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Digital competency adoption and maritime workforce transformation: a mixed-methods PLS-SEM validation of an integrated technology-organization-environment model in indonesian shipping

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ABSTRACT

The maritime sector's digital transformation requires not only technology adoption but also workforce capability development. While the Technology–Organization–Environment (TOE) framework explains organizational technology adoption and TAM/UTAUT explain individual technology use, neither adequately explains how contextual conditions translate into workforce capabilities. Addressing this gap, this study develops and tests a Maritime Human-Capital Transformation Model for Society 5.0, emphasizing human capability and resilience. An exploratory sequential mixed-methods design was employed, comprising in-depth interviews with 15 maritime stakeholders from four stakeholder groups, followed by a survey of 250 maritime professionals analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrated satisfactory reliability and validity across all constructs. Qualitative findings identified three competency dimensions: hard digital skills, socio-technical skills, and psychological readiness. Quantitative results showed that Technological Readiness, Organizational Support, and Environmental Pressure significantly influenced Digital Competency Adoption and Human Capital Transformation Effectiveness. Technological Readiness had the strongest effect on Digital Competency Adoption ($\beta = 0.586$, $p < 0.001$), while Digital Competency Adoption positively influenced transformation effectiveness ($\beta = 0.364$, $p < 0.001$) and partially mediated all three TOE relationships. The model explained 51.5% of the variance in Digital Competency Adoption and 50.9% in Human Capital Transformation Effectiveness. These findings extend the TOE framework by positioning digital competency adoption as a key mechanism linking contextual conditions to human-capital transformation in the maritime sector, advancing a human-centered approach to digitalization aligned with Society 5.0.

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Introduction

Maritime transport is a backbone of global trade, and the sector is now experiencing accelerated digital transformation through artificial intelligence, big data analytics, the Internet of Things, automation, and integrated information systems. These technologies are reshaping vessel operations, port services, and organizational decision-making, gradually transforming maritime activities into interconnected cyber-physical

systems (Fruth & Teuteberg, 2017; Munim et al., 2020; Raza et al., 2023). Evidence from maritime organizations shows, however, that technology alone is insufficient: successful transformation also depends on organizational capacity, external pressures, workforce readiness, and change management (Jović et al., 2022; Vial, 2019).

The transition from Industry 4.0 toward Society 5.0 broadens this perspective. Society 5.0 and the related Industry 5.0 agenda emphasize a human-centered model in which technology serves to strengthen human capability, well-being, and resilience rather than to replace people (Mourtzis et al., 2022; Nahavandi, 2019; Xu et al., 2021). This orientation is highly relevant to shipping, where future systems will combine advanced automation with continued human judgment, supervision, and decision-making (Shahbakhsh et al., 2022). Seafarers, officers, engineers, and shore-based personnel increasingly need digital literacy, data interpretation, cybersecurity awareness, and adaptive decision-making in addition to traditional technical proficiency (Belabyad et al., 2025; Narayanan et al., 2023; Sharma & Kim, 2022). The distinction is substantive rather than a relabeling: whereas Industry 4.0 evaluates digitalization chiefly by connectivity, automation, and efficiency, Society 5.0 and Industry 5.0 make human capability, well-being, and resilience explicit criteria of success (Mourtzis et al., 2022; Xu et al., 2021). For maritime organizations, this shifts the analytical question from whether technology is adopted to whether the workforce becomes more capable as a result.

This shift creates new challenges for maritime human-resource development. Technological complexity alters established occupational roles, redistributes tasks between ship and shore, increases reliance on digital information, and imposes new cognitive and organizational demands on personnel. The ability to use technology must therefore be accompanied by the capacity to adapt to changing work systems, communicate across human-technology interfaces, and learn continuously. Consequently, maritime digitalization requires not only new technical skills but also changes in training systems, organizational culture, and human-resource management practices (Narayanan et al., 2023; Theotokas et al., 2024; Warner & Wäger, 2019).

Despite growing attention to maritime digitalization, two gaps remain. First, the literature has explained *what* competencies future maritime work requires, but offers less empirical explanation of *how* technological and organizational conditions are translated into effective human-capital transformation (Theotokas et al., 2024). Second, digital competency is usually treated as an outcome of training rather than as a transformation mechanism. The Technology-Organization-Environment (TOE) framework explains digital adoption as the product of technological, organizational, and environmental conditions and has been applied in maritime transport (Jović et al., 2022; Oliveira & Martins, 2010), yet it has rarely been connected to the transformation of the workforce that must operate the new systems. Competing explanations do not close these gaps. Individual acceptance models such as the Technology Acceptance Model and UTAUT explain the intention to use a system (Davis, 1989; Venkatesh et al., 2003) but not whether use builds lasting capability; socio-technical systems theory stresses the joint optimization of people and technology but does not specify measurable drivers (Baxter & Sommerville, 2011); and maritime competency-mapping studies identify the skills future seafarers need without testing what produces them (Mallam et al., 2020; Sharma & Kim, 2022). Even within TOE research, workforce capability usually enters as an antecedent of adoption, for example as technology competence (Baker, 2012; Zhu & Kraemer, 2005), rather than as an outcome that adoption conditions must generate. Reviews of digital transformation and maritime digitalization likewise call for evidence on how organizations convert technology into human and organizational capability (Munim et al., 2020; Sanchez-Gonzalez et al., 2019; Verhoef et al., 2021).

