

Technical Competence, Technology Mastery, and Ship Pilot Performance: The Mediating Role of SIPANDU

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ABSTRACT

Purpose – This study examines the direct and mediated effects of technical competence and technology mastery on ship pilot performance through the effectiveness of the Pilotage Information System (SIPANDU) at the Class II Harbormaster and Port Authority Office of Bontang. **Methodology** – An explanatory cross-sectional survey was administered to 52 active pilots and analysed using partial least squares structural equation modelling. Measurement quality was assessed with indicator loadings, average variance extracted, composite reliability, Cronbach's alpha, the Fornell–Larcker criterion, and the heterotrait–monotrait ratio. **Findings** – Technical competence and technology mastery improved performance. Technology mastery strongly predicted SIPANDU effectiveness, whereas technical competence did not. SIPANDU neither affected performance nor mediated the two capability–performance relationships. Reliability was high, but one SIPANDU indicator loaded weakly (0.478) and HTMT values indicated discriminant-validity concerns. **Conclusion** – Individual operational and digital capabilities contribute more directly to safety-critical pilotage performance than an administratively oriented information system. The structural findings should nevertheless be interpreted cautiously until the measurement model is refined and replicated. **Novelty** – The study separates individual digital capability from organisational system effectiveness and identifies parallel rather than mediated routes to frontline performance.

Keywords: Technical competence; technology mastery; SIPANDU; ship pilot performance;

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INTRODUCTION

Ship pilotage is a safety-critical port service in which pilots must integrate local knowledge, vessel characteristics, hydrometeorological conditions, traffic information, bridge-team communication, and time-critical judgement. These demands are especially relevant in Bontang, East Kalimantan, where industrial and export activities generate complex vessel movements. Pilot performance therefore extends beyond safe manoeuvring to punctuality, procedural compliance, communication quality, risk anticipation, and service continuity.

The thesis records several operational challenges, including vessel–jetty contact, delayed pilot response, interruptions to the pilotage information system, a barge near miss, and inconsistencies in scheduling data. These events do not prove a single cause, but they show that performance depends on alignment among technical competence, digital capability, information quality, and coordination. Recent maritime evidence likewise treats pilotage as an occupation in which workload, fatigue, automation, and training quality can affect safe performance (Barbarewicz et al., 2019; Oldenburg et al., 2021; Gregory et al., 2020; Westin & Lundberg, 2025).

Technical competence is the applied ability to interpret waterways and weather, understand vessel behaviour, plan manoeuvres, communicate with bridge and shore teams, identify hazards, and select timely corrective action. Simulator research shows that credible assessment must capture professional judgement and task performance rather than rely solely on formal certification or subjective impressions (Ernstsen & Nazir, 2020; Kim et al., 2021). A competence framework developed specifically for maritime pilots similarly emphasises the integration of knowledge, skills, and abilities across training and operational practice (Aun, 2024).

Digitalisation adds a second capability requirement. Pilots use AIS, radar, ECDIS, portable pilot units, communication systems, and organisational platforms. Technology mastery refers to the capacity to operate these tools, interpret their outputs, troubleshoot routine problems, and adapt use to operational demands. Research on predictor automation indicates that trust and effective use depend on training, understanding, transparency, and experience rather than availability alone (Westin et al., 2019; Westin & Lundberg, 2025). Evidence from other work settings also shows that digital competence improves task–technology fit and performance when technology supports the task actually being performed (Hizam et al., 2021).

SIPANDU differs from bridge-navigation technology because its principal functions are pilotage requests, scheduling, vessel information, administration, and coordination. Information-system success depends on the combined quality of the system, information, service, use, user satisfaction, and net benefits; recent synthesis also warns that these relationships vary across contexts and levels of analysis (Jeyaraj, 2020). Thus, a platform may improve administrative processing without directly improving a pilot’s manoeuvring performance.

Previous studies have examined maritime competence, simulator performance, fatigue, automation, and information-system success, but limited evidence explains whether an administrative pilotage platform transmits the effects of individual capability to frontline performance. This study addresses that gap by testing the direct effects of technical competence and technology mastery on SIPANDU effectiveness and pilot performance, and by testing SIPANDU effectiveness as a mediator. The study contributes a parallel-pathway explanation: individual capabilities may improve performance directly even when the organisational system remains peripheral to real-time navigation.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Technical competence

Technical competence represents task-specific knowledge, skill, and judgement applied under operational constraints. In pilotage, it includes local waterway knowledge, interpretation of current and weather, understanding of ship handling, standard communication, emergency response, and risk mitigation. Recent pilotage scholarship positions competence as a multidimensional professional resource that must be developed through supervised practice, simulation, assessment, and reflective learning (Ernstsen & Nazir, 2020; Aun, 2024; Issa-Zadeh & Garay-Rondero, 2025).

