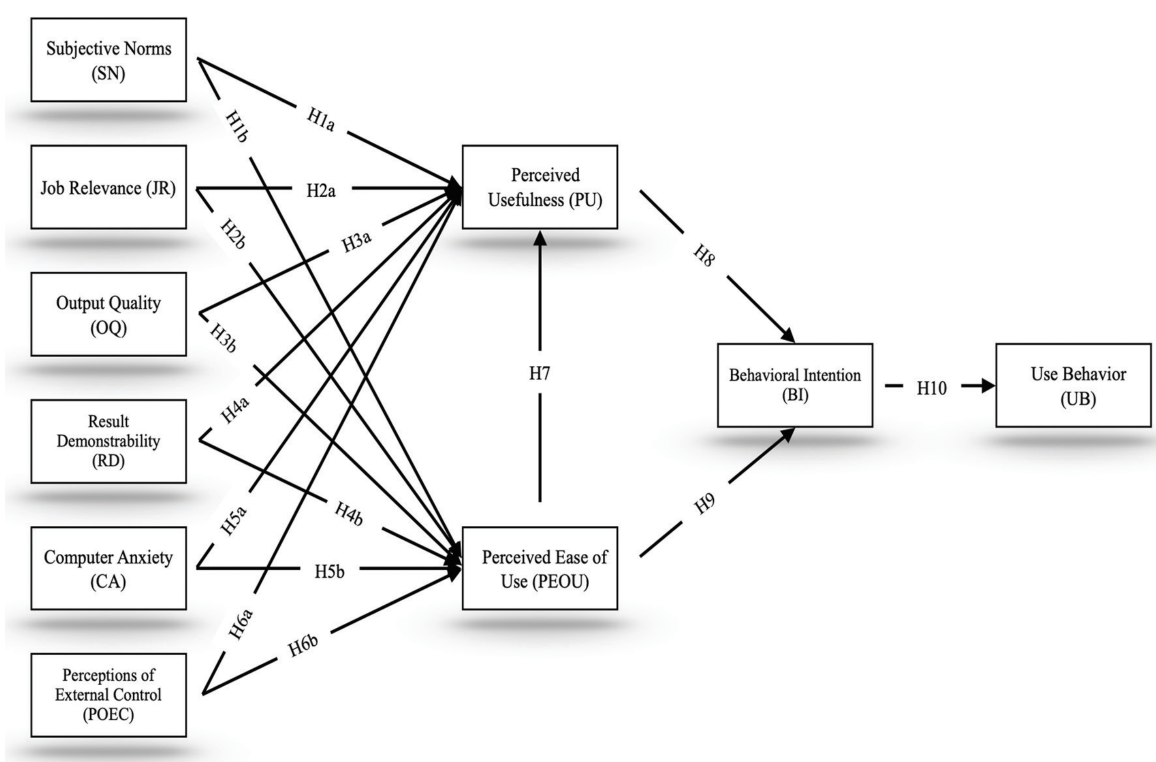

***Figure 2.** Representation of the proposed hypotheses*

well as a well-defined factor structure, a sample size as small as 50 may be deemed sufficient, as long as it surpasses the number of variables [38].

These guidelines provide researchers with a framework for many scenarios and contingencies. However, it is important to always consider the particulars of the research environment and aims when establishing a suitable sample size.

The current study involved the collection of data from a sample of 570 people who were actively involved in the maritime logistics industry. Given the wide array of vocational fields within the sector and the inherent difficulties in obtaining sufficient data from each, this study primarily concentrates on two domains: maritime logistics (ship-based), which pertains to activities conducted on ships, and terrestrial logistics (port-based), which encompasses operations carried out in ports.

After the preliminary analysis, 31 questionnaires with careless or inconsistent responses were removed from the dataset. As a result, the final sample size for further analyses consisted of 539 responses. Throughout the data collection process, a comprehensive set of statistical controls was implemented, which encompassed various procedures such as assessing normal distribution, conducting reliability assessments, and performing factor analyses. The subsequent portions of the study will offer a comprehensive analysis and understanding of the results obtained by employing these specific methodological approaches.

After eliminating outliers from our dataset, we analyzed demographic characteristics. Data were classified based on gender, age, professional experience, educational attainment, and occupational field. The findings of the analyses are shown in Table 1.