This study therefore develops and tests an integrated model of maritime human-capital transformation for Society 5.0 that links the TOE dimensions with digital competency adoption and human-capital transformation effectiveness. Using an exploratory sequential mixed-methods design in the Indonesian maritime context, it makes three contributions: it extends the TOE framework from technology adoption to human-capital transformation; it positions digital competency adoption as a mediating mechanism; and it integrates qualitative evidence on emerging Maritime 5.0 competencies with structural-model testing to inform regulators, shipping companies, and Maritime Education and Training (MET) institutions.

Accordingly, the study addresses three research questions. RQ1: What competencies do maritime stakeholders consider necessary for human-capital transformation toward Society 5.0, and which technological, organizational, and environmental conditions drive or impede them? RQ2: To what extent do technological readiness, organizational support, and environmental pressure predict digital competency adoption and human-capital transformation effectiveness? RQ3: Does digital competency adoption mediate the effects of these conditions on transformation effectiveness? RQ1 is answered through semi-structured interviews with 15 purposively selected stakeholders (senior practitioners, shipping-company managers, academics, and regulators), and RQ2-RQ3 through a survey of 250 Indonesian seafarers, ship officers, technical personnel, and shipping-company staff, recruited by purposive and snowball sampling and analyzed with PLS-SEM.

Literature Review and Hypothesis Development

Four complementary perspectives underpin the model. Human Capital Theory views knowledge and skills as productive resources whose value emerges when they are developed and applied at work (Ployhart & Moliterno, 2011). Socio-Technical Systems Theory holds that technological and social subsystems must be developed jointly if advanced technology is to produce its intended outcomes (Baxter & Sommerville, 2011). Dynamic Capabilities Theory explains how organizations sense change and reconfigure resources, including workforce competencies, in turbulent environments (Teece, 2007; Warner & Wäger, 2019). The TOE framework integrates these views by explaining transformation through technological, organizational, and environmental contexts (Oliveira & Martins, 2010; Zhu & Kraemer, 2005).

Accordingly, technological readiness, organizational support, and environmental pressure are conceptualized as the contextual drivers of maritime human-capital transformation, while digital competency adoption is positioned as the workforce capability that connects these conditions with transformation effectiveness. This positioning responds to calls to view digital transformation as a continuous process of capability building rather than the mere acquisition of technology (Vial, 2019; Warner & Wäger, 2019).

Technological Readiness, Organizational Support, and Environmental Pressure

Technological readiness refers to the extent to which digital maritime technologies are perceived as advantageous, compatible with existing operations, and easy to learn and operate (Zhu & Kraemer, 2005). When digital systems provide tangible operational benefits, personnel are more likely to integrate them into work practices, improving performance and adaptability (Jović et al., 2022). Increasing technological sophistication also requires personnel to master new systems: automation changes rather than removes the human element, raising the level of digital, supervisory, and system-oriented skills required (Belabyad et al., 2025; Sharma & Kim, 2022). As workplace technology changes, competency development becomes embedded in employees' everyday interaction with technological systems (Narayanan et al., 2023). In maritime operations this is increasingly important because vessels and shipping organizations depend on interconnected systems, real-time operational data, and digitally supported decision-making; the benefits of technology, however, materialize only when systems are compatible with organizational processes and meaningfully incorporated into daily work (Fruth & Teuteberg, 2017; Jović et al., 2022).

H1. Technological readiness positively affects human-capital transformation effectiveness.

H2. Technological readiness positively affects digital competency adoption.

Organizational support comprises top-management commitment, training opportunities, and an innovation-supportive culture. Resistance to change, organizational silos, and inadequate capabilities can prevent maritime organizations from realizing the benefits of digital technology, whereas culture, agility, and change management facilitate transformation (Raza et al., 2023). Maritime human-resource management must therefore evolve alongside technology by providing reskilling and upskilling during the digital transition (Theotokas et al., 2024). Management commitment provides direction and resources, training allows employees to acquire the knowledge required for new technologies, and an innovation-oriented culture reduces resistance and encourages experimentation, all of which should strengthen both competency adoption and transformation outcomes.

H3. Organizational support positively affects human-capital transformation effectiveness.

H4. Organizational support positively affects digital competency adoption.

Environmental pressure consists of competitive, regulatory, and customer or business-partner demands. Shipping operates in a highly competitive and extensively regulated international environment, and these forces push organizations toward integrated digital processes and require personnel whose competencies match new operational and regulatory requirements (Fruth & Teuteberg, 2017; Jović et al., 2022). The changing role of the human element in autonomous and digitally advanced shipping illustrates this relationship, as external expectations increasingly shape the competencies required of seafarers and maritime education and training (Shahbakhsh et al., 2022).

H5. Environmental pressure positively affects human-capital transformation effectiveness.

H6. Environmental pressure positively affects digital competency adoption.

Digital Competency Adoption as a Mediating Mechanism

Digital competency adoption is the extent to which maritime personnel develop and apply the capabilities required in a digitally transformed environment, captured here as mastery of digital systems, operational-data interpretation, and cybersecurity awareness (Moen et al., 2024; Narayanan et al., 2023). Stronger competency adoption should improve operational performance, adaptability, and alignment with organizational digital strategy. Because technology generates value only when people can use it productively (Baxter & Sommerville,

2011; Ployhart & Moliterno, 2011), digital competency adoption is also expected to transmit part of the effects of the three TOE conditions to transformation effectiveness. These three indirect effects are tested in the mediation analysis.

