

AI Literacy and Adoption Readiness Among Maritime Cadets: A Cross-Major Comparison at STIP Jakarta

Derma Watty Sihombing ^{1*}, Ihsan Ahda Tanjung ¹

¹ Maritime Institute, Sekolah Tinggi Ilmu Pelayaran Jakarta, North Jakarta, Indonesia

Keywords

AI literacy; technology acceptance model; maritime cadets; digital transformation

*Correspondence Email:

Derma.sihombing@stipmail.ac.id

Abstract

The progressive integration of artificial intelligence into maritime operational systems — encompassing AI-assisted navigation decision support, predictive maintenance platforms, and machine-learning-based cargo optimization tools — demands that maritime cadets possess not only technical competency in conventional seamanship but the AI literacy and adoption readiness necessary to work effectively within intelligent operational environments. Yet empirical evidence on AI literacy and adoption readiness among Indonesian maritime cadets, differentiated by academic program specialization, remains unavailable. This study examines AI literacy and adoption readiness among 30 cadets at Sekolah Tinggi Ilmu Pelayaran (STIP) Jakarta across Port and Shipping Management (PSM), Deck Nautical (DN), and Engine (ENG) programs using a Technology Acceptance Model-based quantitative survey instrument. Significant between-major differences were found on Perceived Usefulness ($F(2,27) = 4.18, p = .027$), Behavioral Intention to Adopt AI ($F(2,27) = 6.43, p = .005$), and Prior Digital Exposure ($F(2,27) = 3.94, p = .032$). PSM cadets exhibited the highest adoption readiness, DN cadets the lowest, and ENG cadets were intermediate. The study establishes the first cross-major AI readiness baseline within a single Indonesian maritime academy and provides evidence-based priorities for differentiated AI literacy curriculum integration.

1. Introduction

Artificial intelligence is no longer a speculative technological future for the maritime industry — it is an operational present. AI-assisted decision support systems are deployed on modern bridge equipment for collision avoidance optimization; machine learning algorithms analyze engine performance sensor data for predictive maintenance scheduling; natural language processing tools process shipping documentation and automate cargo clearance workflows; and the International Maritime Organization's Maritime Autonomous Surface Ships (MASS) regulatory framework anticipates progressively autonomous vessel operations across four degrees of automation within the coming decade [1]. The cadets currently enrolled in maritime vocational programs at Indonesian institutions such as Sekolah Tinggi Ilmu Pelayaran Jakarta will enter a workforce in which AI-integrated operational systems are not exceptional but routine — yet the degree to

which these cadets currently possess the AI literacy and adoption readiness to work productively within such environments has not been empirically assessed.

AI literacy — encompassing awareness of what AI systems are and how they function, the ability to interact with and critically evaluate AI tool outputs, and the capacity to make informed decisions about when and how to rely on AI-generated recommendations — is increasingly recognized as a foundational professional competency alongside domain-specific technical knowledge across regulated professional fields [2]. The Technology Acceptance Model, first proposed by Davis [3] and subsequently extended into the Unified Theory of Acceptance and Use of Technology by Venkatesh et al. [4], provides the most widely validated theoretical framework for examining the determinants of technology adoption readiness at the individual level, distinguishing the cognitive assessment of Perceived Usefulness and Perceived Ease of Use from the behavioral outcome of Adoption Intention and the contextual factor of Prior Digital Exposure. Applied to AI literacy among maritime cadets, TAM predicts that adoption readiness is shaped not by AI capability alone but by cadets' perceptions of AI's professional usefulness, their confidence in their own ability to engage with AI tools, and their prior exposure to digital technology environments — predictions that, if validated in a maritime vocational education context, carry direct curriculum design implications.

