Enhancing KALK Simulator-Based Learning: The Mediating Role of Competency and Strategic Human Resource Management Implications for Cadet Performance

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ABSTRACT

Maritime vocational education must ensure that graduates possess competencies aligned with dynamic industry standards, safety protocols, and operational readiness. The use of simulator-based platforms such as KALK has emerged as a strategic approach to enhance applied learning by replicating real-world maritime scenarios. However, the optimal use of KALK simulators and institutional resources remains underexplored, particularly regarding how these elements contribute to competence development. Empirical gaps persist in understanding whether competence emerges directly from simulator-based inputs or through mediating learning outcomes. Additionally, the role of human resource (HR) management in sustaining simulation effectiveness has received limited attention. This study employed a quantitative explanatory design involving 87 maritime cadets, analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM). Findings show that the simulator KALK significantly enhances both learning outcomes and competence, while supporting infrastructure improves learning outcomes but has no direct impact on competence. Learning outcomes partially mediate the relationship between simulator use and competence, and fully mediate the relationship between infrastructure and competence. These results highlight the need for structured simulator integration, robust HR capacity building, and competency-driven curriculum design. Optimizing KALK-based learning requires aligning simulator use and infrastructure with measurable outcomes and targeted HR strategies. This alignment ensures that simulator investments translate into sustainable competence development and workforce readiness in maritime education.

I. Introduction

Vocational education plays a pivotal role in aligning educational systems with the evolving demands of industry by emphasizing practical skills and measurable competencies that enhance graduate employability (Li & Rohayati, 2024; Wang et al., 2024). Within outcome-based education (OBE) frameworks, vocational programs are structured around clearly articulated competencies that learners must demonstrate upon completion of their studies, ensuring that learning processes are directly linked to labor market expectations (Li & Rohayati, 2024; Wang et al., 2024). Such frameworks not only define expected performance standards but also promote mutual recognition of qualifications across sectors, thereby facilitating smoother transitions from education to employment (Li et al., 2023). The establishment of industry-aligned standards further reinforces the relevance of vocational curricula by ensuring that graduates possess skills that meet contemporary professional requirements (Wu et al., 2024; Ronzhina et al., 2021). In this context, maritime vocational education is a strategic domain where competency development is critical, given the safety-sensitive, high-precision nature of maritime operations.

To strengthen competency development, vocational institutions are increasingly adopting experiential approaches such as project-based learning (PBL) and immersive digital technologies. PBL has been shown to significantly improve critical thinking and problem-solving skills by involving students in authentic, real-world challenges that reflect professional practice (López et al., 2023; Yolnasdi et al., 2025). This approach is especially relevant in maritime education, where hands-on training and situational judgment are essential for operational readiness (Köpeczi-Bócz, 2024; Kwak et al., 2022). Alongside PBL, the integration of augmented reality (AR), simulation systems, and other immersive

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technologies has been linked to better learning outcomes and increased student engagement (Lee & Hsu, 2021; Nidhom et al., 2022). Among these, the KALK simulator platform has attracted attention as a context-specific solution designed for maritime environments, allowing cadets to experience realistic, high-stakes operational scenarios. As a structured simulation environment, KALK not only offers maritime-specific content but also supports pedagogical design aligned with competence-based frameworks.

However, simply having access to simulation technology like KALK is not enough; its effective use depends on various supporting factors, including teaching strategies, student engagement, and institutional preparedness. Poor integration of simulator-based learning can lead to superficial use, which fails to achieve the desired learning outcomes and skill improvements. Human resource management (HRM) thus becomes a key factor in this process. Successful simulator-based teaching requires educators who are not only skilled in technology but also proficient in outcome-focused teaching methods. Well-designed faculty training programs, workload support, and HR policies that encourage instructional innovation are essential to maximize the benefits of simulation tools like KALK. In this context, HRM plays a strategic role in building capacity, ensuring that simulator use leads to sustainable educational advancement outcomes.

Despite these advances, implementing technology-integrated learning environments does not automatically ensure better learning outcomes. A common issue involves insufficient training and support for teachers in technology integration. Educators who lack both pedagogical and technical skills with digital tools often revert to traditional teaching methods, thereby limiting the transformative potential of educational technologies (Ahmad et al., 2023; Eyadat, 2023; Ganjoo et al., 2024). Without ongoing professional development focused on instructional design and technology alignment, digital tools may be underused or misapplied (Rahardjo, 2024; Yu & Ismail, 2025). Studies suggest that unfamiliarity with emerging technologies can lead teachers to view digital systems as add-ons rather than core components of their teaching strategies, thereby weakening their influence on learning outcomes (Yang, 2025; Wang et al., 2024).

Another important issue is the mismatch between technological tools and educational goals. Technology should be intentionally integrated into coherent teaching frameworks rather than used as isolated innovations (Mahanani et al., 2024; Susantiningrum et al., 2023). When digital systems fail to support meaningful learning experiences or lack interactive and reflective features, they contribute little to the development of competencies (Chen, 2025; Yang et al., 2025). Improper or unstructured use of advanced tools, such as augmented reality, can even cause confusion and cognitive overload, reducing the intended learning benefits (Kablitz, 2025; Azman et al., 2025). Additionally, student engagement significantly influences the effectiveness of technology. Learners may resist technological tools if they see them as irrelevant or too complex, leading to decreased participation and lower learning outcomes (Ronzhina et al., 2021; Shi et al., 2025). Low intrinsic motivation and frustration when navigating unfamiliar systems can further inhibit engagement and skill development (Mori, 2023; Maquiling & Desabella, 2025).