From a dynamic-capabilities perspective, technological developments and external pressures are signals that organizations must sense, whereas training, management commitment, and innovation-oriented practices are mechanisms for seizing these opportunities; digital competency adoption is the point at which workforce capabilities are actually reconfigured (Teece, 2007; Warner & Wäger, 2019). Technological readiness may therefore contribute to transformation by encouraging employees to develop the competencies required by available systems, organizational support may facilitate this process through training and mentoring, and environmental pressure may stimulate it by increasing the organizational need for digitally capable personnel. Together, H1-H7 and the three indirect relationships form the proposed model shown in Figure 1.

H7. Digital competency adoption positively affects human-capital transformation effectiveness.

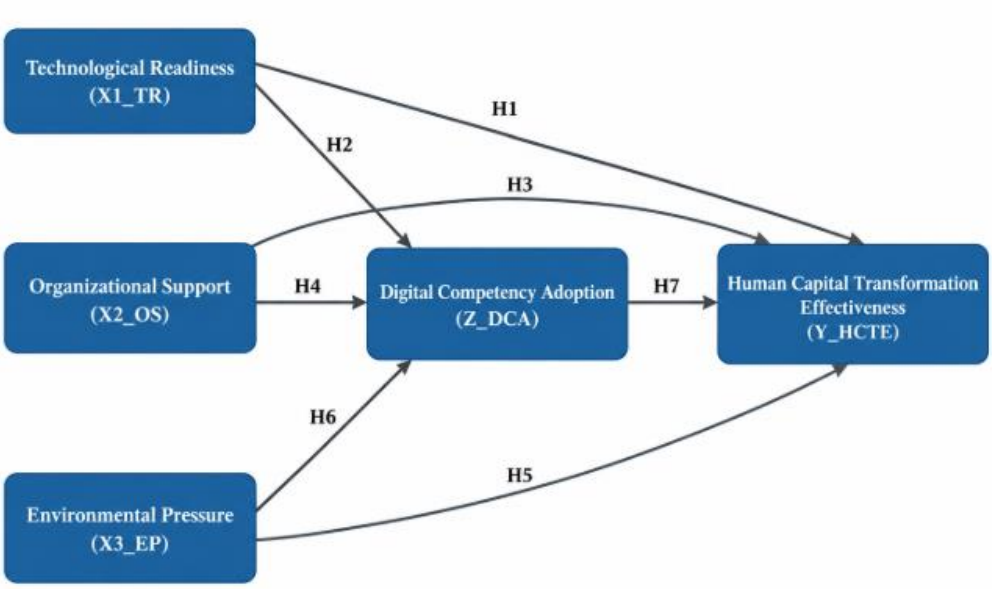


Figure 1. Proposed Maritime Human-Capital Transformation Model for Society 5.0

Method

An exploratory sequential mixed-methods design (QUAL → QUAN) was adopted within a pragmatic paradigm so that stakeholder insights could inform the measurement constructs and structural model (Ivankova et al., 2006). The qualitative phase involved 15 purposively selected informants from Jakarta, Surabaya, and Semarang: five senior practitioners (masters and chief engineers from tanker, container, LNG, and bulk-carrier operations), three shipping-company managers responsible for crewing and human-capital development, four academics, and three regulators or maritime-association representatives, with 14 to 27 years of experience. Semi-structured interviews explored digitalization, emerging competency requirements, organizational support, external pressures, and barriers to transformation, and were complemented by curricula, training documents, and regulations. Informants were selected through criterion-based purposive sampling: each had direct involvement in shipboard digital operations, crewing and human-capital development, maritime education, or regulation, and the four groups were combined to obtain maximum variation in perspective. Sample adequacy was judged by saturation: interviews were coded concurrently, and no new codes emerged after interview […], with the remaining interviews used to confirm saturation. This is consistent with empirical evidence that 9-17 interviews usually suffice to reach saturation in relatively homogeneous samples with a focused aim (Guest et al., 2006; Hennink & Kaiser, 2022; Malterud et al., 2016).

The quantitative phase surveyed 250 active seafarers, ship officers, technical personnel, and shipping-company staff involved in digitally supported operations, recruited through purposive and snowball sampling via professional networks, alumni groups, and company channels. The instrument contained 15 five-point Likert indicators, three per construct: Technological Readiness (TR: relative advantage, compatibility, ease of learning), Organizational Support (OS: management commitment, training availability, innovation culture), Environmental Pressure (EP: competitive, regulatory, and business-partner pressure), Digital Competency Adoption (DCA: digital-system mastery, data interpretation, cybersecurity awareness), and Human Capital

Transformation Effectiveness (HCTE: operational performance, workforce adaptability, competency-strategy alignment). The sample size was checked against three criteria. The largest number of structural paths pointing at a construct is four (HCTE), so the ten-times rule requires at least 40 cases (Hair et al., 2019); a G*Power analysis for four predictors ($f^2 = .15$, $\alpha = .05$, power = .95) requires 129 cases (Faul et al., 2009); and the more conservative inverse square root method, based on the smallest direct path coefficient ($\beta = .170$) at the 5% significance level, requires 214 cases (Kock & Hadaya, 2018). The 250 responses therefore exceed all three requirements.

The qualitative findings informed the instrument directly, linking the QUAL and QUAN phases. The technological drivers and barriers raised by informants (efficiency and safety benefits, fit with existing operations, and the learning burden of complex systems) were operationalized as relative advantage, compatibility, and ease of learning (TR); management commitment, training availability, and innovation culture became the OS indicators; competitive, regulatory, and charterer pressures became the EP indicators; the competency gaps emphasized most often (system mastery, data literacy, and cybersecurity awareness) became the DCA indicators; and the outcomes informants associated with successful transformation (operational performance, adaptability, and strategic alignment) became the HCTE indicators. Indicator definitions were aligned with established TOE operationalizations (Oliveira & Martins, 2010; Zhu & Kraemer, 2005). Socio-technical skills and psychological readiness were retained as qualitative dimensions and were not converted into survey constructs; this choice is discussed among the limitations.