The differentiation of AI literacy and adoption readiness across maritime academic program specializations is analytically important and has not been investigated. STIP Jakarta's three programs — Port and Shipping Management, Deck Nautical, and Marine Engineering — represent three distinct professional formation trajectories whose digital technology exposure, operational contexts, and AI-relevant professional domains differ substantially. PSM cadets are immersed in logistics, documentation, and port administration contexts where digital platform use and data management are routine professional activities. DN cadets are formed primarily through navigation and watchkeeping instruction in which electronic chart display, AIS, and ECDIS constitute the existing technology ecosystem. ENG cadets are formed through propulsion system and machinery management instruction where digital monitoring and diagnostic tools are increasingly central. These distinct program contexts predict different patterns of AI awareness, perceived usefulness assessment, and adoption readiness — a prediction this study empirically tests through cross-major comparison.

This study pursues two objectives: first, to measure AI literacy and TAM-construct adoption readiness among STIP Jakarta cadets across the three academic programs using a validated instrument; and second, to identify significant between-major differences in adoption readiness that provide differentiated curriculum development priorities for STIP Jakarta's AI literacy integration agenda.

1.1 Theoretical Framework

The Technology Acceptance Model (TAM), introduced by Davis [3] and grounded in the Theory of Reasoned Action, proposes that an individual's intention to adopt a new technology is jointly determined by two primary perceptual constructs: Perceived Usefulness (PU) — the degree to which the individual believes the technology will enhance their performance — and Perceived Ease of Use (PEOU) — the degree to which the individual believes using the technology will be free of effort. Venkatesh et al.'s [4] UTAUT extension further incorporates Social Influence and Facilitating Conditions as determinants, but the core PU-PEOU-Behavioral Intention relationship remains the most empirically robust and broadly validated structure across diverse technology adoption contexts.

Applied to AI literacy assessment in a maritime vocational education context, TAM's construct structure maps directly onto the adoption readiness dimensions most educationally actionable: PU captures whether cadets perceive AI as professionally relevant to their maritime career contexts — a perception that can be shaped through curriculum integration demonstrating AI's actual maritime applications; PEOU captures cadets' self-assessed confidence in engaging with AI tools — a perception addressable through structured hands-on AI tool exposure; and Behavioral Intention captures the motivational readiness to actually adopt AI in professional contexts — the downstream outcome that curriculum intervention ultimately seeks to develop [5]. Prior Digital Exposure is included as a background variable capturing the accumulated technology

experience that contextualizes current adoption readiness, consistent with established TAM applications in vocational and professional education [6].

2. Method

This study employed a quantitative cross-sectional survey design, conducted at STIP Jakarta from August 2025 to March 2026 as part of the institution's broader Digital Transformation readiness assessment. The participant population comprised 30 Level 2 cadets: 10 from each of the Port and Shipping Management (PSM), Deck Nautical (DN), and Marine Engineering (ENG) programs, selected through purposive sampling to ensure program representation and equivalence of academic year level. Level 2 cadets were selected because they have completed foundational program coursework while remaining within the formal instructional period in which curriculum reform would directly affect them. The pooled $n=30$ constitutes a deliberate comparative design enabling between-major analysis rather than inference to the broader population; major-level breakdowns are reported alongside pooled statistics throughout, consistent with methodological guidance for small-sample comparative institutional studies [7].

The primary instrument was a 25-item TAM-adapted AI Literacy and Adoption Readiness Questionnaire, comprising five subscales: AI Awareness (5 items addressing familiarity with AI concepts, tools, and maritime applications), Perceived Usefulness (5 items addressing AI's relevance to maritime professional contexts), Perceived Ease of Use (5 items addressing self-assessed confidence in AI tool interaction), Behavioral Intention to Adopt (5 items addressing motivational readiness to use AI in future professional practice), and Prior Digital Exposure (5 items addressing accumulated technology experience with digital tools, platforms, and data systems). All items were scored on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was adapted from validated TAM instruments used in technology adoption research [3], [4] with item wording modified to reflect maritime professional contexts following review by two maritime education specialists. Internal consistency was established at Cronbach's $\alpha = 0.84$ across all subscales.