Beyond pedagogical alignment, the quality of supporting infrastructure greatly influences the success of technology-based instruction. Institutions lacking sufficient technological resources, reliable hardware, or stable internet connectivity encounter significant obstacles in creating effective digital learning environments (Yusop et al., 2022; Nwadi et al., 2025). Disruptions caused by inadequate infrastructure can discourage both educators and students, lowering the potential impact of simulation-based learning (Lavoie, 2026; Verboven et al., 2025). Therefore, institutional policies and strategic planning are crucial for fostering sustainable technology integration (Cvijic et al., 2025; Toshtemirova et al., 2025). Clear policies that promote professional development, curriculum alignment, and ongoing evaluation increase the chances that technological investments lead to improved educational outcomes (Eyadat, 2023; Kablitz, 2025). Moreover, collaborative learning environments enhance the benefits of technology-enhanced teaching by promoting knowledge sharing and collective problem-solving among students and faculty (Williams-York et al., 2024; Merino-Soto et al., 2024).

The relationship between learning outcomes and competence development can be grounded in competence-based education (CBE) and outcome-based education (OBE). CBE stresses aligning teaching methods with the skills needed for successful job performance, ensuring graduates meet labor market demands (Li & Rohayati, 2024; Wang et al., 2023). Constructive Alignment Theory further states that intended learning outcomes, teaching activities, and assessments must be coherently aligned to promote meaningful learning and skill acquisition (Sutrisno et al., 2025). When assessments genuinely reflect targeted skills and instructional activities support these outcomes, learners are more likely to internalize knowledge and use it effectively in professional settings (Li & Rohayati, 2024; Chen, 2025). Motivation and self-regulated learning (SRL) frameworks also highlight the mediating role of engagement in developing competence, as internal motivation boosts deep learning and long-term skill building (Basori et al., 2023; Brits, 2024; Hassan et al., 2025; Kleszczewska et al., 2022). Interactive and immersive environments, like simulations and virtual reality, further strengthen experiential learning processes that support competence development (Kablitz, 2025; Sánchez-López et al 2024).

Although a substantial body of literature supports the benefits of simulation-based learning, significant research gaps still exist in maritime vocational education. First, empirical evidence quantifying the direct and indirect effects of simulator use on specific competency areas remains limited (Wang et al., 2023; Sánchez-López et al., 2024). Many studies focus on technological innovation without thoroughly measuring skill acquisition or readiness for maritime careers. Second, there is insufficient research integrating simulation into structured competency-based models, raising concerns about inconsistent implementation and outcomes (Rafiq et al., 2023; Yang et al., 2023). Third, learner engagement, motivation, and user experience within maritime simulator environments are underexplored, even though evidence indicates that engaged learners tend to achieve better outcomes (Кравченко et al., 2023; Samsir et al., 2025; Rosales-Torres et al., 2022; Zhou et al., 2022). Finally, there is a lack of long-term studies examining how simulator training influences actual job performance and industry validation, which limits understanding of its professional impact over time (Sutrisno et al., 2025; Santos et al., 2022).

In response to these gaps, this study aims to examine the causal relationships among KALK simulator use, supporting infrastructure, learning outcomes, and competence development, within the framework of maritime vocational education. By positioning competence as a mediating variable, this research advances a practical model to guide HRM strategies and curriculum design. The novelty lies in its integrated approach linking simulator-based learning, human capital investment, and competency-based assessment to inform the optimal utilization of KALK in preparing cadets for professional maritime roles.

A. Learning Outcomes in Vocational Education

Learning outcomes in vocational education are commonly conceptualized across three interrelated domains: cognitive, affective, and psychomotor. This tripartite framework provides a comprehensive structure for evaluating students' mastery of knowledge, attitudes, and practical skills required for professional practice (Li & Rohayati, 2024; Sutrisno et al., 2025; Akmal et al., 2025). In vocational settings, learning outcomes are not limited to theoretical understanding but extend to observable performance and behavioral transformation aligned with occupational standards.

The cognitive domain encompasses mental processes such as remembering, understanding, applying, analyzing, evaluating, and creating. Bloom's taxonomy and its subsequent revisions remain central in structuring cognitive learning objectives, particularly in competency-based curricula that require analytical thinking and problem-solving abilities (Yusop et al., 2022; Setyawan et al., 2025). Within vocational education, cognitive outcomes reflect students' capacity to interpret technical information, diagnose operational problems, and make evidence-based decisions in real-world contexts.

The affective domain covers attitudes, values, motivation, and professional traits important in workplace settings. In vocational programs, affective learning outcomes often include ethical behavior, responsibility, teamwork, and compliance with safety standards (Akmal et al., 2025; Yusop et al., 2024). Approaches to measure this domain usually involve self-report tools, behavioral observations, and reflective assessments to gauge students' engagement and professional attitude. The psychomotor domain emphasizes physical and technical skills needed for task completion. In vocational education, psychomotor outcomes are generally evaluated through performance-based tests, demonstrations, simulations, and industry-aligned skill assessments (Sutrisno et al., 2025; Wu et al., 2024). Rubrics and standardized performance measures are frequently used to assess accuracy, efficiency, and adherence to professional standards.

Assessment strategies in vocational education combine both formative and summative methods. Formative assessments, such as quizzes, practical exercises, and ongoing feedback, track student progress and reinforce learning during instruction (Setyawan et al., 2025; Yusop et al., 2024). Summative assessments, such as certification exams and practical demonstrations, evaluate readiness for employment and overall competency achievement (Yusop et al., 2022; Akmal et al., 2025). Additionally, portfolio assessments and peer/self-assessment techniques are increasingly utilized to document long-term development across different areas and encourage reflective learning (Wu et al., 2024; Li & Rohayati, 2024; Hiim, 2022). Together, these methods highlight the multifaceted nature of learning outcomes in vocational contexts.

B. Educational Applications and Information Systems in Technology-Enhanced Learning

Educational applications and information systems are shaped by several theoretical models that explain their adoption and pedagogical effects. The Technology Acceptance Model (TAM) suggests that perceived usefulness and perceived ease of use greatly influence users' willingness to adopt technological systems (Hermansyah et al., 2025; Yolnasdi et al., 2025). In vocational education, students' and instructors' perceptions of simulator usability and relevance directly impact the success of technology integration.