4. Results

Before conducting the study, the dataset was subjected to a normality examination, which involved examining the kurtosis and skewness of individual variables. The thresholds for these measures were determined to be ±1, in accordance with accepted statistical recommendations [39]. The results obtained indicate that both the kurtosis and skewness values were within the range of ±1, suggesting that there was no substantial departure from normalcy [40]. On the basis of the aforementioned observations, it may be inferred that the dataset conforms to the normal distribution, exhibiting no discernible abnormalities associated with normality.

4.1. Evaluation of the Model's Discriminant and Convergent Validity

The evaluation of the suitability of the dataset employed in this study involved an examination of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. The KMO statistic in SPSS is used as a metric to evaluate the adequacy of the sample size for factor analysis, as stated by Field [41]. This statistical analysis was derived from the examination of correlations and partial correlations among all variables. In essence, it quantifies the extent to which a certain variable may be elucidated isolated from all other variables. According to Hair [42], a KMO value equal to or greater than 0.60 is typically deemed satisfactory for factor analysis. The KMO value obtained for this investigation was determined to be 0.942, indicating a substantial degree of adequacy in the sampling process.

This study seeks to analyze the intricate mechanisms that influence technology adoption in this particular business by employing confirmatory factor analysis (CFA) as a fundamental analytical method. The purpose of the CFA model is to assess the validity and reliability of the theoretical framework that elucidates the adoption of technology. This analysis offers valuable insights into the structural integrity and internal coherence of the scale.

To validate the proposed model, various fit indices were employed to assess how well the model matches observed data. These encompass measures that gage the model's overall fit, the relationship between observed and expected covariance, and other fit statistics. In addition, the study integrates several reliability and validity metrics to thoroughly evaluate the consistency of the measurements and the distinction between the constructs.

Table 1. *Demographic information (n=539)*

Categories		Number of participants	Rate (%)
Gender	Women	149	27.6
	Men	390	72.4
Age	21-30	73	13.5
	31-40	303	56.2
	41-50	110	20.4
	51-60	44	8.2
	61 and over	9	1.7
Education	Associate degree	12	2.3
	Bachelor's degree	390	72.3
	Graduate degree	137	25.4
Professional experience	1-5 years	122	22.6
	6-10 years	117	21.7
	11-15 years	146	27.1
	16-25 years	141	26.2
	26 years and over	13	2.4
Field of occupation	Ship-based	156	28.9
	Port-based	383	71.1

Given these factors, the outcomes of the assessments of validity and reliability are displayed in Table 2. After careful examination, it can be noticed that all values fall within acceptable ranges.

In the realm of evaluating the validity and reliability of the models, a thorough examination of multiple criteria was conducted with considerable attention to detail. The convergence dependability of the study was supported by the average variance extracted (AVE) values, which surpassed the established threshold of 0.5 for all latent constructs. The presence of internal consistency was demonstrated by the consistent surpassing of the 0.7 benchmark by the composite reliability (CR) values. Furthermore, the dependability of the indicators was confirmed by all measures, which showed Cronbach's alpha values exceeding 0.7. The affirmation of discriminant validity was achieved

Table 2. *Validity and reliability tests*

Latent variable	Items	Loadings	α	CR	AVE	MSV	MaxR (H)
Perceived usefulness	PU1	0.77	0.912	0.903	0.571	0.561	0.906
	PU2	0.79					
	PU3	0.799					
	PU4	0.768					
	PU6	0.699					
	PU7	0.676					
	PU8	0.78					
Perceived ease of use	PEOU1	0.755	0.912	0.902	0.536	0.468	0.904
	PEOU2	0.746					
	PEOU3	0.73					
	PEOU6	0.682					
	PEOU7	0.724					
	PEOU8	0.681					
	PEOU9	0.738					
	PEOU10	0.794					
Subjective norms	SN1	0.781	0.824	0.827	0.614	0.468	0.828
	SN2	0.763					
	SN3	0.806					
Job relevance	JR1	0.771	0.800	0.802	0.670	0.464	0.815
	JR2	0.864					
Output quality	OQ1	0.822	0.801	0.802	0.670	0.381	0.802
	OQ2	0.815					
Perceptions of external control	POEC2	0.885	0.782	0.797	0.664	0.110	0.828
	POEC3	0.738					
Computer anxiety	CA1	0.854	0.894	0.895	0.741	0.487	0.900
	CA2	0.895					
	CA3	0.832					
Result demonstrability	RD1	0.838	0.825	0.829	0.708	0.342	0.829
	RD2	0.845					
Behavioral intention	BI1	0.781	0.817	0.852	0.659	0.561	0.857
	BI2	0.851					
	BI3	0.801					
Use behavior	UB1	0.897	0.845	0.852	0.659	0.411	0.877
	UB2	0.818					
	UB3	0.709					
CMIN/DF: 2.812, SRMR: 0.0432, CFI: 0.920, RMSEA: 0.058, IFI: 0.921							