Competence should improve performance because its content corresponds directly to the behaviours being evaluated. A competent pilot recognises weak signals earlier, chooses feasible manoeuvring options, communicates limitations clearly, and corrects deviations promptly. Evidence on simulator-based maritime training supports structured scenarios and explicit assessment criteria as mechanisms for improving and evaluating these behaviours (Kim et al., 2021). Competence may also help pilots understand operational data in SIPANDU, but navigational expertise does not necessarily imply effective use of an administrative platform. Therefore, the first and third hypotheses distinguish system effectiveness from frontline performance.

H1: Technical competence has a positive effect on SIPANDU effectiveness.

H3: Technical competence has a positive effect on ship pilot performance.

Technology mastery

Technology mastery is the ability to understand, operate, evaluate, and adapt digital tools to work requirements. It includes system navigation, information retrieval, interpretation of displays, routine troubleshooting, and the integration of several information sources. Digital competence supports performance when employees can translate system features into task-relevant action (Hizam et al., 2021). However, exposure does not guarantee mastery: workers can be frequent users while relying on shallow routines, a distinction reinforced by research questioning assumptions about naturally capable “digital natives” (Kirschner & De Bruyckere, 2017).

In pilotage, technology mastery can improve SIPANDU use by reducing the effort required to retrieve schedules, validate vessel data, and complete administrative coordination. It can also improve performance directly through AIS, radar, ECDIS, portable pilot units, and communications technology. Studies of pilot automation show that training and system transparency are central to appropriate trust and effective collaboration with automated functions (Westin et al., 2019; Westin & Lundberg, 2025). These mechanisms support two related but distinct hypotheses.

H2: Technology mastery has a positive effect on SIPANDU effectiveness.

H4: Technology mastery has a positive effect on ship pilot performance.

SIPANDU effectiveness and mediation

SIPANDU effectiveness reflects the extent to which the platform provides accurate, timely, understandable, reliable, and useful support for pilotage administration and coordination. Contemporary reviews of information-system success show that technical quality alone is insufficient; value emerges when system functions, information, user capability, organisational processes, and the outcome level are aligned (Jeyaraj, 2020). Evidence from employee information-system use similarly shows that system success can contribute to individual performance, although the strength of that contribution depends on how closely the system supports core work (Aldholay et al., 2018; Tam & Oliveira, 2016).

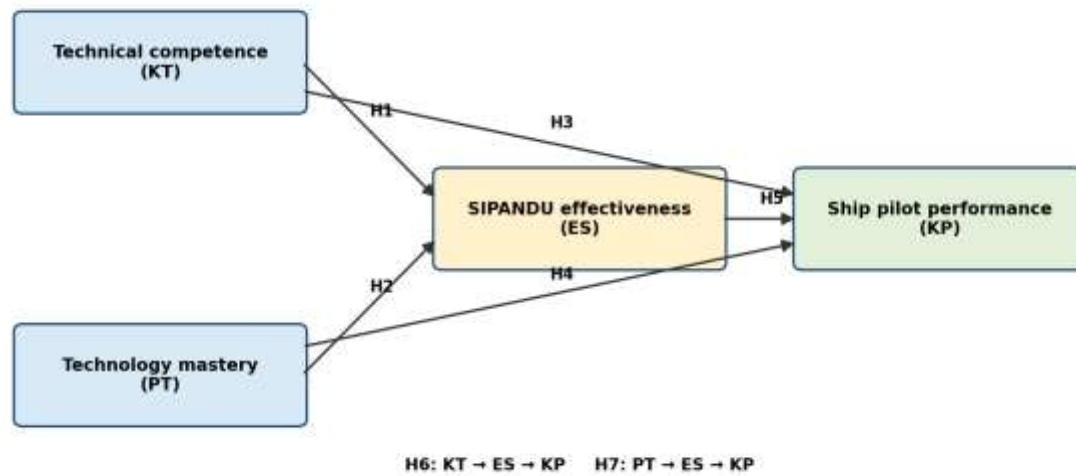
A mediating effect requires a sequential process. For H6, technical competence must first improve SIPANDU effectiveness and that effectiveness must subsequently improve performance. H7 requires the same sequence for technology mastery. If SIPANDU is used mainly for administration, while critical manoeuvring decisions rely on direct communication and navigational devices, the system-to-performance link may be weak even when capable users operate SIPANDU effectively.

