IMPACT OF KNOWLEDGE MANAGEMENT AND PORT DISRUPTION ON PORT PERFORMANCE: PERSPECTIVE OF CAMBODIAN SHIPPERS

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ABSTRACT

Purpose: This study investigates the impact of Knowledge Management (KM) and Port Disruptions (PD) on Port Performance (PP) from the perspective of Cambodian shippers. Specifically, it examines how KM, Human Errors (HE), and PD influence Port Reliability (PR) and overall port performance.

Approach: The research employs a combination of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM) to investigate the relationships between KM, HE, PD, PR, and PP. Data were collected from 200 Cambodian shippers to test the proposed relationships and validate the findings.

Findings: The study finds that KM significantly reduces HE, thereby enhancing PR. PD has a marginally positive effect on PR, indicating that ports handle routine disruptions well but may be unprepared for severe crises. Notably, PD does not have a significant direct impact on PP. Instead, PR emerges as the most influential factor driving PP, highlighting the need to strengthen reliability through effective knowledge management and disruption mitigation strategies.

Research limitations: The study faced limitations in measuring PD due to the exclusion of items irrelevant to Cambodian ports, reducing construct validity. Limited respondent experience with severe disruptions further constrained insights. Enhancing model fit and adding variables can improve robustness and theoretical clarity. As the study focuses on Cambodian shippers, the findings on PD's impact on PR and PP may not generalize to contexts with more frequent severe disruptions.

Practical implications: The findings offer actionable insights for stakeholders. Academic institutions can incorporate these results into logistics curricula and promote further research. Policymakers can develop training and knowledge-sharing policies to reduce HE and enhance PR. Industry practitioners should adopt KM practices, such as training and collaboration, to minimize disruptions and improve reliability, applying academic insights to operational improvements.

Originality: This study integrates KM, HE, PD, PR, and PP into a comprehensive framework, demonstrating KM's indirect role in mitigating PD and highlighting PR as a key driver of PP. By bridging theory and practice, it offers new perspectives on enhancing port performance and resilience, contributing to both academic understanding and industry strategies.

Keywords: Knowledge Management, Port Disruption, Port Reliability, Port Performance, Human Errors

Introduction

Ports are the keystone of global trade and economic activity, functioning as critical hubs for the transportation and exchange of goods. They connect producers, manufacturers, and consumers across continents, ensuring the seamless movement of resources and supporting supply chains that sustain industries and communities. Despite their importance, port operations are often vulnerable to disruptions, both man-made and natural, that can hinder efficiency, reliability, and resilience. The research problem centers on the limited understanding of how KM and HE influence PD and, subsequently, PR and PP. While previous studies have investigated the impact of human errors on occupational accidents (Bowo and Furusho, 2018, Fabiano et al., 2010, Uğurlu et al., 2015) and analyzed the relationship between KM and organizational performance (Al-Bahussin and Elgaraihy, 2013, Asoh et al., 2007), a notable gap remains in exploring how these factors interconnect specifically in the context of port operations. Furthermore, the perspectives of shippers—key stakeholders who initiate and organize the movement of goods—have been underexplored, leaving a critical void in understanding how these dynamics influence their operations and decision-making.

The significance of this research lies in its potential to bridge these gaps and provide actionable insights for both academia and practice. By analyzing the relationship among KM, HE, PD, PR, and PP, this study aims to offer evidence-based strategies for mitigating risks and enhancing port reliability and performance. This is particularly important as man-made disruptions, including labor strikes and accidents, account for over half of port disruptions globally (Lam and Su, 2015). Employing methodologies such as EFA, CFA, and SEM, this research contributes to the academic discourse by uncovering causal relationships and validating theoretical frameworks. The findings will serve as a foundation for developing strategies that port authorities, policymakers, and shipping companies can implement to enhance operational resilience and reliability.