by observing that the maximum shared variance values continually exhibited lower values than their corresponding AVE measures. In addition, the MaxR (H) values were used to assess the explanatory capacity of individual factors. Higher values were seen as evidence of greater contributions of the factors to the overall variance in the dataset.

The researchers employed a measurement model to systematically investigate the factor loadings of observable variables on their respective latent components. The model's structural validity was rigorously evaluated using CFA. The model was subjected to thorough validation procedures that included assessments of both discriminant and convergent validities, as well as reliability metrics, in accordance with the criteria established by Hair [39]. The data shown in Table 2 demonstrate that all constructs in the model achieved a CR score that exceeded the stated threshold of 0.7, thereby confirming the model's dependability. Furthermore, it is worth noting that the factor loadings and AVE values in this study exceeded the minimum standards of 0.7 and 0.5, respectively, as established by Hair et al. [43]. This finding provides additional support for the strong validity of the model. The discriminant and convergent validity were assessed by examining the variance-covariance matrix between the measurement items and their corresponding latent variables. Concurrently, Table 3 provides an illustration of the values that meet the criteria for establishing discriminant validity. The comprehensive statistical analysis supports the sufficiency of the model in accurately capturing the facts. Similarly, the reliability of the questionnaire was validated by employing a cut-off score of 0.7 [44].

4.2. Structural Model (SM) Evaluation

The primary objective of this study was to investigate the relationships between relevant variables and evaluate the effectiveness of a specified theoretical framework. The researchers opted for structural equation modeling (SEM) as the methodological framework to evaluate the adequacy of the proposed model. SEM was selected because of its capability to model intricate connections among various variables and specifically for its capacity to manage latent variables and measurement errors [43].

To conduct SEM analysis on the collected data, a two-step methodology was employed. The measurement model involved performing CFA using AMOS software to establish the connections between observable and latent variables. Following this, the researchers conducted an empirical examination of SEM to assess the hypothesized correlations between the dependent and independent variables. The adequacy of the SEM model was assessed by examining the coefficient parameters and goodness-of-fit indices in accordance with the criteria established in previous scholarly works [43,45].

The SEM results for the causal links of the hypothesized model, and the R^2 results, are depicted in Figure 3. The significance values for all paths were assessed at a p-value of 0.05. In SEM, the coefficient of determination (R^2) gages how well independent variables account for the variability in the dependent variable. To enhance the goodness-of-fit of the SM, covariances were introduced between the error terms. The incorporation of these covariances led to a noticeable improvement in the fit indices of the model.

Accurate representation of data using the suggested model is highly significant, requiring assessment using several fit indices. The indices encompass various fit measures, namely χ^2, RMSEA, CFI, IFI, and SRMR. These indices are frequently used in both CFA and SEM assessments. Based on the data provided in Table 4, fit indices such as CMIN/df, CFI, IFI, RMSEA, and SRMR indicate satisfactory compliance with the accepted criteria.

Table 3. *Discriminant validity*

	PU	PEOU	SN	JR	OQ	POEC	CA	RD	BI	UB
PU	**0.756**									
PEOU	0.674	**0.732**								
SN	0.660	0.684	**0.784**							
JR	0.550	0.574	0.595	**0.819**						
OQ	0.591	0.570	0.617	0.532	**0.819**					
POEC	0.294	0.332	0.118	0.159	0.282	**0.815**				
CA	0.578	0.524	0.501	0.559	0.428	0.264	**0.861**			
RD	0.575	0.542	0.585	0.519	0.564	0.206	0.489	**0.842**		
BI	0.749	0.609	0.599	0.681	0.522	0.153	0.698	0.562	**0.812**	
UB	0.641	0.506	0.376	0.442	0.348	0.314	0.429	0.420	0.531	**0.812**