Qualitative data were analyzed thematically through open coding, categorization, and the construction of a thematic network (Attride-Stirling, 2001; Braun & Clarke, 2006). Quantitative data were analyzed with PLS-SEM (Hair et al., 2019). The measurement model was assessed through loadings (> .70), AVE (> .50), Cronbach's α, composite reliability, and HTMT (< .90) (Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was evaluated through VIF, bootstrapped path coefficients ($t > 1.96$, $p < .05$), R^2, f^2, and Q^2 (Shmueli et al., 2019). Finally, both strands were integrated through a joint-display approach (Fetters et al., 2013). Specifically, the qualitative analysis followed Braun and Clarke's (2006) six-phase thematic analysis, with thematic networks used to organize basic, organizing, and global themes. The TOE framework served as a sensitizing rather than prescriptive lens: codes were generated inductively before being compared with TOE categories, and codes that did not fit TOE were retained. Two researchers coded the transcripts independently; intercoder agreement on […]% of the material was κ = […] (Cohen, 1960; O'Connor & Joffe, 2020), disagreements were resolved through discussion, and an audit trail of coding decisions and analytic memos was kept. Collinearity was judged against a VIF threshold of 5 (Hair et al., 2019). Indirect effects were tested by bootstrapping rather than the Baron-Kenny causal-steps approach, because bootstrapping tests the indirect effect directly without assuming normality; mediation was classified as partial (complementary) when both the indirect and the direct effects were significant and of the same sign (Nitzl et al., 2016; Zhao et al., 2010).

Results and Discussion

Qualitative Findings

Coding produced 126 open codes, 12 categories, and five organizing themes: determinants of digital transformation, the digital competency gap, competency-based transformation mechanisms, the role of digital competency in transformation effectiveness, and policy and education implications. Most participants described transformation as a process that begins with technological, organizational, and environmental conditions, proceeds through competency development, and culminates in better performance and strategic alignment. Table 1 summarizes the drivers and barriers, which map closely onto the three TOE contexts. Not all accounts converged, however: resistance among senior crew, concern about excessive monitoring, and doubts about the investment capacity of smaller firms (Table 1) represent dissenting or qualifying views, and they were retained as barrier categories rather than absorbed into the dominant process narrative.

Figure 2 depicts the thematic network. The first theme concerns structural determinants of transformation; the second captures the digital competency gap, especially in data literacy, cybersecurity awareness, curriculum relevance, and the management of complex systems. The third concerns competency-based transformation mechanisms such as organizational culture, resistance to change, intergenerational mentoring, and continuous learning. The fourth connects digital competency with performance, adaptability, and strategic alignment, and the fifth highlights the need for competency standards, curriculum and certification renewal, and coordination among regulators, industry, and MET institutions. [Representative informant quotations for each theme, with informant codes, are to be inserted here from the interview transcripts.]

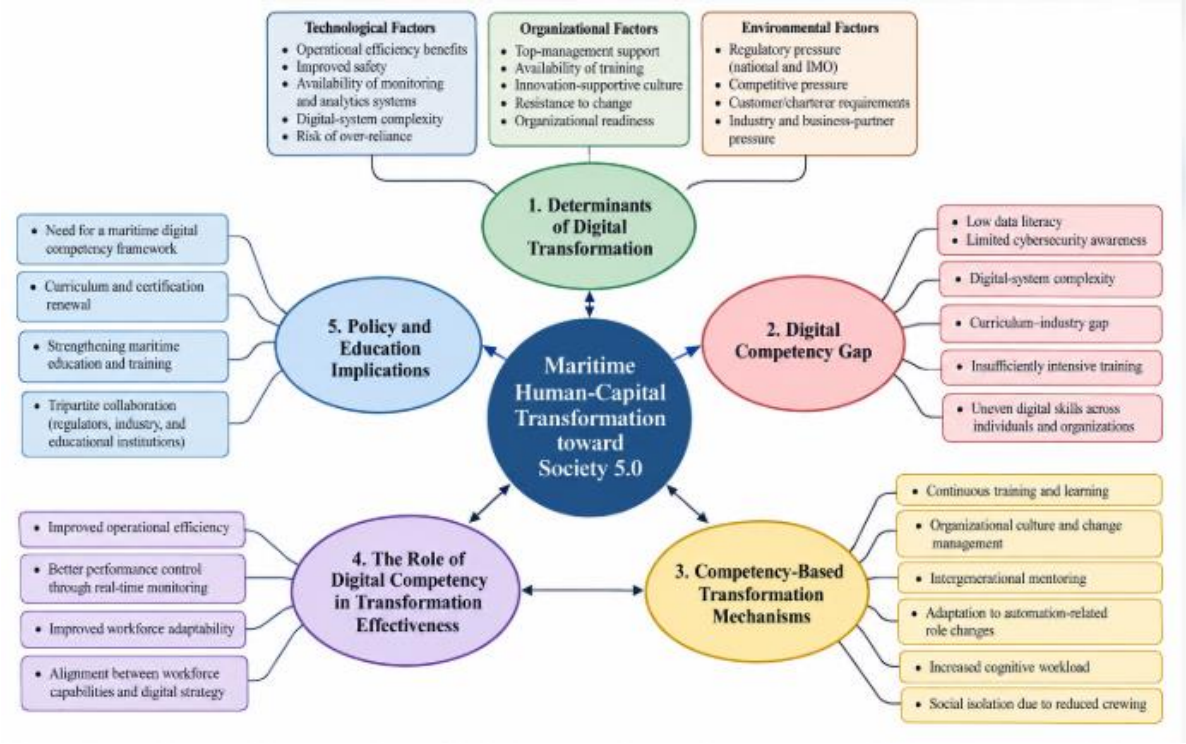


Figure 2. Thematic Network of Maritime Human-Capital Transformation toward Society 5.0