Constructivist learning theory offers another core perspective, highlighting that learners actively build knowledge through interaction and experience. Technology-enhanced settings, especially simulations and project-based platforms, promote experiential learning and real-world problem-solving, leading to deeper understanding and skill transfer (Sutrisno et al., 2025; Ghafara et al., 2025). In these environments, digital tools serve not just as delivery channels but as cognitive scaffolds that encourage exploration and application.

Communities of Practice (CoP) theory emphasizes the social aspect of learning, proposing that knowledge grows through participation in shared practices and collaborative activities (Akmal et al., 2025; Morselli, 2024). Information systems that facilitate communication, collaboration, and peer feedback strengthen collective learning processes in vocational settings. The blended learning framework further combines online and face-to-face formats to leverage the strengths of both (Redmond et al., 2024; Xie, 2021). Educational tools used in blended environments offer flexibility, accessibility, and personalization, accommodating diverse learner needs while maintaining practical engagement.

Despite these theoretical strengths, challenges remain. Unequal access to technological resources and inconsistent infrastructure can hinder effective implementation (Toshtemirova et al., 2025; Fajri et al., 2025). Furthermore, instructor training is essential; without proper professional development, educational technologies might not align with curricular goals (Li & Rohayati, 2024; Yusop et al., 2024). Curriculum alignment is also crucial to ensure that digital tools directly support desired learning outcomes and competency standards (Wu et al., 2024; Hermansyah et al., 2025).

C. Human Resource Management and Instructor Competence in Simulator-Based Education

Effective implementation of simulator-based education requires not only technological investment but also robust human resource (HR) strategies. Instructors' roles are pivotal in transforming digital tools into impactful learning experiences. Instructors must possess both pedagogical and technical competencies to design and facilitate simulation sessions that align with vocational learning outcomes. Therefore, continuous professional development (CPD) is essential to enhance instructors' instructional design capabilities, technological fluency, and assessment literacy (Li & Rohayati, 2024; Yusop et al., 2024).

Strategic HR management in vocational institutions should focus on recruitment, retention, and upskilling of instructors who are capable of operating advanced simulation technologies. Institutions must provide structured support systems, including access to updated training, collaborative planning time, and performance evaluations aligned with educational innovation goals. These efforts ensure the instructional effectiveness of simulators and contribute to sustained learning improvements. Furthermore, managing instructors' competence involves recognizing their role as facilitators of experiential learning rather than just content deliverers, which requires emotional intelligence, adaptability, and leadership.

D. Educational Facilities and Infrastructure in Vocational Education

Educational facilities and infrastructure greatly impact instructional quality and student success. Well-equipped classrooms, labs, and workshop areas enable effective delivery of multimedia-rich lessons and practical experiences (Xie, 2021; Yusop et al., 2022). In vocational settings, physical learning environments are closely tied to hands-on learning opportunities, which are key to developing skills. Research shows that modern technological infrastructure boosts engagement and achievement by supporting interactive and applied learning. Additionally, environmental factors such as safety, comfort, and accessibility influence student motivation and well-being, which in turn affect academic outcomes (Yusop et al., 2022; Dahalan et al., 2023).

Infrastructure also affects instructional effectiveness by enabling the application of innovative pedagogical models such as problem-based learning and blended instruction (Nor et al., 2023; Sutrisno et al., 2025). Well-maintained facilities reduce operational disruptions and create stable learning conditions conducive to skill mastery (Morselli, 2024). Thus, infrastructure serves as both a direct enabler of practice-based training and an indirect contributor to learning engagement and performance.

E. Competence in Competency-Based Education Frameworks and Its Managerial Use

Within competency-based education (CBE), competence is defined as the demonstrated ability to perform tasks effectively in professional contexts, integrating knowledge, skills, and attitudes (Kablitz et al., 2023; Yusop et al., 2024). CBE frameworks emphasize alignment between educational objectives and industry standards to ensure workforce readiness.

Operationalizing competence involves translating broad professional expectations into measurable learning outcomes aligned with cognitive, affective, and psychomotor domains (Álvarez et al., 2024; Kablitz et al., 2023). Cognitive competence includes analytical reasoning and technical knowledge (Fajri et al., 2025; Setiyawan, 2026). Affective competence encompasses ethical behavior, teamwork, and professional attitudes (Fajri et al., 2025; Yolnasdi et al., 2025). Psychomotor competence involves technical execution assessed through simulations, demonstrations, and standardized performance tasks (Setiyawan, 2026; Ghafara et al., 2025).

In managerial contexts, competence data plays a strategic role in human resource development. Institutions can utilize competence assessments to inform recruitment decisions, identify skill gaps, and plan targeted training interventions for both students and staff. Data-driven HR management grounded in learning outcomes helps optimize instructional quality and align institutional practices with labor market demands. Measurement of competence usually combines formative and summative assessments, direct performance evaluations, portfolio documentation, and standardized skills testing aligned with industry benchmarks (Yusop et al., 2024; Fajri et al., 2025; Álvarez et al., 2024). These methods reinforce the idea that competence reflects observable and measurable performance rather than abstract knowledge alone.

Positioning and Research Gap: The reviewed literature indicates that learning outcomes are multidimensional, that technology-enhanced learning environments offer both theoretical and practical advantages, that infrastructure supports instructional quality, and that competence is essential for achieving vocational education outcomes. However, current research often examines these factors separately instead of integrating them into a comprehensive causal framework. There is limited empirical evidence on models' educational applications, supporting infrastructure, learning outcomes, and competence, especially within maritime vocational settings. Furthermore, the impact of instructor competence and human resource management on the improvement of simulation-based environments has not been sufficiently studied. Therefore, a structural model is needed to test both direct and indirect relationships among these components, to better understand how simulator systems, infrastructure, and HR practices influence competence development and observable learning outcomes.