PU: Perceived usefulness, PEOU: Perceived ease of use, SN: Subjective norms, JR: Job relevance, OQ: Output quality, POEC: Perceptions of external control, CA: Computer anxiety, RD: Result demonstrability, BI: Behavioral intention, UB: Use behavior

Table 4. Summary of fit indices

Fit Indices	CMIN/DF	CFI	IFI	RMSEA	SRMR
Acceptable fit	<5	>0.90	>0.90	<0.08	<0.08
Obtained fit CFA	2.812	0.920	0.921	0.058	0.043
Obtained fit SEM	3.080	0.906	0.907	0.062	0.054

Table 5 presents an overview, encapsulating the outcomes of the hypothesis testing conducted in this study. This table is prepared to provide a clear and concise summary of the hypotheses that were supported and those that were not, based on the empirical data analyzed. The acceptance or rejection of these hypotheses is grounded in statistical significance and adheres to the standards of the adopted methodology.

5. Discussion of the Findings

The results from the AMOS analysis clearly support the significant influence of all variables examined in this study. SN had a significant impact on both PU (H1a: $\beta=0.293$, $p<0.05$) and PEOU (H1b: $\beta=0.413$, $p<0.05$). The magnitude of these β-coefficients emphasizes the considerable role of SN in affecting both PU and PEOU. The findings underscore the critical impact of SN on shaping individuals' acceptance and approaches towards adopting new technologies, reinforcing the necessity to consider subjective norms in understanding technology adoption dynamics.

Based on the SEM analysis, it is evident that JR significantly influences PEOU (H2b: $\beta=0.172$, $p<0.05$), indicating a favorable relationship. However, no statistically significant relationship was observed between JR and PU (H2a: $p>0.05$). While JR's effect on PEOU is significant, its impact on PU remains undetermined. Notably, similar studies have yielded mixed results regarding JR's impact on PU, with some findings indicating a negligible influence [46], while others report a significant effect [47,48]. This highlights the complexity of JR's relationship with PU and the need for further investigation, especially in the context of technology adoption.

The analysis of SEM reveals a significant relationship between OQ and PU (H3a: $\beta=0.151$, $p<0.05$), indicating that as OQ increases, PU also improves. However, no significant relationship was found between OQ and PEOU (H3b: $p>0.05$). These findings suggest that while OQ impacts PU, it does not significantly influence PEOU. Hart and Porter [49], in their research on on-line analytical processing, discovered a positive correlation between OQ and PU, thereby affirming OQ's influence on PU. Similarly, Davis et al. [50] observed a positive impact of OQ on PU in their examination of computer technology.

The findings of the study indicate that RD had a significant effect on PU (H4a: $\beta=0.147$, $p<0.05$) but did not have a significant impact on PEOU (H4b: $p>0.05$). SEM analysis confirmed a notable association between RD and PU, with a β value of 0.147, reflecting a moderate effect size. Despite its significance for PU, the p-value for the RD-PEOU relationship surpassed the 0.05 threshold, indicating its lack of significance within this dataset. This aligns with various studies in the literature, where RD is frequently observed to positively influence PU in different contexts [22,49]. In essence, RD emerges as a key factor in shaping user opinions on technology's utility but does not appear to affect their views on its usability.

The presence of CA had a statistically significant impact on both PU (H5a: $\beta=0.237$, $p<0.05$) and PEOU (H5b: $\beta=0.100$, $p<0.05$). The SEM study indicates a significant relationship between CA and both PU and PEOU, with the standardized beta coefficients being 0.237 for PU and 0.100 for PEOU, both significant at the 0.05 level. As CA increases, there is a corresponding decrease in the perception of the usefulness and ease of use of computer applications. These findings underscore the ramifications of CA on technology usage and are supported by other studies in the literature, highlighting the influence of CA on technology adoption and user experience [51-54].