Literature Review

Ports are critical to global trade, yet they face persistent challenges related to KM, PD, PR, PP, and HE. The existing literature provides valuable insights into these factors but reveals gaps in understanding their interconnections and implications for operational resilience and efficiency. KM is recognized as a key enabler of organizational performance through continuous learning, knowledge sharing, and innovation. Studies highlight that KM facilitates operational efficiency by promoting trust, collaboration, and knowledge transfer across organizations (Al-Bahussin and Elgaraihy, 2013, Zhou et al., 2021). Maritime knowledge clusters and firms' absorptive capacities are shown to enhance performance, yet the direct role of KM in mitigating human errors and improving port reliability remains underexplored (Asoh et al., 2007).

PD, caused by natural disasters or man-made events, significantly affects global supply chains by halting material flows and causing economic losses (Lam and Su, 2015). Resilience frameworks, such as the Port Supply Chain Disruption (PSCD) model, combine risk management and business continuity to enhance port operations (Loh and Thai, 2015). However, these models often fail to capture cascading risks and their broader implications within port-hinterland networks (Kuang et al., 2021). PR and PP are closely linked to timely, accurate, and efficient service delivery. PR is influenced by infrastructure reliability, network configuration, and customer satisfaction, while PP balances internal efficiency and external service quality to meet stakeholder demands (Woo et al., 2011, Yue and Mangan, 2023). Despite these advancements, inconsistencies in definitions and measurement approaches hinder their universal application across diverse operational contexts.

HE remains the leading cause of maritime accidents, contributing to 75–96% of incidents (Antao and Soares, 2019). Errors are categorized into individual, team, application, and voyage management issues, often exacerbated by skill gaps and reliance on technology (Uğurlu et al., 2015). Limited research addresses how KM can reduce human errors in maritime settings. Although theoretical models like KM Theory, the PSCD framework, and error categorization frameworks provide structured approaches to these challenges, significant gaps remain. Specifically, the literature lacks integrated models linking KM, PD, PR, PP, and HE. Additionally, cascading disruption risks and the inconsistent application of PR metrics require further exploration. Addressing these gaps is crucial for developing comprehensive strategies to enhance port resilience and optimize operational performance.

Research Methodology

Data Collection

This study adopts a questionnaire-based design to investigate KM, HE, PD, PR, and PP among Cambodian shippers. The seven-step questionnaire process, adapted from (Stone, 1993), includes defining data needs, selecting items, designing questions, and piloting. Closed questions using Likert scales capture respondents' agreement or importance levels on key variables, ensuring clarity and reliability. Data collection involves pretesting and piloting the questionnaire to refine its validity and reliability. Two pilot tests, each with 15 respondents, assess framing, sequence, and comprehension. The final questionnaire is distributed online over two months, supported by follow-ups to enhance response rates. Demographic data, such as job title and years of experience, complement the scaled responses for non-biased responses. Sample selection focuses on Cambodian shippers, defined within the study's scope. Measurement items are derived from established literature to align with research objectives. Targeting professionals in shipping operations ensures relevant and actionable insights.

Data analysis techniques

The study employs SEM as the primary analytical tool to examine the complex relationships among latent and observed variables. Covariance-Based SEM (CBSEM) was chosen over Partial Least Squares (PLS) SEM due to its emphasis on theory testing, parameter estimation, and comprehensive goodness-of-fit measures, which align with the confirmatory nature of this research (Hair et al., 2010, Chao, 2011). SEM integrates EFA and CFA to validate measurement models before assessing structural relationships, ensuring robust construct validity and reliability. The analysis follows the six stages of SEM outlined by Hair et al. (2010).

EFA is utilized to identify underlying structures within the data, grouping related factors and evaluating measurement components' unidimensionality, reliability, and validity. Principal Component Analysis (PCA) is chosen for factor extraction, with varimax rotation applied to simplify the factor structure (Sawangwong and Chaopaisarn, 2021). EFA focuses on PD and PR, while other variables are based on previously validated findings from the literature.