II. Method

A. Research Design

This study employed a quantitative research approach with a causal explanatory design to examine the relationships among four principal constructs: use of the KALK simulator application (X1), supporting infrastructure (X2), competence (Y), and learning outcomes (Z). The design aimed to test both direct and indirect (mediated) effects among variables within a structured theoretical framework. The causal model assumes that simulator use and infrastructure influence competence and learning outcomes, with competence also mediating these relationships.

Selecting a quantitative design aligns with the objective of testing hypotheses and estimating the magnitude of relationships among latent constructs. Structural Equation Modeling (SEM) based on Partial Least Squares (PLS) was used as the primary analytical technique because it allows simultaneous estimation of measurement and structural models and is suitable for complex mediation analysis.

PLS-SEM was chosen for several methodological reasons. First, it is distribution-free and does not require multivariate normality, making it suitable for educational datasets with moderate sample sizes (Yu & Ismail, 2025; Jaedun et al., 2022). Second, it handles multidimensional constructs such as learning outcomes and competence, which encompass cognitive, affective, and psychomotor aspects (Li & Rohayati, 2024; Maksum et al., 2025). Third, it allows for rigorous mediation testing using bootstrapping methods to estimate indirect effects and confidence intervals (Daoyan & Disi, 2024; Wang et al., 2024). Lastly, PLS-SEM supports theory testing and development by assessing model fit and predictive relevance in educational research (Maksum et al., 2025; Chen, pollutants: 2025).

B. Population, Sample, and Research Setting

The research was conducted at Sekolah Tinggi Ilmu Pelayaran (STIP) Jakarta, specifically within the KALK Study Program. The target population included 653 second year (Level 2) cadets enrolled in 2022 (N = 653). Due to time and resource constraints, not all members of the population participated in the study. A sample of 87 students was selected for the main survey (n = 87). The sampling process involved non-probability and purposive elements, along with simple random sampling principles, as outlined in the institutional methodology documentation. The sample size was deemed sufficient for PLS-SEM analysis, which accommodates moderate sample sizes and complex models. Before the main survey, a pilot test was conducted with 30 respondents (n = 30) to assess the instrument's validity and reliability. The pilot data were analyzed using SPSS version 26 for initial measurement calibration items.

C. Instrumentation and Data Collection Procedures

Primary data were collected using a structured questionnaire based on a five-point Likert scale. The instrument included four constructs: KALK simulator use (X1: 10 items), supporting infrastructure (X2: 10 items), competence (Y: 7 items), and learning outcomes (Z: 16 items). Secondary data consisted of institutional documentation related to infrastructure and academic aspects of implementation.

Table 1. Likert Scale Scoring Weights

Response Category	Code	Score
Strongly Agree	SS	5
Agree	S	4
Neutral	N	3
Disagree	TS	2
Strongly Disagree	STS	1

[a] (Source: Sugiyono, 2017)

Table 1 presents the scoring weights assigned to each response category in the Likert scale used in this research instrument. There are five levels of attitudinal responses, each represented by a specific code and corresponding numerical score. The response "Strongly Agree" (SS) is assigned the highest score of 5, indicating a very strong level of agreement with the given statement. This is followed by "Agree" (S) with a score of 4, and "Neutral" (N) with a mid-point score of 3, reflecting a neutral or undecided stance.

The two remaining categories are "Disagreed" (TS), which is scored 2, and "Strongly Disagree" (STS), which has the lowest score of 1, indicating strong disagreement. This scoring scheme converts qualitative responses into quantitative data, making it easier to perform statistical analyses, such as calculating mean scores and testing validity and reliability. The weight assignment is structured to ensure consistency in measuring respondents' perceptions across different research context variables.

The questionnaire was distributed online using Google Forms. After data collection, responses were tabulated and screened for completeness before statistical analysis.

Table 2. Instrument Blueprint (Extracted Structure)

Variable	Dimension	Indicator	Scale
Competence (Y)	Knowledge	Understanding SOP and regulations	Likert
Competence (Y)	Skills	Technical ability; training participation	Likert
Competence (Y)	Attitude	Professional ethics; responsibility; rejecting intervention	Likert

Table 2 outlines the instrument blueprint for measuring the competence variable (Y) used in this study. The competence construct is divided into three core dimensions: knowledge, skills, and attitude, each aligned with specific indicators and measured on a Likert scale.

The knowledge dimension includes indicators such as understanding Standard Operating Procedures (SOPs) and relevant regulations, reflecting the cognitive aspect of vocational competence. The skills dimension is represented by indicators such as technical ability and participation in training, which capture respondents' practical capabilities. Meanwhile, the attitude dimension emphasizes professional ethics, a sense of responsibility, and the ability to reject inappropriate intervention, highlighting the affective qualities essential to workplace behavior.

This blueprint was extracted from institutional instrument design documentation, ensuring alignment with the institution's competency standards. The use of the Likert scale for each indicator allows for the quantification of qualitative attitudes and behaviors, thereby facilitating rigorous statistical analysis. Overall, this structured framework provides a comprehensive, multidimensional assessment of students' competence in a vocational education context.

Although full blueprint details for X1, X2, and Z were not entirely retrievable from the searchable excerpt, coded item evidence (X11–X110; X21–X210; Y1–Y7; Z1–Z16) confirms a structured operationalization across constructs.

D. Data Analysis Procedures

Data analysis consisted of two main stages: (1) instrument testing using SPSS and (2) structural modeling using SmartPLS.

1) Instrument Validity and Reliability (SPSS)

Item validity was assessed by comparing r-count values with r-table thresholds at $\alpha = 0.05$ and $df = n - 2$. Items were considered valid when the r-count exceeded the r-table and was positive. Additionally, corrected item-total correlations were evaluated against a minimum threshold of 0.30. Reliability was evaluated using Cronbach's Alpha, with $\alpha \geq 0.60$ considered acceptable. Complementary standards from the literature recommend Cronbach's Alpha ≥ 0.70 and Composite Reliability ≥ 0.70 for strong internal consistency (Кравченко et al., 2023; Keller et al., 2025).