The study found that POEC had a statistically significant effect on PEOU (H6b: $\beta=0.172$, $p<0.05$). However, it did not have a significant influence on PU (H6a: $p>0.05$). SEM results underscored POEC's influence on PEOU, with a β of 0.172, significant at the 5% level. This suggests that individuals perceiving higher external control are more likely to find the system user-friendly. However, POEC's impact on PU was found to be insignificant, suggesting that PU and PEOU are influenced differently by external control factors. These findings align with various studies in the field. Fisher [55] highlighted the importance of external factors in shaping technology perceptions. Venkatesh [23] integrated external factors into the TAM, emphasizing their role. Additionally, research by Abbad et al. [56] in Jordan's banking sector supports the idea that external variables significantly influence PEOU, corroborating the impact of external control on technology acceptance. These studies affirm that external factors such as POEC significantly influence PEOU, as observed in this study, but their impact on PU may differ.

The study revealed that PEOU had a significant impact on both PU (H7: $\beta=0.203$, $p<0.05$) and BI (H9: $\beta=0.331$, $p<0.05$). SEM analysis supports these associations, with both p-values indicating statistical significance at the 5% alpha level. The positive β coefficients suggest that as perceptions of a system's ease of use rise, there is a corresponding increase in its PU and BI. In summary, user friendliness

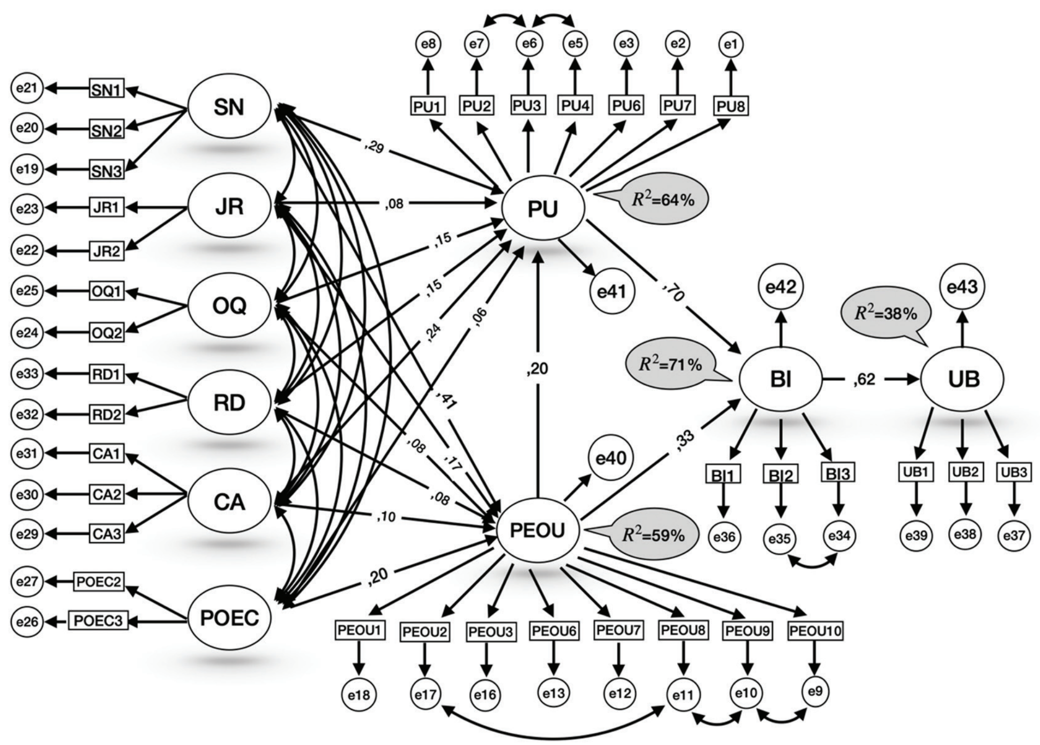

Figure 3. Output produced by the structural model (SM)

Table 5. *Hypotheses testing results*

Hypotheses	Impact	β value	P	Status
H1a	SN→PU	0.293	0.001	Acceptance
H1b	SN→PEOU	0.413	***	Acceptance
H2a	JR→PU	0.08	0.115	Rejection
H2b	JR→PEOU	0.172	0.002	Acceptance
H3a	OQ→PU	0.15	0.019	Acceptance
H3b	OQ→PEOU	0.08	0.161	Rejection
H4a	RD→PU	0.15	0.010	Acceptance
H4b	RD→PEOU	0.08	0.126	Rejection
H5a	CA→PU	0.24	***	Acceptance
H5b	CA→PEOU	0.10	0.042	Acceptance
H6a	POEC→PU	0.06	0.165	Rejection
H6b	POEC→PEOU	0.20	***	Acceptance
H7	PEOU→PU	0.20	***	Acceptance
H8	PU→BI	0.70	***	Acceptance
H9	PEOU→BI	0.33	***	Acceptance
H10	BI→UB	0.62	***	Acceptance