Building on EFA, CFA tests hypotheses regarding factor structure and confirms relationships between observed variables and latent constructs. CFA validates port performance measures as outlined by (Woo et al., 2011). Items are retained if their factor loadings exceed 0.5 for new items and 0.6 for established items; those below these thresholds are removed. Validity is ensured by achieving an AVE of 0.50 or higher, and discriminant validity is assessed using Modification Indices (MI) in AMOS, with MI values greater than 15 indicating redundancy. To avoid multicollinearity, correlations between exogenous constructs are kept below 0.85. Fit indices such as Chi-Square ($p > 0.05$), RMSEA (< 0.08), GFI (> 0.90), Adjusted GFI (AGFI), CFI, TLI, and Normed Fit Index (NFI) (all greater than 0.90) are applied, with a Chi-Square/degrees of freedom ratio below 3.0 indicating a good fit. Reliability is measured using Cronbach’s alpha (greater than 0.70) and CR (greater than 0.60) (Awang, 2014).

After completing CFA, SEM is employed to test the hypotheses and validate theoretical relationships between variables. SEM analyzes observed means, variances, and covariances through structural parameters such as factor loadings and regression paths. AMOS software is utilized due to its ability to analyze complex relationships, test theoretical models, and assess model fit. Its user-friendly graphical interface facilitates visualization and interpretation of results. Additionally, AMOS is recognized for its flexibility in handling missing data, robustness with non-normal distributions (Byrne, 2013), and capacity to conduct mediation and moderation analyses (Kline, 2011).

Result

Descriptive analysis, EFA, and CFA

A survey targeting logistics professionals via LinkedIn involved sending connection requests to approximately 1,411 individuals. With an acceptance rate of 31%, the survey was distributed to 411 individuals, resulting in 201 responses and a 15% response rate. Respondents were primarily Managers or Assistant Managers (40.77%) with 1–5 years of industry experience (63.86%). Over half were employed by foreign-owned companies, and 50.50% worked in small to medium-sized enterprises with 1–250 employees. The study ensured robust data preparation by addressing missing data, outliers, and normality. Missing data, identified as MCAR through Little's test ($p > 0.05$), was imputed using the EM method, which preserves relationships between variables and is suitable for Likert scale data. Outliers were analyzed using Mahalanobis D^2, with decisions to retain all the items. Normality was confirmed as skewness (-2 to +2) and kurtosis (up to +7) values fell within acceptable ranges, validating the dataset for further analysis.

EFA identified distinct dimensions within PD and PR. For PD, four factors emerged: Operation Issues (OI), Security Incidents (SI), External Disruptions (ED), and Technical Failures (TF), with strong loadings and a KMO of 0.787, indicating suitability for factor analysis. For PR, three factors were derived: Service Reliability (SR), Operational Efficiency (OE), and Delivery Consistency (DC) supported by a high KMO of 0.842. These findings validate the constructs' multidimensionality, with well-defined factor groupings and robust item loadings. The CFA process was undertaken to ensure the reliability and validity of the measurement model, evaluating constructs using Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's Alpha. CFA assessed model fit through indices like χ^2/df, GFI, RMSEA, CFI, and TLI, meeting thresholds for acceptable or good fit. The process involved refining the model in iterative steps:

1. **Evaluating Factor Loadings**: Items with loadings below 0.40 were flagged for removal. However, theoretically relevant items like KM-1 were retained despite low statistical contributions due to their significance in representing key constructs.

2. **Addressing Redundancy**: Standardized residual covariances and modification indices (MI ≥15) identified overlapping items, such as KM-4 and KM-3, leading to the removal of KM-4 to improve fit.

3. **Final Assessment**: The refined model demonstrated strong fit indices (e.g., χ^2/df = 2.5, GFI = 0.92, RMSEA = 0.08, CFI = 0.91, TLI = 0.90), indicating reliable and valid constructs with internal consistency, convergent validity, and discriminant validity, supporting next structural analysis.

After the elimination process and calculation of validity and reliability, the refined constructs demonstrated an acceptable internal consistency and model fit. The results, including the final factor loadings, CR, AVE, and Cronbach's Alpha for each construct, are presented in Tables 1 to 5 for KM, PD, PP, PR, and HE, respectively. These tables provide insights into the refined measurement model, ensuring that constructs are supported in the subsequent structural analysis.