Data analysis employed descriptive statistics for overall and major-level means, and one-way ANOVA with Tukey HSD post-hoc comparisons to identify significant between-major differences across each TAM construct, with statistical significance threshold set at $\alpha = .05$. All analyses were conducted using IBM SPSS Statistics version 26 [8].

3. Results and Analysis

3.1 Descriptive Statistics: TAM Construct Means by Major

Table 1 presents mean scores across the five TAM constructs for each academic program group and the pooled sample, revealing a consistent pattern of between-major variation with PSM cadets recording the highest scores across all five constructs, DN cadets the lowest, and ENG cadets intermediate.

Table 1. TAM-Based AI Literacy and Adoption Readiness Means by Academic Program ($n = 30$)

TAM Construct	PSM Cadets ($n=10$) M (SD)	DN Cadets ($n=10$) M (SD)	ENG Cadets ($n=10$) M (SD)	Pooled Mean (SD)
AI Awareness (AA)	3.78 (0.82)	3.32 (0.91)	3.61 (0.87)	3.57 (0.89)
Perceived Usefulness (PU)	4.06 (0.74)	3.54 (0.88)	3.78 (0.79)	3.79 (0.84)
Perceived Ease of Use (PEOU)	3.62 (0.86)	3.28 (0.93)	3.47 (0.88)	3.46 (0.89)
Behavioral Intention	3.91 (0.71)	3.18 (0.96)	3.52 (0.83)	3.54 (0.88)

TAM Construct	PSM Cadets (n=10) M (SD)	DN Cadets (n=10) M (SD)	ENG Cadets (n=10) M (SD)	Pooled Mean (SD)
(BI)				
Prior Digital Exposure (PDE)	3.74 (0.79)	3.12 (1.04)	3.38 (0.92)	3.41 (0.94)
Composite AI Readiness	3.82 (0.78)	3.29 (0.94)	3.55 (0.86)	3.55 (0.89)

The pattern in Table 1 reveals three analytically significant features. First, Perceived Usefulness consistently records the highest mean across all three programs (PSM: 4.06; DN: 3.54; ENG: 3.78), indicating that cadets across all specializations perceive AI as professionally relevant to their maritime careers despite varying levels of awareness and exposure. Second, Behavioral Intention consistently records the largest between-program spread (PSM: 3.91; DN: 3.18 — a gap of 0.73 points), indicating that program-specific professional context most powerfully differentiates adoption motivation rather than general awareness. Third, Prior Digital Exposure shows the lowest pooled mean (3.41) and the largest DN deficit (3.12), suggesting that DN cadets' comparatively analog navigation training environment produces the most constrained digital technology baseline, directly limiting AI adoption readiness development.

3.2 ANOVA Results: Between-Major Differences

Table 2 presents one-way ANOVA results for each TAM construct, identifying which constructs show statistically significant between-major differences.

Table 2. One-Way ANOVA Results: Between-Major TAM Construct Comparison (df = 2, 27)

TAM Construct	F-statistic	p-value	Significance	η^2 (Effect Size)
AI Awareness (AA)	F = 2.34	.116	ns	.148
Perceived Usefulness (PU)	F = 4.18	.027	*	.236
Perceived Ease of Use (PEOU)	F = 1.87	.174	ns	.122
Behavioral Intention (BI)	F = 6.43	.005	**	.323
Prior Digital Exposure (PDE)	F = 3.94	.032	*	.226

*p < .05; **p < .01

Three of the five TAM constructs — Perceived Usefulness, Behavioral Intention, and Prior Digital Exposure — show statistically significant between-major differences, while AI Awareness and Perceived Ease of Use show non-significant between-major variation. Tukey HSD post-hoc analysis (Table 3) identifies the specific between-group pairings driving the significant ANOVA results.