Participants viewed technological drivers efficiency and safety benefits and the availability of real-time monitoring as enabling faster operational responses and more transparent use of data, while system complexity, cybersecurity vulnerability, and excessive dependence on automation were seen as risks. Organizational drivers centered on management commitment, training availability, and an innovation-supportive culture, whereas resistance among senior crew, uneven digital literacy, shallow training, and concerns about excessive monitoring constrained change. Environmental drivers comprised regulatory requirements, competition, and charterer expectations, although disparities in investment capacity and slow renewal of curricula and certification limited their effect.

Table 1. Drivers and Barriers of Maritime Human-Capital Transformation

TOE Context	Drivers	Barriers
Technology	Efficiency and safety benefits; real-time monitoring and analytics	System complexity; over-reliance on automation; cybersecurity risk
Organization	Top-management support; training (e-learning, workshops, mentoring); innovation culture	Resistance among senior crew; digital-literacy gaps; shallow training; perceived excessive monitoring
Environment	National and IMO-related regulation; competitive pressure; charterer demands for data transparency and emissions reporting	Uneven investment capacity of smaller firms; slow synchronization of curricula and certification

The analysis also revealed three complementary dimensions of Maritime 5.0 competency (Table 2). *Hard digital skills* provide the technical foundation; *socio-technical skills* enable these capabilities to be applied within integrated human-technology and ship-shore systems; and *psychological readiness* supports sustained adaptation to change, cognitive workload, and real-time performance monitoring.

Table 2. Maritime 5.0 Competency Dimensions

Dimension	Core Competency Components
Hard digital skills	Mastery of shipboard and company digital systems; operational data literacy; digital reporting; basic cybersecurity practice
Socio-technical skills	Human-technology collaboration without over-reliance; data-based ship-shore coordination; digital communication; adaptation to automation-related role changes
Psychological readiness	Openness to change; digital self-efficacy; learning agility; resilience under data-based monitoring; cognitive-load management

The prominence of hard digital skills is consistent with evidence that automation does not eliminate the human element but raises the importance of digital, supervisory, and system-oriented capabilities among maritime professionals (Belabyad et al., 2025; Sharma & Kim, 2022). Cybersecurity was a recurring concern: participants reported uneven awareness and exposure to phishing, malware, and inappropriate digital practices, indicating that cyber capability should become a routine component of workforce development rather than an isolated technical responsibility (Moen et al., 2024).

The socio-technical dimension shows that competence cannot be reduced to individual technological proficiency: personnel must coordinate simultaneously with digital systems, crew members, shore-based staff, and procedures, which supports human-centered and scenario-based approaches to maritime training (Erstad et al., 2023). Psychological readiness adds a further layer. Participants associated digitalization with heavier cognitive demands, continuous learning, changing occupational roles, and concern about real-time monitoring, suggesting that technical upskilling alone cannot guarantee adaptation (Belabyad et al., 2025; Sharma & Kim, 2022).

These findings confirm that maritime digital transformation is not solely technological. Similar barriers resistance to change, organizational culture, and insufficient capabilities have been reported in liner shipping (Raza et al., 2023), and maritime HRM research calls for systematic reskilling rather than one-off introductory training (Theotokas et al., 2024). Cybersecurity emerged as both a competency gap and a technological risk, consistent with evidence of limited cyber awareness among seafarers and calls for structured, role-specific, and simulator-supported training (Erstad et al., 2023; Moen et al., 2024; Oruc et al., 2024).

Compared with competing frameworks, the five themes are partly confirmatory and partly novel. The drivers and barriers in the first theme recapitulate established TOE logic (Jović et al., 2022; Zhu & Kraemer, 2005), and the competency gap in the second theme overlaps with competency inventories for digitalized and autonomous shipping (Mallam et al., 2020; Sharma & Kim, 2022). What these inventories and individual acceptance models (Davis, 1989; Venkatesh et al., 2003) do not offer is the content of the third and fourth themes: an account of the organizational mechanisms through which competencies are built and of how those competencies are linked to transformation outcomes. The psychological readiness dimension also extends acceptance-based explanations, which address attitudes toward a specific system rather than an enduring readiness to adapt to continuous change.

Measurement Model

All 15 loadings exceeded .70 (.918-.956), AVE ranged from .856 to .900, Cronbach's α from .916 to .945, and composite reliability from .947 to .964 (Table 3). All HTMT values were below .90 (.032-.704; Table 4), the highest being between DCA and HCTE, confirming discriminant validity (Henseler et al., 2015). Indicator VIFs ranged from 3.057 to 4.925, except EP1 (5.547). Given the strong validity evidence, EP1 was retained, but the very high reliability coefficients and this localized collinearity suggest that future versions of the scale should refine item wording (Hair et al., 2019).