Constructs	**Items**	**Std. loadings**	**t-value**	**AVE**	**CR**	**Cronbach's α**
Knowledge Management (KM)	KM1	0.389	4.387	0.325	0.767	0.766
	KM2	0.504	5.348			
	KM3	0.575	5.845			
	KM5	0.650	6.288			
	KM6	0.611	6.065			
	KM7	0.659	6.331			
	KM8	0.556	-			

Table 1 Reliability and Validity Assessment of KM Construct

Constructs	**Items**	**Std. loadings**	**t-value**	**AVE**	**CR**	**Cronbach's α**
Security Incidents (SI)	SI-1	0.835	8.980	0.647	0.842	0.824
	SI-2	0.941	8.794			
	SI-4	0.599	-			
External Disruptions (ED)	ED-1	0.615	6.523	0.448	0.842	0.793
	ED-3	0.752	7.351			
	ED-4	0.789	7.517			
	ED-5	0.598	6.403			
	ED-6	0.563	-			
Technical Failures (TF)	TF-2	0.426	4.633	0.310	0.842	0.633
	TF-3	0.619	5.989			
	TF-4	0.512	5.331			

	TF-5	0.643	-			

Table 2 Reliability and Validity Assessment of PD Construct

Constructs	Items	Std. loadings	t-value	AVE	CR	Cronbach's α
Service Quality (SQ)	SQ1	0.692	8.668	0.526	0.847	0.844
	SQ2	0.785	9.622			
	SQ3	0.699	8.743			
	SQ4	0.750	9.278			
	SQ5	0.695	-			
Cargo Operation (CAO)	CAO1	0.760	8.021	0.565	0.793	0.778
	CAO2	0.861	8.083			
	CAO3	0.613	-			

Table 3 Reliability and Validity Assessment of PP Construct

Constructs	Items	Std. loadings	t-value	AVE	CR	Cronbach's α
Service Reliability (SR)	SR1	0.913	12.050	0.712	0.880	0.874
	SR2	0.883	11.925			
	SR3	0.723	-			
Delivery Consistency (DC)	DC1	0.650	6.284	0.390	0.760	0.750
	DC2	0.704	6.541			
	DC3	0.672	6.396			
	DC4	0.530	5.540			
	DC5	0.549	-			

Table 4 Reliability and Validity Assessment of PR Construct

Constructs	Items	Std. loadings	t-value	AVE	CR	Cronbach's α
Team Management Errors (TME)	TME1	0.611	9.045	0.600	0.855	0.850
	TME3	0.815	13.086			
	TME4	0.798	12.736			
	TME5	0.852	-			
Individual Errors (IE)	IE1	0.511	6.173	0.425	0.681	0.601
	IE4	0.609	7.138			
	IE5	0.802	-			

Table 5 Reliability and Validity Assessment of HE Construct

The fit indices for the measurement models in Table 6 indicate acceptable levels despite exceeding some ideal thresholds. For KM, the RMSEA of 0.098 and TLI of 0.857 are slightly above preferred values but are considered reasonable for complex or exploratory models (Browne & Cudeck, 1993; Hu & Bentler, 1999). Similarly, PP shows a χ^2/df of 3.511 and RMSEA of 0.112, which exceed ideal limits but fall within acceptable ranges for complex models, supported by strong CFI (0.926) and TLI (0.891). For HE, while the RMSEA of 0.099 is above the threshold, high CFI (0.954) and TLI (0.925) indicate good model fit overall. These deviations are consistent with literature recommendations for complex models, confirming the adequacy of the measurement models.

Constructs	Items	χ^2/df	GFI	RMSEA	CFI	TLI
KM	7	2.918	0.949	0.098	0.904	0.857
PD	12	2.133	0.923	0.075	0.925	0.902
PP	8	3.511	0.934	0.112	0.926	0.891
PR	8	2.131	0.953	0.075	0.965	0.948
HE	7	2.979	0.946	0.099	0.954	0.925

Table 6 Measurement Models

Structural Equation Modeling (SEM)

The SEM analysis tested relationships among key constructs: KM, HE, PD, PR, and PP. The model included 5 main constructs, divided into 10 sub-constructs, measured by 45 indicators. Key findings in Figure 1 showed that KM positively impacts PR (H3) and reduces HE (H6), while HE significantly reduces PD (H7). PD negatively affects PR (H4), and PR strongly enhances PP (H5). However, the paths KM → PD (H1) and HE → PP (H8) were not significant. Goodness-of-Fit indices indicate moderate model fit, with $\chi^2/df = 2.597$, RMSEA = 0.089, and marginally acceptable values for GFI (0.694), CFI (0.710), and TLI (0.689). While some relationships were supported with direct significance, others highlighted indirect effects. Table 7 summarizes the results of the hypotheses testing, showing that while most hypotheses are supported, such as H2, H3, H4, H5, H6, and H7, hypotheses H1 and H8 are not supported based on their p-values and estimates.