2) Structural Equation Modeling (PLS-SEM)

The structural model was analyzed using SmartPLS software. The analysis followed two major steps: evaluation of the outer (measurement) model and evaluation of the inner (structural) model.

Convergent validity was assessed using loading factors (>0.70 preferred; 0.50–0.60 acceptable in exploratory stages) and Average Variance Extracted (AVE > 0.50). Discriminant validity was examined using cross-loadings and comparisons of the square roots of the AVEs with inter-construct correlations.

The inner model was evaluated using path coefficients, t-statistics, and p-values (bootstrapping), R^2 (explained variance), Q^2 (predictive relevance), effect size (f^2), and collinearity diagnostics (VIF). Bootstrapping procedures were used to test the significance of direct and indirect (mediated) relationships (Daoyan & Disi, 2024; Wang et al., 2024).

E. Validity, Reliability, and Ethical Considerations

Content validity was supported through alignment of questionnaire items with established theoretical constructs and vocational competency frameworks (Wu et al., 2024; Feng, 2026). Construct validity was assessed through SEM-based factor evaluation (Hassan et al., 2025). Criterion-related validity may be inferred through comparison between perceived competence and performance indicators (Olaya et al., 2025).

Reliability standards incorporated Cronbach's Alpha, Composite Reliability, and internal consistency evaluation. Test–retest reliability is recommended in vocational research contexts to ensure the stability of responses over time (Yan et al., 2025; Yolnasdi et al., 2025). Ethically, participation was voluntary and based on informed consent, as outlined in the questionnaire introduction. Respondent anonymity and confidentiality were maintained by excluding identifying information from datasets. The sampling process avoided discriminatory exclusion and adhered to equitable research principles in educational settings. Overall, the methodological structure integrates rigorous measurement validation and causal modeling to examine both direct and mediated effects of simulator usage and infrastructure on competence and learning outcomes within maritime vocational environments education.

III. Results and Discussion

A. Instrument Testing: Validity and Reliability (Pilot Test, n = 30)

Before the main survey, the research instrument was pilot tested with 30 respondents to evaluate item validity and reliability using SPSS version 26. Validity testing involved comparing R-value results with the r-table threshold (0.3061, $\alpha = 0.05$; df = n − 2). All items across the four constructs, KALK Simulator Use (X1), Supporting Infrastructure (X2), Competence (Y), and Learning Outcomes (Z), were considered valid because each R-value exceeded 0.3061 and was positive. Reliability was assessed through Cronbach's Alpha, with all constructs exceeding the minimum reliability threshold ($\alpha \geq 0.60$), indicating strong internal consistency.

Table 3. Validity and Reliability Test Results (Pilot Test, n = 30)

Item	Variable	r-count	Cronbach's Alpha	Interpretation
X11 – X110	Simulator Use (X1)	0.603 – 0.944	0.913	Valid & Reliable
X21 – X210	Supporting Infrastructure (X2)	0.561 – 0.914	0.949	Valid & Reliable
Y1–Y7	Competence (Y)	0.638 – 0.969	0.949	Valid & Reliable
Z1–Z16	Learning Outcomes (Z)	0.842 – 0.945	0.988	Valid & Reliable

[b] Source: Processed pilot data (SPSS output)

Table 3 shows the results of the validity and reliability tests for the research instruments, based on pilot test data from 30 respondents. Validity was evaluated using the r-count correlation between each item's score and the total score of its respective variable. All items showed r-count values above 0.561, surpassing the common minimum validity threshold of 0.30. This confirms that all items are valid and suitable for measuring their respective constructs.

Reliability was assessed using Cronbach's Alpha coefficient. All four variables displayed very high internal consistency, with alpha values as follows: Simulator Use (0.913), Supporting Infrastructure (0.949), Competence (0.949), and Learning Outcomes (0.988). These values are well above the standard minimum threshold of 0.70, indicating that each set of items reliably measures the intended construct.

Overall, the table confirms that the instruments used in this study are both valid and reliable. The strong validity and reliability scores provide a solid foundation for proceeding with the main data collection and enhance the credibility of the research results. The high alpha values (0.913–0.988) demonstrate that the items reliably measure their intended constructs and are appropriate for structural analysis.

B. Respondent Profile and Descriptive Statistics (n = 87)

The final dataset consisted of 87 respondents (Level 2 KALK cadets). Table 4 shows the demographic breakdown of respondents by gender, with 87 students participating in the study. Of these, 67 respondents (77%) were male, and 20 respondents (23%) were female. All participants were second-year students, as noted in Table 5.

Table 4. Respondent Demographics (n = 87)

Category	f	%
Male	67	77.0
Female	20	23.0
Total	87	100

[c] All respondents were second-year students (100%).

Table 5. Descriptive Statistics - Simulator Use (X1)

Code	Min	Max	Mean	SD
X11	1	5	3.966	1.039
X12	1	5	3.736	1.205
X13	2	5	4.000	1.067
X14	1	5	3.609	1.103
X15	2	5	4.034	0.966
X16	1	5	4.034	0.915
X17	2	5	4.161	0.974
X18	2	5	4.310	0.946
X19	2	5	4.126	0.895
X110	3	5	4.322	0.622

This distribution reflects the typical gender makeup in maritime vocational education settings, which tend to be male-dominated, a common trend in technical and maritime fields. Despite the gender disparity, both groups are well represented in the data, allowing for a more comprehensive analysis of perceptions, especially regarding simulator use and skill development. Understanding this demographic context is essential for interpreting the results, particularly concerning institutional and gender-specific factors. Additionally, since all participants are in their second year, they share a relatively similar level of academic exposure and experience with simulation-based learning.