Table 3. Measurement Model Assessment

Construct	Loadings	Cronbach's α	CR	AVE
Technological Readiness (TR)	.941-.944	.938	.960	.890
Organizational Support (OS)	.947-.952	.945	.964	.900
Environmental Pressure (EP)	.938-.956	.942	.963	.896
Digital Competency Adoption (DCA)	.918-.933	.916	.947	.856
HC Transformation Effectiveness (HCTE)	.928-.943	.927	.954	.873

The consistently high loadings and AVE values indicate strong convergence among indicators within each construct. The highest HTMT value, between DCA and HCTE (.704), is theoretically reasonable because competency adoption is expected to contribute to transformation effectiveness, yet the two constructs remain empirically distinct. Overall, the measurement model provides sufficient evidence of reliability and validity to proceed with structural analysis, while the reliability and collinearity observations are reported transparently so that the structural results can be interpreted with appropriate caution.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

Construct	TR	OS	EP	HCTE	DCA
Technological Readiness (TR)					
Organizational Support (OS)	.032				
Environmental Pressure (EP)	.119	.157			
HC Transformation Effectiveness (HCTE)	.464	.459	.293		
Digital Competency Adoption (DCA)	.589	.390	.269	.704	

Structural Model and Mediation

All seven hypotheses were supported (Table 5). The model explained 51.5% of the variance in DCA and 50.9% in HCTE, and positive Q^2 values (.432 and .445) indicated predictive relevance (Shmueli et al., 2019).

Table 5. Hypothesis Testing Results and Indirect Effects

Hyp.	Path	β	t	p	f^2	Decision
H1	TR → HCTE	.261	4.669	< .001	.082	Supported
H2	TR → DCA	.586	15.057	< .001	.693	Supported
H3	OS → HCTE	.280	5.320	< .001	.129	Supported
H4	OS → DCA	.339	8.446	< .001	.230	Supported
H5	EP → HCTE	.170	3.500	.001	.051	Supported
H6	EP → DCA	.266	6.325	< .001	.140	Supported
H7	DCA → HCTE	.364	5.960	< .001	.134	Supported
	TR → DCA → HCTE (indirect)	.213	5.533	< .001	-	Partial mediation
	OS → DCA → HCTE (indirect)	.123	4.745	< .001	-	Partial mediation
	EP → DCA → HCTE (indirect)	.097	4.053	< .001	-	Partial mediation

Technological Readiness exerted the strongest effect on DCA (β = .586; f^2 = .693). This result echoes participants' accounts that system complexity and data-driven operations create new learning demands, and indicates that technology functions not only as infrastructure but as a direct stimulus for competency renewal (Belabyad et al., 2025; Jović et al., 2022). Organizational Support affected DCA (β = .339) more strongly than HCTE (β = .280), suggesting that management commitment, training, and mentoring work primarily by enabling employees to convert organizational digitalization into individual capability (Raza et al., 2023; Theotokas et al., 2024). This is consistent with research showing that resistance to change and inadequate organizational capabilities can limit digital transformation even when appropriate technology is available, and with calls for maritime HRM to become strategically involved in reskilling during the digital transition (Vial, 2019).

Environmental Pressure had significant but the weakest direct effect on HCTE (β = .170; f^2 = .051). Regulatory, competitive, and charterer demands therefore appear to create urgency rather than capability: they become effective when translated into internal learning and competency development. In shipping, where regulation, customer expectations, and international competition frequently compel adaptation, the significant effect of Environmental Pressure on DCA (β = .266) suggests that external demands create organizational incentives to strengthen digital competence, while the eventual transformation of human capital depends on internal mechanisms. The contrast between its significant path coefficient and small effect size also illustrates that statistical significance does not necessarily imply a large substantive contribution. DCA, in turn, significantly predicted HCTE (β = .364) and partially mediated all three TOE relationships, with the strongest indirect path running from TR through DCA (β = .213). The TOE conditions thus influence human capital both directly and through workforce competency.

Because all direct effects remained significant alongside significant indirect effects, DCA operates as a partial rather than full mediator. This pattern extends the conventional TOE interpretation: technological, organizational, and environmental contexts do not merely determine whether digitalization occurs, but their effects on human capital are partly transmitted through competency development. It also supports a socio-technical reading of transformation, in which technology produces value only when employees can operate, interpret, and adapt to it, and in which organizational support and external pressure become meaningful when they stimulate actual learning (Baxter & Sommerville, 2011; Vial, 2019). At the same time, approximately half of the variance in both endogenous constructs remains unexplained, indicating that additional determinants lie outside the model. Bootstrap-based 95% confidence intervals, computed as $\beta \pm 1.96$ SE with SE = β/t, excluded zero for every path: TR → DCA [.510, .662], OS → DCA [.260, .418], EP → DCA [.184, .348], TR → HCTE [.151, .371], OS → HCTE [.177, .383], EP → HCTE [.075, .265], and DCA → HCTE [.244, .484], as well as for the indirect effects TR → DCA → HCTE [.138, .288], OS → DCA → HCTE [.072, .174], and EP → DCA → HCTE [.050, .144]. Because the data are cross-sectional, this mediation pattern is consistent with, but does not prove, the hypothesized causal order; a reverse process in which effective transformation stimulates further competency adoption, or a common cause such as organizational digital maturity, cannot be ruled out.

Integrated Model and Theoretical Implications

The joint display showed strong convergence between the two strands: the drivers identified by participants were all significant predictors, and the competency gaps they emphasized data literacy, cybersecurity awareness, and complex-system mastery corresponded to the central role of DCA in the structural model. Table 6 summarizes the principal points of integration, and Figure 3 presents the resulting integrated model. Socio-technical skills

and psychological readiness, however, were identified qualitatively and were not measured as separate latent constructs; they are therefore presented as an expanded competency architecture requiring further validation.