H5: SIPANDU effectiveness has a positive effect on ship pilot performance.

H6: SIPANDU effectiveness mediates the effect of technical competence on ship pilot performance.

H7: SIPANDU effectiveness mediates the effect of technology mastery on ship pilot performance.

Figure 1. Research framework



METHOD

This study used an explanatory cross-sectional survey of all 52 active ship pilots who met the study criteria at the Class II KSOP of Bontang. Purposive eligibility required at least one year of pilotage experience, prior use of SIPANDU, and willingness to participate. All respondents were men, reflecting the workforce composition at the study site.

A structured questionnaire used a five-point Likert scale. Technical competence and technology mastery were each measured with five indicators; SIPANDU effectiveness used five indicators; and ship pilot performance used seven indicators. The constructs covered procedural and navigational skill, digital-system capability, perceived information-system effectiveness, and self-reported operational performance. Documentation and contextual interviews were used only to support interpretation.

PLS-SEM was used to test direct and indirect relationships. The measurement model was assessed using indicator loadings, average variance extracted (AVE), composite reliability (CR), Cronbach's alpha, the Fornell–Larcker criterion, and HTMT. The structural model was assessed using path coefficients, bootstrapped p-values, R^2 , f^2 , model goodness of fit, and predictive relevance. Following current PLS-SEM guidance, statistical significance was interpreted together with effect size and measurement quality rather than as a stand-alone decision rule (Hair et al., 2019, 2020; Shmueli et al., 2019). Because the data were cross-sectional, self-reported, and derived from a small single-port sample, the results indicate associations rather than definitive causal effects.

RESULTS AND DISCUSSION

Respondent profile

The 52 respondents were all men. The largest age group was 41–50 years (38.5%), 42.3% held a bachelor's degree, and 36.5% had more than 20 years of service. This experienced profile strengthens respondents' familiarity with complex pilotage operations but may reduce variation because established professionals can share similar routines and evaluations.

Table 1. Respondent profile

Age	≤30 years	6	11.5
Age	31–40 years	14	26.9
Age	41–50 years	20	38.5
Age	>50 years	12	23.1
Education	Senior high/vocational	10	19.2

Education	Diploma	18	34.6
Education	Bachelor's	22	42.3
Education	Master's	2	3.9
Tenure	≤5 years	5	9.6
Tenure	6–10 years	10	19.2
Tenure	11–20 years	18	34.6
Tenure	>20 years	19	36.5

Source: Processed survey data (2026).

Measurement model

Table 2 combines indicator loadings, AVE, CR, and Cronbach's alpha as requested. Reliability was high for every construct (CR = 0.920–0.962; α = 0.878–0.961). Most loadings exceeded 0.70, but ES1 loaded at 0.478 and therefore requires review. The AVE values reported in the thesis exceeded 0.50; however, the combination of ES1 = 0.478 and AVE = 0.817 should be rechecked against the original SmartPLS output because the figures are not arithmetically consistent when calculated from the displayed loadings. The article retains the thesis-reported AVE values but flags this discrepancy rather than treating convergent validity as unqualified.

Table 2. Convergent validity and reliability

Construct	Indicator loadings	AVE	CR	Cronbach's α
Technical competence	KT1=0.879, KT2=0.913, KT3=0.890, KT4=0.926, KT5=0.904	0.815	0.944	0.943
Technology mastery	PT1=0.893, PT2=0.893, PT3=0.791, PT4=0.885, PT5=0.925	0.772	0.931	0.926
SIPANDU effectiveness	ES1=0.478, ES2=0.908, ES3=0.940, ES4=0.880, ES5=0.864	0.817	0.920	0.878
Ship pilot performance	KP1=0.904, KP2=0.911, KP3=0.863, KP4=0.935, KP5=0.956, KP6=0.868, KP7=0.862	0.811	0.962	0.961

Source: SmartPLS output reported in the thesis (2026).

Discriminant validity was examined using the Fornell–Larcker criterion and HTMT. The diagonal in Table 3 is the square root of AVE; off-diagonal values are construct-score correlations calculated from the 52 response records in the thesis appendix. Several correlations exceeded the relevant diagonal value, particularly KT–PT, KT–KP, and PT–KP. Table 4 reinforces this concern: all HTMT ratios were above the conservative 0.85 threshold and four exceeded 1.00. These results indicate insufficient empirical separation among the four self-reported constructs. The path coefficients should therefore be interpreted as preliminary, and item wording—especially overlapping capability and performance statements—should be refined before replication.