1) Descriptive Statistics - KALK Simulator Use (X1)

Means ranged from 3.609 to 4.322, indicating generally positive perceptions.

The highest mean (4.322) was observed for item X110, indicating strong confidence in the application's use after training. Table 5 presents the descriptive statistics for the Simulator Use variable (X1), which includes 10 items (X11-X110). Each item is rated on a Likert scale from 1 to 5. The mean scores range from 3.609 (X14) to 4.322 (X110), suggesting generally positive perceptions of simulator use among respondents. The highest average score (4.322) for item X110 reflects strong student confidence in using the application after training.

Standard deviations (SD) range from 0.622 to 1.205, indicating moderate variability in responses. Notably, item X14 has the lowest mean (3.609), suggesting areas where students felt less confident or experienced. Items X18 and X17 also show relatively high mean scores, indicating positive perceptions of simulator functionality and relevance. Overall, the data suggest that students view simulator-based training as an effective and engaging learning method in their vocational education. The high mean scores and acceptable variability support the conclusion that simulators positively contribute to skill development and confidence in maritime vocational training education.

2) Descriptive Statistics - Supporting Infrastructure (X2)

Means ranged from 3.598 to 4.276.

Table 6. Descriptive Statistics - Supporting Infrastructure (X2)

Code	Min	Max	Mean	SD
X21	1	5	4.034	0.930
X22	1	5	3.874	0.952
X23	1	5	3.598	1.048
X24	1	5	3.713	0.996
X25	1	5	4.080	0.902
X26	2	5	4.092	0.796
X27	2	5	4.276	0.714
X28	2	5	4.184	0.760
X29	2	5	4.195	0.701
X210	2	5	4.253	0.698

Infrastructure received overall positive ratings, especially for availability (X27 mean = 4.276). Table 6 presents the descriptive statistics for the variable "Supporting Infrastructure" (X2), which includes ten indicators (X21-X210). The table displays the minimum and maximum scores, mean values, and standard deviations (SD) for each item based on Likert-scale responses. Overall, the data suggest positive perceptions of institutional infrastructure.

The highest mean score is observed in item X27 (mean = 4.276), indicating that respondents rated infrastructure availability most favourably. This suggests that access to learning facilities and tools was perceived as adequate and consistent. Other items, such as X210 (mean = 4.253) and X29 (mean = 4.195), also received high ratings, reflecting satisfaction with infrastructure quality and reliability of the infrastructure.

Standard deviation values across items range from 0.698 to 1.048, indicating moderate variability in responses. This suggests general agreement among respondents, although some differences exist in perceptions of specific aspects, such as maintenance (X23, mean = 3.598, SD = 1.048). In summary, the findings indicate that supporting infrastructure was evaluated positively, especially in terms of availability, functionality, and relevance to educational needs in a vocational learning environment.

3) Descriptive Statistics - Competence (Y)

Means ranged from 3.828 to 4.471.

Table 7. Descriptive Statistics - Competence (Y)

Code	**Min**	**Max**	**Mean**	**SD**
Y1	1	5	3.828	0.955
Y2	2	5	4.437	0.659
Y3	2	5	4.471	0.679
Y4	2	5	4.046	0.680
Y5	2	5	4.402	0.690
Y6	3	5	4.448	0.586
Y7	2	5	4.276	0.694

The highest mean (4.471) was observed for perceived ability to use the simulator. Table 7 shows descriptive statistics for the variable "Competence" (Y), measured through seven indicators (Y1–Y7). Each item was rated using a Likert scale, with results including minimum and maximum scores, mean values, and standard deviations (SD). Among the indicators, Y3 had the highest average score (4.471), suggesting that respondents felt especially confident in their perceived ability to use the simulator. This indicates a strong sense of technical competence gained through training or experience. Other items, such as Y2 (mean = 4.437) and Y6 (mean = 4.448), also received high ratings, demonstrating a generally positive perception of competence across different areas. Conversely, Y1 had the lowest mean score (3.828) and the highest standard deviation (0.955), implying more varied responses and potentially lower confidence in the area assessed by that item. The relatively low SD values for most items (ranging from 0.586 to 0.955) suggest moderate consistency among participant responses. Overall, the table indicates that most students perceived themselves as competent, especially in simulation-related skills, highlighting the importance of hands-on learning for developing vocational skills competence.

4) Descriptive Statistics - Learning Outcomes (Z)

Table 8. Means ranged from 3.563 to 4.460. Descriptive Statistics - Learning Outcomes (Z)

Code	**Min**	**Max**	**Mean**	**SD**
Z1	1	5	4.161	0.926

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Code	Min	Max	Mean	SD
Z2	1	5	4.218	1.005
Z3	1	5	3.563	0.885
Z4	1	5	4.218	0.882
Z5	1	5	4.172	0.918
Z6	1	5	4.080	0.852
Z7	2	5	4.057	0.768
Z8	2	5	4.115	0.855
Z9	2	5	3.874	0.818
Z10	2	5	4.310	0.826
Z11	1	5	4.437	0.924
Z12	1	5	3.782	1.104
Z13	1	5	4.207	0.954
Z14	2	5	4.218	0.827
Z15	1	5	4.034	0.946
Z16	3	5	4.460	0.625

Z16 (Mean = 4.460) recorded the highest agreement.

Table 8 shows descriptive statistics for the Learning Outcomes variable (Z), assessed using 16 indicators (Z1–Z16). The data includes minimum and maximum values, mean scores, and standard deviations (SD) for each item, based on a Likert scale. The mean scores range from 3.563 (Z3) to 4.460 (Z16), reflecting a generally high level of agreement among respondents regarding their learning outcomes. Z16 recorded the highest mean score (4.460) and the lowest standard deviation (0.625), indicating strong consensus and confidence in the outcome it measures. Other high-scoring items include Z10 (4.310) and Z11 (4.437), which support positive perceptions of learning achievements. Conversely, Z3 had the lowest mean (3.563), with a relatively modest SD (0.885), possibly indicating lower perceived achievement or relevance in that specific area. Overall, the narrow SD range (0.625 to 1.104) suggests responses were consistent across items. These results imply that most students believe they effectively achieved the intended learning outcomes, especially in areas related to practical application and personal understanding, further confirming the validity of the learning process in the vocational education context.