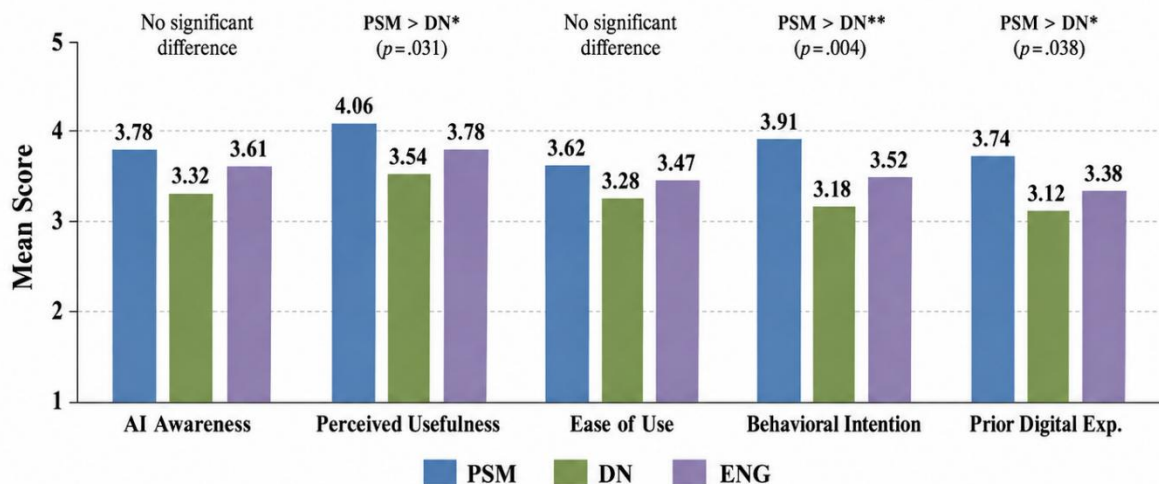
Table 3. Tukey HSD Post-Hoc Comparisons for Significant TAM Constructs

Construct	Comparison Pair	Mean Difference	p-value
Perceived Usefulness (PU)	PSM vs. DN	+0.52	.031
	PSM vs. ENG	+0.28	.261
	ENG vs. DN	+0.24	.384
Behavioral Intention (BI)	PSM vs. DN	+0.73	.004

Construct	Comparison Pair	Mean Difference	p-value
	PSM vs. ENG	+0.39	.108
	ENG vs. DN	+0.34	.193
Prior Digital Exposure (PDE)	PSM vs. DN	+0.62	.038
	PSM vs. ENG	+0.36	.207
	ENG vs. DN	+0.26	.441

Post-hoc analysis reveals that the significant ANOVA effects for all three constructs are driven by the PSM-versus-DN contrast specifically: PSM cadets score significantly higher than DN cadets on Perceived Usefulness (+0.52, $p = .031$), Behavioral Intention (+0.73, $p = .004$), and Prior Digital Exposure (+0.62, $p = .038$), while ENG cadets do not differ significantly from either PSM or DN on any construct. The ENG intermediate position — consistently scoring between PSM and DN without reaching significance against either — suggests a technology adoption readiness trajectory more advanced than the DN program's analog navigation environment but less digitally immersed than the PSM program's logistics and documentation operational context.

Figure 1 presents composite AI readiness scores across the three programs, visualizing the between-major pattern and its relationship to individual TAM constructs.