Table 3. Fornell–Larcker criterion

Construct	KT	PT	ES	KP
KT	0.903			
PT	0.941	0.879		
ES	0.884	0.928	0.904	
KP	0.959	0.941	0.891	0.901

Note: Diagonal values are $\sqrt{AVE}$; off-diagonal values are correlations calculated from thesis appendix data.

Table 4. Heterotrait–monotrait ratio

Construct pair	HTMT	Assessment
KT–PT	1.007	Not established
KT–ES	0.968	Not established
KT–KP	1.006	Not established
PT–ES	1.029	Not established
PT–KP	0.997	Not established
ES–KP	0.966	Not established

Source: Calculated from the 52 item-level response records in the thesis appendix (2026).

Structural model

The inner model showed high explanatory power (table 5). Technical competence and technology mastery explained 89.9% of the variance in SIPANDU effectiveness, while technical competence, technology mastery, and SIPANDU effectiveness explained 93.2% of ship pilot performance. The model goodness-of-fit index, calculated as $\sqrt{(\text{mean AVE} \times \text{mean } R^2)}$, was 0.856. The thesis-reported Stone–Geisser aggregate predictive relevance was $Q^2 = 0.993$. These large values suggest strong in-sample explanation, but they should not be interpreted as out-of-sample predictive accuracy because PLSpredict statistics were not available and the constructs displayed discriminant-validity concerns.

Table 5. Inner-model evaluation

Criterion	SIPANDU effectiveness	Ship pilot performance	Interpretation
R^2	0.899	0.932	High in-sample explanatory power
Model GoF	0.856	0.856	Large descriptive fit index
Q^2 (aggregate)	0.993	0.993	Positive predictive relevance; verify with PLSpredict
Main f^2 effects	KT→ES=0.000; PT→ES=0.057	KT→KP=0.691; PT→KP=0.051; ES→KP=0.013	KT→KP large; PT paths small; ES→KP negligible

Source: Thesis results (2026); GoF calculated from reported AVE and R^2 values.

Hypothesis Results

Table 6. Direct and indirect effects

Hypothesis and relationship	β or t	p-value	Decision
H1: Technical competence → SIPANDU effectiveness	$\beta = -0.020$	0.926	Rejected
H2: Technology mastery → SIPANDU effectiveness	$\beta = 0.967$	<0.001	Supported
H3: Technical competence → pilot performance	$\beta = 0.640$	<0.001	Supported
H4: Technology mastery → pilot performance	$\beta = 0.249$	0.031	Supported
H5: SIPANDU effectiveness → pilot performance	$\beta = 0.094$	0.341	Rejected
H6: Technical competence → SIPANDU → performance	$t = 0.050$	0.960	Rejected
H7: Technology mastery → SIPANDU → performance	$t = 1.043$	0.297	Rejected

Source: Processed survey data (2026).

Discussion

Table 6 shows that technical competence was the strongest direct predictor of performance ($\beta = 0.640$; $p < 0.001$), supporting H3, with a large f^2 of 0.691. This result is consistent with simulator research showing that performance in pilotage depends on the integration of situational cues, manoeuvring knowledge, communication, and judgement under realistic task conditions (Ernstsen & Nazir, 2020). It also supports the knowledge–skills–abilities approach proposed for maritime-pilot development (Aun, 2024). The finding implies that recurrent assessment should focus on critical tasks—approach planning, under-keel clearance, tug use, bridge-resource communication, degraded equipment, and recovery from deteriorating manoeuvres—rather than generic classroom attendance.

Technology mastery also improved performance ($\beta = 0.249$; $p = 0.031$), supporting H4, although its effect was smaller ($f^2 = 0.051$). This finding agrees with Hizam et al. (2021), who found that digital competence enhances task–technology fit and performance, and with Westin and Lundberg (2025), who

showed that pilots' understanding, training, and trust shape the use of predictor automation. In Bontang, mastery covers both SIPANDU and operational technologies such as AIS, radar, and ECDIS. The direct path is therefore plausible because these tools provide immediate decision support even when SIPANDU remains administrative.