C. *Measurement Model (Outer Model PLS-SEM)*

Reliability and validity were reassessed using SmartPLS.

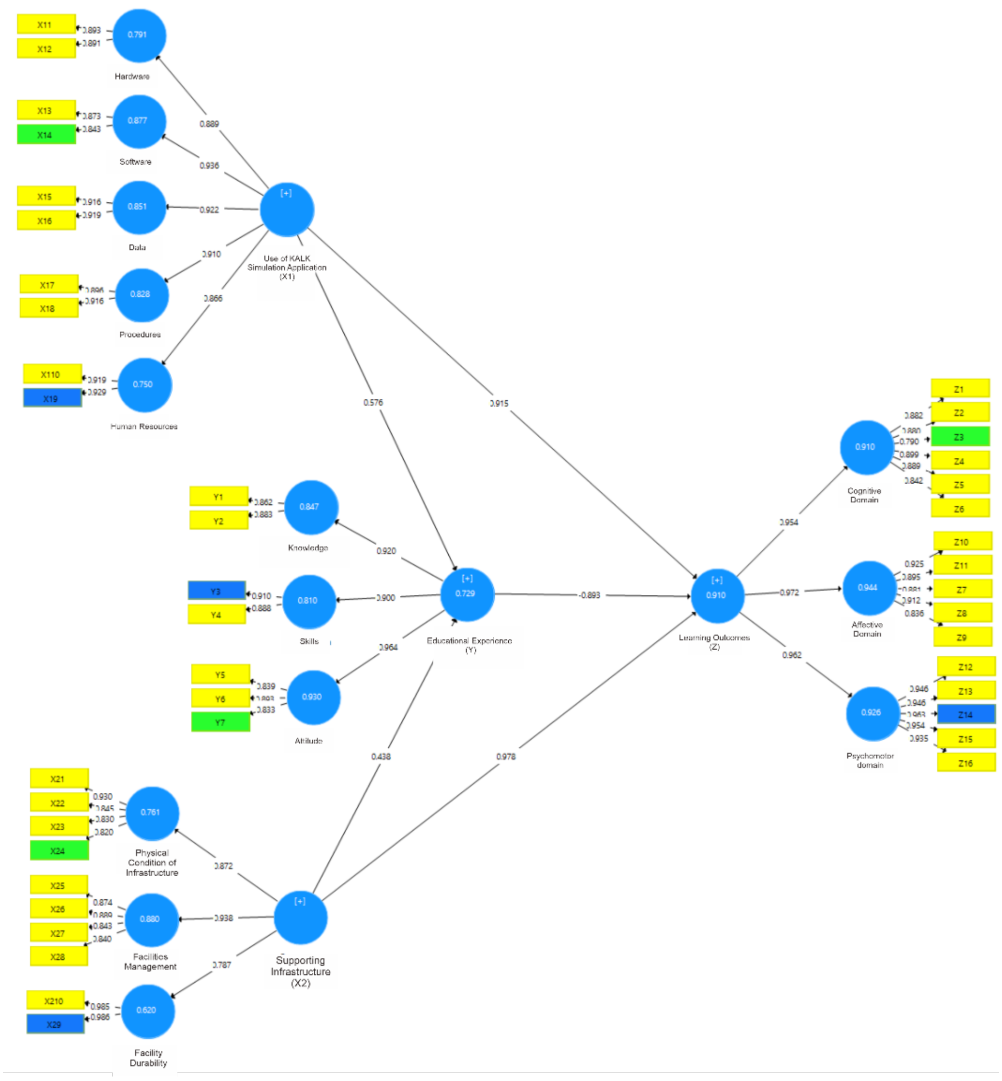

Fig. 1.FiStructural Model - Outer Model

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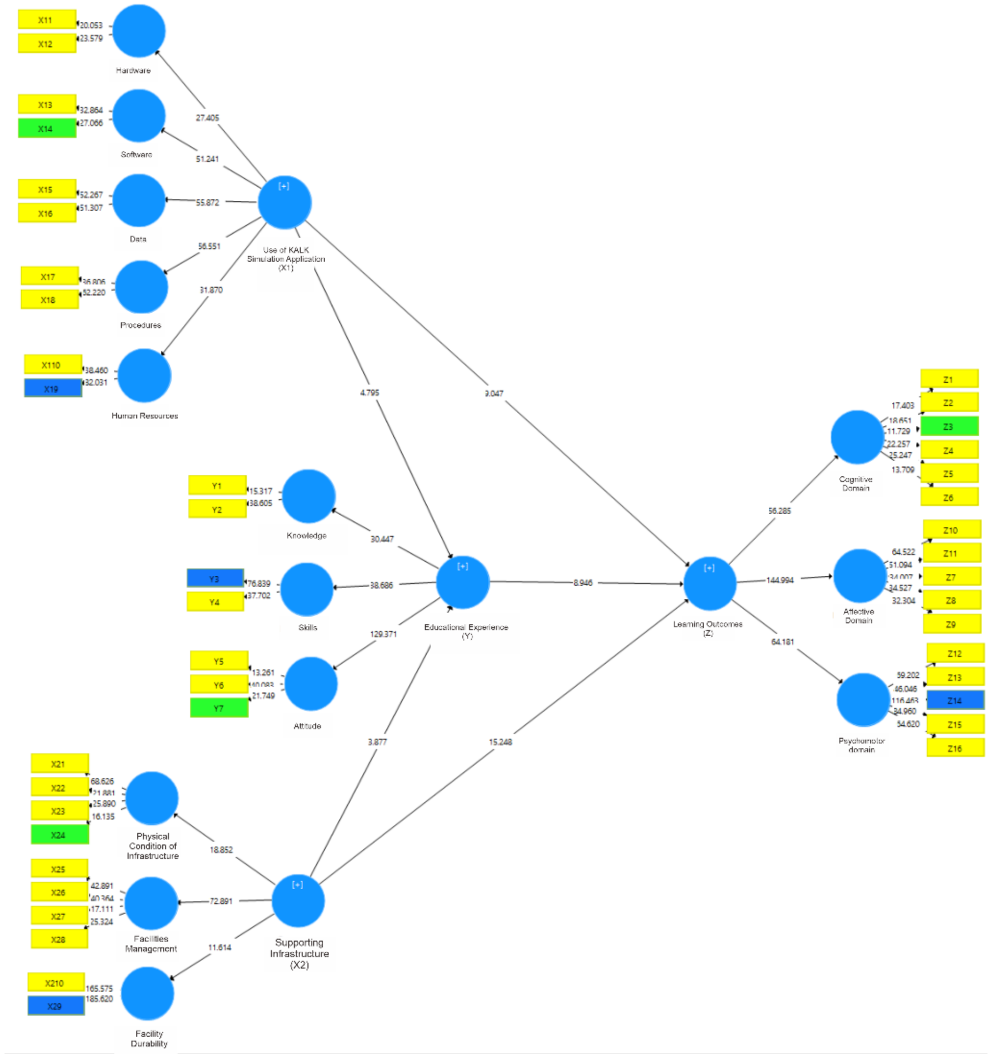

Fig. 2. Structural Model - Inner Model

Table 9. Internal Consistency Reliability

Construct	Cronbach's Alpha	Composite Reliability	rho_A
X1	0.919	0.932	0.926
X2	0.944	0.952	0.947
Y	0.914	0.926	0.920
Z	0.980	0.982	0.980

[d] All values exceeded 0.70.

Table 9 shows the internal consistency reliability results for four key constructs in the study: Simulator Use (X1), Supporting Infrastructure (X2), Competence (Y), and Learning Outcomes (Z). The reliability measures used are Cronbach's Alpha, Composite Reliability (CR), and rho_A. All Cronbach's Alpha values exceed 0.90, far above the accepted threshold of 0.70, confirming high internal consistency among items within each construct. Specifically, Learning Outcomes (Z) has the highest alpha (0.980), followed by Supporting Infrastructure (X2) at 0.944, indicating excellent reliability. Composite Reliability values range from 0.926 to 0.982 and exceed the recommended threshold of 0.70, supporting the measurement model's strength. The rho_A values, which further validate the reliability of the constructs, also show strong consistency, with all values ranging from 0.920 to 0.980. These findings confirm that the instrument used to measure the four latent variables is statistically reliable, as the items within each construct consistently reflect the intended concepts. This high internal consistency enhances the credibility of further analyses, including structural equation modeling and hypothesis testing.

Table 10. Convergent Validity (AVE)

Construct	AVE
X1	0.578
X2	0.669
Y	0.643
Z	0.523

[e] All AVE values were > 0.50, confirming convergent validity.

Table 10 shows the Average Variance Extracted (AVE) values for the constructs used in the study: Simulator Use (X1), Supporting Infrastructure (X2), Competence (Y), and Learning Outcomes (Z). AVE is an important measure of convergent validity, indicating how much variance items within a construct share. All constructs had AVE values above the recommended cutoff of 0.50, confirming acceptable convergent