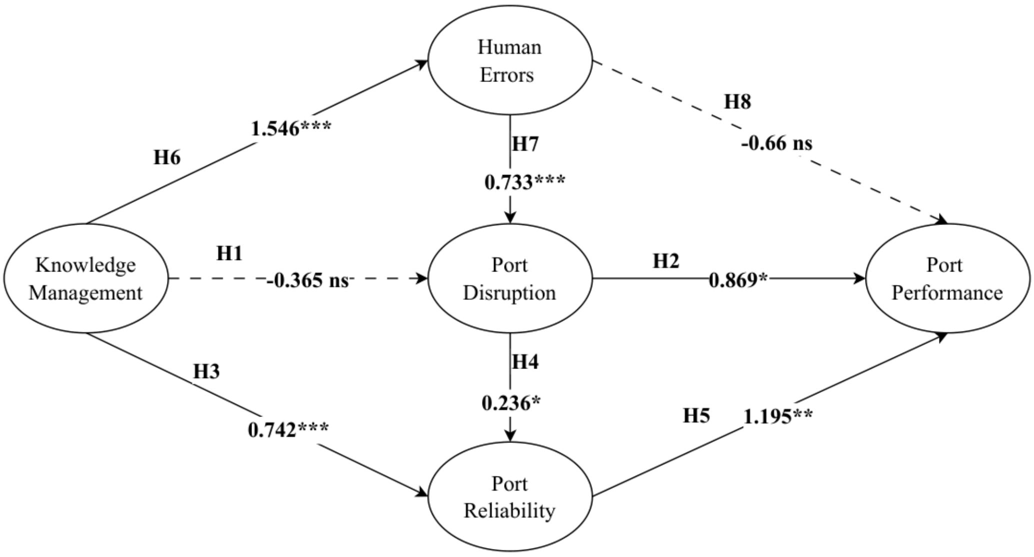

Figure 1 SEM Results

χ2/df = 2.597 (χ2 = 2082.619, df = 802); GFI = 0.694; RMSEA= 0.089; CFI = 0.710; TLI = 0.689
*** p < 0.001; ** p < 0.05; *p < 0.1; ns = not supported

Hypotheses		**Estimate**	**P-value**	**Result**
H1	The increase in KM leads to a decrease in PD.	-0.365	0.184	Not supported
H2	The decrease in PD leads to an increase in PP.	0.869	0.081*	Supported
H3	The increase in KM leads to an increase in PR.	0.742	***	Supported
H4	The decrease in PD leads to an increase in PR.	0.236	0.055*	Supported
H5	The increase in PR leads to an increase in PP.	1.195	0.007**	Supported
H6	The increase in KM leads to a decrease in HE.	1.546	***	Supported
H7	The decrease in HE leads to a decrease in PD.	0.733	***	Supported
H8	The decrease in HE leads to an increase in PP.	-0.660	0.136	Not supported

Table 7 Summary of Hypotheses Result

KM indirectly reduces PD by first minimizing HE. KM significantly improves HE management, supporting the idea that structured knowledge-sharing and employee training reduce errors in port operations. While KM does not directly impact PD, its indirect effect through HE is substantial, emphasizing that error reduction is a key mechanism through which KM enhances operational stability and prevents disruptions. These findings align with resilience-focused frameworks like Loh and Thai's (2015) PSCD model, highlighting KM's role in improving employee skills and reducing vulnerabilities. Similarly, the strong relationship between HE and PD underscores HE as a critical factor in mitigating disruptions, consistent with research by Lam and Su (2015) and Kuang et al. (2021) on the importance of managing internal vulnerabilities to ensure stable port operations