Technology mastery strongly predicted SIPANDU effectiveness ($\beta = 0.967$; $p < 0.001$), supporting H2. Digitally capable pilots can navigate menus, retrieve and verify data, complete workflow steps, and resolve routine problems more effectively. This pattern aligns with recent information-system research showing that user capability and task alignment influence whether system quality becomes meaningful use and net benefit (Jeyaraj, 2020). Nevertheless, the unusually high coefficient, high R^2 , and HTMT concerns suggest that technology-mastery and SIPANDU-effectiveness items may share wording or respondent response patterns. Replication should separate general digital capability from platform-specific ease and usefulness more sharply.

Technical competence did not affect SIPANDU effectiveness ($\beta = -0.020$; $p = 0.926$), rejecting H1. The result indicates that manoeuvring expertise, environmental assessment, ship knowledge, and maritime communication do not automatically translate into effective use of an administrative platform. This distinction is consistent with automation research: professional expertise and automation competence are complementary but not interchangeable, so targeted reskilling and transparent system design remain necessary (Westin et al., 2019). KSOP should therefore assess navigational and digital competency as separate domains.

SIPANDU effectiveness did not significantly improve pilot performance ($\beta = 0.094$; $p = 0.341$; $f^2 = 0.013$), rejecting H5. The finding contrasts with studies in which well-aligned information systems improve individual outcomes (Tam & Oliveira, 2016; Aldholay et al., 2018), but it is understandable in this setting because SIPANDU supports scheduling, records, and coordination rather than real-time manoeuvring. A system can create administrative value at organisational level while showing little effect on self-rated frontline performance. Future evaluation should therefore include vessel waiting time, dispatch accuracy, data-error rates, processing time, and coordination outcomes, not only individual performance.

The indirect effects were nonsignificant for technical competence ($t = 0.050$; $p = 0.960$) and technology mastery ($t = 1.043$; $p = 0.297$), rejecting H6 and H7. Mediation could not occur because the SIPANDU-effectiveness-to-performance path was weak. The results support a parallel-pathway interpretation: technology mastery improves SIPANDU effectiveness, while technical competence and technology mastery improve performance through capabilities used at the point of action. SIPANDU has not yet become the operational bridge between capability and performance.

The findings have practical implications. Competency development should use full-mission simulation, structured debriefing, near-miss learning, and objective behavioural criteria, consistent with recent maritime training research (Ernstsen & Nazir, 2020; Kim et al., 2021). Digital training should integrate SIPANDU with AIS, radar, ECDIS, communications, and degraded-mode scenarios. SIPANDU development should prioritise user-centred workflows, reliable real-time data, interoperability, clear alerts, and documented fallback procedures. Fatigue and work scheduling also require attention because maritime pilots operate under irregular and demanding conditions that can affect work ability and safety (Barbarewicz et al., 2019; Gregory et al., 2020; Oldenburg et al., 2021).

A final limitation concerns measurement. The weak ES1 loading, high inter-construct correlations, and HTMT ratios above recommended thresholds mean that the direct paths may partly reflect overlapping self-report measures. This does not erase the observed associations, but it reduces confidence that the constructs are empirically distinct. A revised instrument should remove or rewrite ES1, avoid performance wording inside capability items, conduct cognitive interviews, test a larger multi-port sample, and compare the revised reflective model with theoretically defensible alternatives.

CONCLUSION

The study answered all seven hypotheses. H2, H3, and H4 were supported: technology mastery improved SIPANDU effectiveness, while technical competence and technology mastery improved pilot performance. H1, H5, H6, and H7 were rejected: technical competence did not improve SIPANDU effectiveness, SIPANDU effectiveness did not improve performance, and SIPANDU did not mediate either capability–performance relationship. Technical competence was the strongest direct predictor of performance. The comparison with recent maritime and information-system studies indicates that the findings are theoretically plausible when system–task alignment is considered. Competence and navigational technology operate at the point of action, whereas SIPANDU currently supports administration and coordination. Therefore, KSOP should develop technical and digital capability together but evaluate each with distinct criteria, while redesigning SIPANDU around operationally relevant information and interoperable workflows. The conclusions remain provisional because the sample was small, single-site, cross-sectional, entirely male, and based on self-reports. More importantly, ES1 had a weak loading and the Fornell–Larcker and HTMT results indicated discriminant-validity problems. Future research should refine the instrument, collect objective performance and system-log data, use larger multi-port samples, conduct longitudinal or quasi-experimental evaluation after training or system upgrades, and apply PLSpredict or holdout validation. Research should also examine recruitment and career pathways for women because the absence of women in the current sample limits gender-sensitive interpretation.

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