PU: Perceived usefulness, PEOU: Perceived ease of use, SN: Subjective norms, JR: Job relevance, OQ: Output quality, POEC: Perceptions of external control, CA: Computer anxiety, RD: Result demonstrability, BI: Behavioral intention, UB: Use behavior

is pivotal in shaping users' views on a system's value and their inclination to engage with it. This finding aligns with numerous studies in the literature that consistently demonstrate the significant influence of PEOU on both PU and BI in various technological contexts [21,22,30].

PU was found to have a statistically significant positive effect on BI (H8: β=0.703, p<0.05). The SEM analysis showed a robust association between PU and BI, with a substantial β of 0.703, significant at the 5% alpha level. This indicates that users are more likely to use a system they perceive as useful. In conclusion, these results reinforce the pivotal role of PU in determining users' bis, aligning with the core principles of TAM. This is supported by extensive research in the literature, validating the positive impact of PU on BI as a fundamental assertion of TAM [21,22,48].

The variable of BI had a significant impact on UB (H10: β=0.618, p<0.05). SEM analysis confirmed this association with a standardized beta coefficient of 0.618, which was statistically significant at the 5% alpha level. This suggests that an increase in BI correlates with a rise in UB. These findings indicate that BI is a key predictor of UB, thereby reaffirming the core tenets of TAM. Numerous studies in the literature also find BI to be a crucial factor influencing actual system use, validating the importance of BI and UB in TAM for predicting technology adoption [21,22,30].

6. Conclusion

This research has elucidated the intricate dynamics between various independent variables and their collective impact on the dependent variable, offering valuable insights that can inform the development of more nuanced and effective strategies. This study has crafted a detailed analytical tool, shedding light on the multifaceted interactions and relationships within the theoretical model applied to the digital transformation of the maritime transportation logistics sector.

The results corroborate the significance of classical factors such as PU and PEOU in the TAM, especially in the context of the maritime transportation logistics industry's digital transformation. Furthermore, specific determinants such as industry characteristics and digital capabilities were also found to be instrumental. Notably, investment in digital technologies and the enhancement of digital capabilities have emerged as decisive factors for swift and effective adaptation to digital transformation within the maritime logistics sector. This underscores the imperative for organizations to foster and expand their digital capabilities to take the lead in adopting and implementing digital technologies, thereby securing a competitive edge.

The outputs also acknowledge the separate impact of different aspects, including CA, SN, OQ, JR, POEC, and RD. Each of the aforementioned variables exhibits varied degrees of interaction with PU and PEOU, consequently influencing the dynamics of digital adoption within the maritime logistics sector. Furthermore, beliefs concerning external control, particularly institutional support and infrastructural readiness, emerge as significant, emphasizing the essential role of organizations in adeptly spearheading digital initiatives and fostering a conducive environment for digital transformation.

The aforementioned insights play a crucial role in comprehending the present condition of digital integration in maritime transportation logistics. However, they also emphasize the necessity for continuous study to completely unravel the intricate nature of digital transformation. The ongoing investigation is essential for determining the most effective approaches to effectively include and assimilate digital technologies in this field.

The proposed research has a limitation that needs to be addressed. A single country was the source for selecting 539 participants. Conducting a study that involves participants from different countries can improve this study. Additionally, the research methodology was confined to the use of SEM and TAM. Moreover, enhancing geographical representation and refining data gathering methodologies will contribute to enhancing the comprehensiveness of the study. It might be advisable for future studies to conduct a study in which maritime sector employees assess the factors that influence the digital transformation process using multi-criteria decision-making methods to improve the results of this study.

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Authorship Contributions

Concept design: O. Gündoğan, and T. Keçeci, Data Collection or Processing: O. Gündoğan, and T. Keçeci, Analysis or Interpretation: O. Gündoğan, Literature Review: O. Gündoğan, Writing, Reviewing and Editing: O. Gündoğan, and T. Keçeci.

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