Paths		Direct Effect	Indirect Effect	Total Effect
H6	KM --> HE	0.862	0.000	0.862
H7	HE --> PD	1.180	0.000	1.180
H1	KM --> PD	-0.327	1.018	0.691
Indirect effect of KM on PD through HE: KM → HE → PD				

Table 8 Direct and Indirect Effects of KM, HE, and PD

HE indirectly improves PP by first reducing PD. While the direct effect of HE on PP is non-significant, its indirect impact through PD is substantial. The significant relationship between HE and PD demonstrates that managing HE effectively mitigates disruptions, which then enhances PP. This aligns with Loh and Thai's (2015) PSCD model, emphasizing that reducing disruptions fosters operational continuity, efficiency, and customer satisfaction. Managing HE is thus critical for maintaining stability and indirectly improving performance.

Paths		Direct Effect	Indirect Effect	Total Effect
H7	HE --> PD	1.180	0.000	1.180
H2	PD --> PP	0.996	0.323	1.319
H8	HE --> PP	-1.215	1.556	0.341
Indirect effect of HE on PP through PD: HE → PD → PP				

Table 9 Direct and Indirect Effects of HE, PD, and PP

Discussion and Conclusion

Result discussion

The SEM analysis demonstrated moderate model fit, with indices reflecting reasonable adequacy despite being slightly below ideal thresholds, due to the model's complexity. KM significantly enhances PR (H3), which in turn strongly impacts PP (H5), emphasizing PR's role as a mediator in ensuring operational reliability. Although KM does not directly reduce PD (H1), it indirectly mitigates disruptions by reducing HE (H6, H7), highlighting the importance of knowledge-sharing and training to minimize human errors. HE significantly impacts PD (H7), underscoring its role in preventing disruptions, but its direct effect on PP (H8) was non-significant, suggesting an indirect influence through PD. PR emerged as pivotal in enhancing PP, acting as a buffer against disruptions, and ensuring service continuity. Interestingly, the positive relationship between PD and PR (H4) suggests overconfidence in reliability due to limited exposure to severe disruptions, while PD's marginal effect on PP (H2) reflects ports' resilience. These findings underscore the importance of KM, PR, and HE management in enhancing port performance and ensuring service continuity despite potential disruptions.

This study examines KM's role in mitigating PD caused by HE and its impact on PR and PP. The findings reveal that effective KM practices indirectly reduce PD by minimizing HE, which strongly influences disruptions. While PD has a limited direct effect on PP, PR significantly enhances PP and buffers against disruptions. By addressing key gaps, the study clarifies KM's impact on port reliability and performance, highlighting PR’s mediating role and integrating KM, HE, PD, PR, and PP as interconnected factors in port management. The results stress prioritizing KM practices and strengthening PR to improve operational efficiency and resilience.

Practical and Theoretical contribution

This study provides actionable insights for stakeholders to enhance port performance through targeted KM practices and HE reduction. Academic Institutions can integrate these findings into logistics curricula, using practical examples to enrich education and promote further research on KM's role in operational resilience. Policymakers are encouraged to develop policies that emphasize training and knowledge-sharing initiatives to improve port resilience and efficiency, leveraging these findings to strengthen logistics frameworks. Industry Practitioners can use the study's recommendations to enhance operations by addressing common disruptions through KM and employee training, thereby improving reliability and overall performance. Theoretical Contributions include empirical evidence of KM's critical role in improving PR and its indirect impact on PP, reinforcing the importance of integrating KM and human factors in risk management frameworks to ensure operational stability and efficiency.

Research limitation and Future study

This study faced limitations in capturing the practical realities of PD in Cambodia, as some factors derived from prior research were not relevant or previously encountered by local operators, affecting construct reliability and validity. Despite these challenges, the research establishes a foundational framework for future studies. Future research should aim to improve the model fit by exploring alternative specifications and incorporating additional variables to enhance robustness. Additionally, the absence of a direct link between KM and PP suggests unexplored mediators, such as technological advancements or customer satisfaction, which should be examined to deepen understanding and improve the model's explanatory power.

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