Table 6. Joint Display of Qualitative and Quantitative Findings

Qualitative Finding	Quantitative Evidence	Integrated Interpretation
System complexity and increasingly digital equipment create new learning demands	TR → DCA: β = .586; f^2 = .693	Technology is the strongest stimulus for competency renewal
Management commitment, training, and mentoring reduce resistance to change	OS → DCA: β = .339; OS → DCA → HCTE: β = .123	Organizational support works largely by enabling competency development
Regulation, competition, and charterer demands accelerate digitalization	EP → HCTE: β = .170; f^2 = .051	External pressure creates urgency rather than capability
Gaps in data literacy and cybersecurity awareness limit performance	DCA → HCTE: β = .364; three partial mediations	Digital competency is the core transformation mechanism
Transformation is a systemic, multi-factor process	R^2 = .515 (DCA), .509 (HCTE); $Q^2 > 0$	Model is explanatory and predictive, but other determinants remain

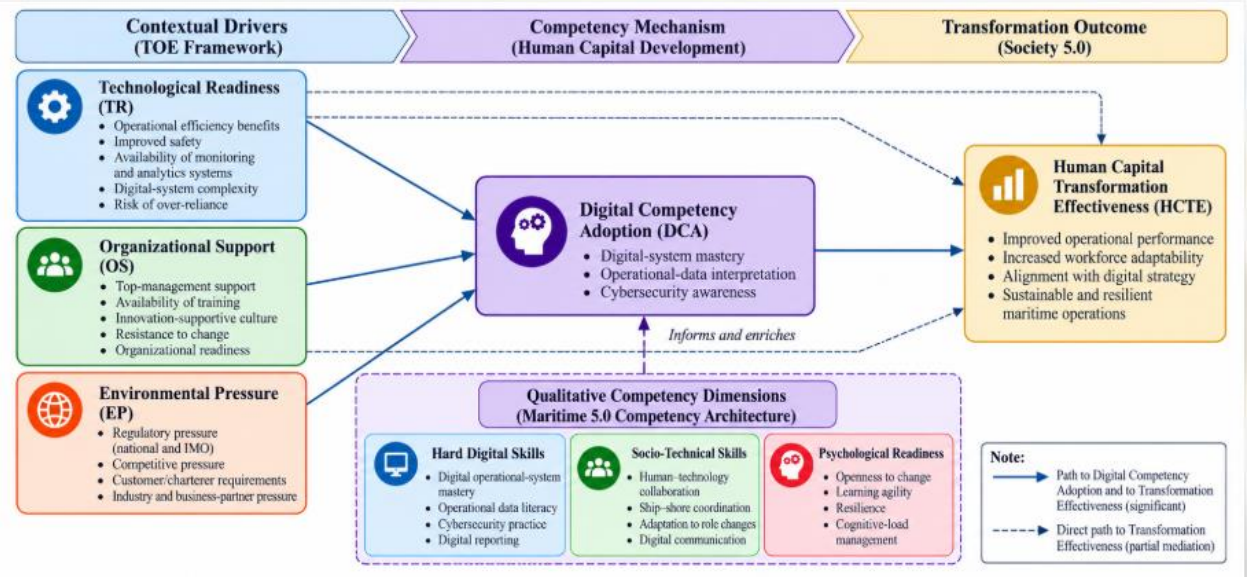


Figure 3. Integrated Maritime Human-Capital Transformation Model for Society 5.0

Theoretically, the study extends the TOE framework from organizational technology adoption to human-capital transformation by introducing competency development as an intermediate mechanism (Oliveira & Martins, 2010; Zhu & Kraemer, 2005). It supports Human Capital Theory by showing that digital competencies are a productive resource whose value depends on internalization and application (Ployhart & Moliterno, 2011), Dynamic Capabilities Theory by showing how workforce capabilities are reconfigured in response to technological and environmental change (Teece, 2007; Warner & Wäger, 2019), and Socio-Technical Systems Theory by demonstrating that technological value depends on people's capacity to operate and integrate new systems (Baxter & Sommerville, 2011). Collectively, these results frame maritime digital transformation as a human-centered capability-building process consistent with Society 5.0 (Mourtzis et al., 2022; Xu et al., 2021). What distinguishes this contribution from earlier TOE applications is the outcome and the mechanism: prior TOE studies, including those that consider human resources, treat workforce competence as an input to adoption (Baker, 2012; Zhu & Kraemer, 2005), whereas the present model treats it as the channel through which adoption conditions produce human-capital outcomes, a link that neither TOE nor acceptance models (Davis, 1989; Venkatesh et al., 2003) specify. For Human Capital Theory, the findings identify contextual antecedents of capability formation; for Dynamic Capabilities Theory, they locate reconfiguration at the level of individual competency; and for Socio-Technical Systems Theory, they estimate how much of the technical subsystem's effect is carried by the social subsystem.

The resulting model can be read at three levels. At the first level, Technological Readiness, Organizational Support, and Environmental Pressure act as contextual drivers. At the second level, Digital Competency

Adoption operates as the principal mediating mechanism, enriched qualitatively by hard digital skills, socio-technical skills, and psychological readiness. At the third level, transformation effectiveness is reflected in improved operational performance, workforce adaptability, and alignment between employee competencies and digital strategy. Transformation should therefore be judged not by the presence of digital technology but by whether that technology contributes to a more capable and adaptable maritime workforce.

Practical Implications

For regulators, the results highlight the need for digital competency standards that go beyond equipment operation to cover operational data literacy, cybersecurity awareness, and safe work within integrated human-technology systems. Aligning national regulations, international requirements, certification, and training standards would narrow the gap between technological development and workforce preparedness, and a sustained tripartite mechanism among regulators, industry, and academia would accelerate the updating of competency requirements.