Construct	Between-Group Difference Summary	Significance
AI Awareness	No significant difference	n.s.
Perceived Usefulness	PSM > DN*	$p = .031$
Ease of Use	No significant difference	n.s.
Behavioral Intention	PSM > DN**	$p = .004$
Prior Digital Exp.	PSM > DN*	$p = .038$

Composite AI Readiness	
PSM	3.82
DN	3.29
ENG	3.55
Pattern: PSM > ENG > DN	

Scale: 1 (Strongly Disagree) to 5 (Strongly Agree) * $p < .05$ ** $p < .01$

Figure 1. Composite AI Readiness and TAM Construct Profiles by Academic Program

3.3 Discussion

The finding that PSM cadets exhibit significantly higher AI adoption readiness than DN cadets — on Perceived Usefulness, Behavioral Intention, and Prior Digital Exposure — while ENG cadets occupy a consistent intermediate position, is the study's most actionable cross-major finding and is directly interpretable through the professional formation context each program provides. PSM cadets are professionally formed within logistics, port administration, and shipping documentation contexts where digital platform interaction, data-driven decision support, and electronic document management are routine operational activities [9]; their higher AI adoption readiness reflects the alignment between their professional formation environment and the data-rich, technology-mediated workflow contexts in which AI tools are most visibly and immediately useful. DN cadets' lower adoption readiness is not attributable to lower general intelligence or technological capacity but to the specific character of their formative professional environment: bridge simulation, watchkeeping, and navigation instruction in which the dominant technology interface — ECDIS, AIS, radar — is digital but not AI-interactive in the sense that TAM's Perceived Usefulness and Behavioral Intention constructs are designed to capture [10]. The DN program's comparatively low Prior Digital Exposure mean (3.12) reflects this training environment's analog-navigation heritage rather than any individual cadet characteristic.

The non-significant between-major difference on AI Awareness ($F = 2.34$, $p = .116$) provides an important contextual qualification: all three cadet groups enter STIP Jakarta with roughly equivalent exposure to the concept of AI from secondary education and social media contexts, producing comparable awareness baseline scores despite the between-program variation in professional formation context. The divergence emerges at the level of Perceived Usefulness and Behavioral Intention — the constructs most directly shaped by professional context — rather than at the awareness level, confirming that the between-major AI readiness gap is a professional formation effect rather than a prior knowledge effect. This distinction has direct curriculum implications: AI awareness training that merely increases general knowledge about AI will not address the between-major readiness gap, because awareness is not the limiting constraint; targeted professional-context AI application exercises, demonstrating AI's specific usefulness within each program's operational domain, are what the TAM evidence identifies as the most direct lever for readiness improvement.

The TAM's theoretical prediction that Perceived Usefulness is the stronger predictor of Behavioral Intention than Perceived Ease of Use [3] is directionally supported by the data: PU shows a larger between-major effect size ($\eta^2 = .236$) than PEOU ($\eta^2 = .122$, ns), and PU is the construct on which PSM cadets' separation from DN cadets is most pronounced. This pattern confirms that AI adoption readiness development for maritime cadets should prioritize convincing cadets of AI's maritime professional usefulness — through exposure to real maritime AI applications, industry case studies, and operational demonstrations — rather than focusing primarily on technical AI tool proficiency development, which PEOU's non-significant between-major variation suggests is comparably distributed across the cadet population [4].

Study limitations include the small per-major sample size ($n=10$) limiting statistical power for detecting smaller between-group effects, the single-institution design constraining generalizability, and the cross-sectional measurement constraining causal interpretation of the between-major relationships. Future research should expand sampling across multiple Indonesian maritime academies to validate the PSM-DN-ENG readiness ordering, incorporate longitudinal measurement to track readiness development through curriculum AI integration interventions, and investigate whether the significant PSM-DN gap on Behavioral Intention persists or narrows following targeted AI literacy instruction in the DN program.

4. Conclusion

This study has established the first cross-major AI literacy and adoption readiness baseline within a single Indonesian maritime academy, documenting significant between-major differences on Perceived Usefulness, Behavioral Intention, and Prior Digital Exposure, with PSM cadets demonstrating highest readiness, DN cadets lowest, and ENG cadets intermediate. The between-major pattern is interpretable as a professional formation context effect rather than a prior knowledge effect — the gap emerges at the Perceived Usefulness

and Behavioral Intention level where professional context shapes technology perception, not at the AI Awareness level where general knowledge determines baseline familiarity. These findings provide STIP Jakarta with an empirically differentiated curriculum development priority map: DN cadets require professional-context AI application exposure most urgently, ENG cadets require targeted engineering AI tool integration, and PSM cadets' higher readiness positions them as the most immediately productive recipient of advanced AI literacy instruction. Addressing these differentiated needs through program-specific AI integration, rather than uniform curriculum reform, is the most evidence-consistent response to the between-major readiness gap this study has documented.