For shipping companies, technology investment should be accompanied by structured workforce development. Continuous reskilling and upskilling linked to actual shipboard and ship-shore systems, mentoring between senior and junior crew, and transparent communication about monitoring can reduce resistance and speed adoption. Cybersecurity deserves particular attention: technical controls should be combined with recurrent, role-specific training, drills, and incident-reporting exercises (Moen et al., 2024; Oruc et al., 2024).

To operationalize these findings, Table 7 translates the qualitative competency dimensions into a proposed Maritime 5.0 competency framework with observable behavioral indicators that can support curriculum design, training, recruitment, and assessment. Because the socio-technical and psychological dimensions were not validated as separate latent constructs, the framework should be treated as a proposal requiring psychometric validation before adoption as a standardized instrument.

Table 7. Proposed Maritime 5.0 Competency Framework

Dimension	Core Competency	Main Behavioral Indicators
Hard digital skills	Digital operational-system mastery	Operates systems independently; enters operational data; verifies system outputs
	Operational data literacy	Reads dashboards; identifies basic anomalies; responds to alarms and performance indicators
	Digital documentation and reporting	Maintains digital logs; submits timely reports; ensures ship-shore data consistency
	Cybersecurity awareness and practice	Manages access and passwords; recognizes phishing; follows incident-reporting procedures
Socio-technical skills	Human-technology collaboration	Critically evaluates system recommendations; performs cross-checks; maintains situational awareness
	Cross-functional digital communication	Conducts digital handovers; communicates operational status using data; coordinates across units
	Data-based ship-shore coordination	Coordinates operational plans; responds to remote instructions; maintains shared data accuracy
	Adaptation to automation-related role changes	Reorganizes workload; prioritizes risk-based tasks; adapts to revised procedures
Psychological readiness	Learning agility	Participates actively in training; learns independently; uses feedback to improve
	Digital self-efficacy	Experiments with new system functions; performs basic troubleshooting; seeks help appropriately
	Resilience under data-intensive work	Maintains focus under real-time monitoring; regulates stress; preserves decision quality
	Openness to change	Supports new practices; reduces resistance; demonstrates adaptive behavior

For MET institutions, curricula should integrate operational digital systems, data interpretation, cybersecurity, ship-shore coordination, automation-related role changes, and adaptive learning into learning outcomes. Simulator-based, project-based, and industry-linked learning supported by internships, industry lecturers, and micro-credentials can translate theoretical knowledge into the operational competence required in digitally intensive and increasingly autonomous shipping (Erstad et al., 2023; Sharma & Kim, 2022).

Conclusions

This study developed and empirically validated a Maritime Human-Capital Transformation Model for Society 5.0. Qualitative evidence from 15 stakeholders revealed that maritime competency extends beyond technical proficiency to include hard digital skills, socio-technical skills, and psychological readiness. Survey evidence from 250 respondents showed that technological readiness, organizational support, and environmental pressure significantly improve digital competency adoption and human-capital transformation effectiveness, with technological readiness being the strongest driver of competency adoption. Digital competency adoption improved transformation effectiveness and partially mediated all TOE effects (bootstrapped indirect effects of .213, .123, and .097, all with 95% confidence intervals excluding zero), indicating that contextual conditions do not automatically produce workforce transformation; their effects are realized when personnel develop and apply the required competencies. Unlike earlier TOE studies, which treat workforce competence as an input to technology adoption, the model specifies competency adoption as the mechanism through which adoption conditions become human-capital outcomes. The study extends the TOE framework from technology adoption toward human-capital transformation and reinforces Human Capital, Dynamic Capabilities, and Socio-Technical Systems theories by showing that maritime digitalization requires the simultaneous development of technology, organizational capability, and workforce competence. Maritime transformation strategies should therefore integrate technological investment with continuous upskilling, change management, cybersecurity development, and competency-based curriculum reform. Within the Society 5.0 perspective, the objective of maritime digitalization should extend beyond automation and efficiency toward a workforce that is digitally competent, adaptive, resilient, and able to work effectively with advanced technologies.

Several limitations should be noted. Purposive and snowball sampling limits statistical generalization to the entire Indonesian maritime workforce, and the cross-sectional design cannot capture how competencies develop over time. Socio-technical skills and psychological readiness were identified qualitatively but not measured as separate constructs, and the very high reliability coefficients and the elevated VIF of one environmental-pressure indicator suggest that the scale should be refined. Future research should develop and validate scales for the broader Maritime 5.0 competency dimensions, conduct multi-group analyses across professional groups, experience levels, and vessel types, employ longitudinal designs, incorporate determinants such as leadership, safety culture, and organizational digital maturity, and test the model in smart ports, autonomous-ship operations, and other national contexts. Further threats to validity should also be acknowledged. Because all survey data were self-reported by the same respondents at one point in time, common method bias cannot be fully ruled out (Podsakoff et al., 2003), and the cross-sectional design limits causal inference: the mediation model fits the data but does not exclude reverse causality, in which effective transformation stimulates further competency adoption, or confounding by unmeasured factors such as organizational digital maturity. The three-dimensional competency framework derived qualitatively has not yet been tested for construct validity, so its dimensions should be treated as propositions. Finally, because the TOE framework served as a sensitizing lens during coding, the five-theme structure may partly reflect researcher framing rather than participant experience, although inductive coding and the retention of non-TOE codes were used to limit this risk.

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