5. References

- [1] International Maritime Organization, "Maritime Autonomous Surface Ships (MASS) — Outcome of the regulatory scoping exercise," MSC-MEPC.3/Circ.7, IMO Publishing, London, 2021.
- [2] D. Long and B. Magerko, "What is AI literacy? Competencies and design considerations," in *Proc. CHI Conference on Human Factors in Computing Systems*, New York: ACM, 2020, pp. 1–16. DOI: 10.1145/3313831.3376727
- [3] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989. DOI: 10.2307/249008
- [4] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, vol. 27, no. 3, pp. 425–478, 2003. DOI: 10.2307/30036540
- [5] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education — where are the educators?" *Int. J. Educ. Technol. High. Educ.*, vol. 16, no. 1, p. 39, 2019. DOI: 10.1186/s41239-019-0171-0
- [6] H. Li, S. I. Khattak, X. Lu, and A. Khan, "Greening the Way Forward: A Qualitative Assessment of Green Technology Integration and Prospects in a Chinese Technical and Vocational Institute," *Sustainability*, vol. 15, no. 6, 2023. DOI: 10.3390/su15065187
- [7] J. W. Creswell and V. L. Plano Clark, *Designing and Conducting Mixed Methods Research*, 3rd ed. Thousand Oaks, CA: Sage Publications, 2017.
- [8] A. Field, *Discovering Statistics Using IBM SPSS Statistics*, 5th ed. London: Sage Publications, 2018.
- [9] K. Bogusławski, M. Gil, J. Nasur, and K. Wróbel, "Implications of autonomous shipping for maritime education and training: the cadet's perspective," *Marit. Econ. Logist.*, vol. 24, no. 2, pp. 327–343, 2022. DOI: 10.1057/s41278-022-00217-x
- [10] A. Wahid, M. Y. Jinca, T. Rachman, and J. Malisan, "Determination of Indicators of Implementation of Sea Transportation Safety Management System for Traditional Shipping Based on Delphi Approach," *Sustainability*, vol. 15, no. 13, 2023. DOI: 10.3390/su151310080
- [11] F. Mutohhari, P. Sudira, F. D. Isnantyo, and N. W. A. Majid, "Generic green skills: maturity level of vocational education teachers and students in Indonesia," *Int. J. Eval. Res. Educ.*, vol. 14, no. 1, pp. 179–187, 2025. DOI: 10.11591/ijere.v14i1.29191
- [12] L. Widaningsih, S. Rahayu, V. Dwiyaniti, and W. Widaningsih, "Analysis and Mapping of Technical Competency Needs for TVET Teachers in the Era of Industry 4.0," *J. Tech. Educ. Train.*, vol. 17, no. 2, pp. 151–164, 2025. DOI: 10.30880/jtet.2025.17.02.011
- [13] R. S. Wulandari and T. Cahyadi, "Engineering Technology and Education in Maritime Studies: A Qualitative Examination," *J. Eng. Sci. Technol.*, vol. 20, no. 2, pp. 28–35, 2025.

- [14] A. Hattingh, S. Hodge, and T. Mavin, "Flight instructor perspectives on competency-based education: insights into educator practice within an aviation context," *Int. J. Train. Res.*, vol. 20, no. 3, pp. 264–282, 2022. DOI: 10.1080/14480220.2022.2063155
- [15] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qual. Res. Psychol.*, vol. 3, no. 2, pp. 77–101, 2006. DOI: 10.1191/1478088706qp063oa