validity. Specifically, Supporting Infrastructure (X2) had the highest AVE of 0.669, showing strong agreement among items. Competence (Y) and Simulator Use (X1) also showed AVEs of 0.643 and 0.578, respectively, indicating substantial shared variance among their items. Although Learning Outcomes (Z) had the lowest AVE at 0.523, it still meets the minimum standard, meaning the indicators under this construct properly represent the underlying factor. In summary, the AVE results in this table confirm that each construct is well-measured by its observed indicators, supporting the overall quality and suitability of the measurement model for further structural equation analysis.

D. Structural Model (Inner Model)

Collinearity diagnostics indicated acceptable VIF values.

Table 11. Inner VIF Values

Path	VIF
X1 → Z	1.623
X2 → Z	1.623
X1 → Y	4.946
X2 → Y	4.277
Z → Y	5.420

[f.] All VIF values were below critical thresholds (≤ 5–10).

Table 11 shows the Inner Variance Inflation Factor (VIF) values for each path in the structural model, evaluating multicollinearity among predictor constructs. VIF indicates how much the variance of a regression coefficient is inflated by multicollinearity. A common threshold for VIF is ≤ 5, though values up to 10 are sometimes acceptable in complex models. The results reveal that all VIF values are below the critical limit, indicating that multicollinearity is not an issue in this study. The paths from Simulator Use (X1) and Supporting Infrastructure (X2) to Learning Outcomes (Z) have the lowest VIFs (1.623), showing minimal collinearity. The VIFs for X1 → Y and X2 → Y are 4.946 and 4.277, respectively, both within acceptable ranges, suggesting moderate but manageable collinearity. The highest VIF (5.420) was observed for the path from Learning Outcomes (Z) to Competence (Y). Although this slightly exceeds the ideal limit of 5, it remains below the more lenient cutoff of 10, indicating the model is still statistically acceptable. Overall, the VIF analysis confirms that the predictor constructs in the model are sufficiently independent, supporting the robustness of the structural equation modeling results.

Table 12. Effect Size (f^2)

Path	f^2
X1 → Z	0.551
X2 → Z	0.327
X1 → Y	0.272
X2 → Y	0.021
Z → Y	0.330

[g.] Large effects were observed for X1 → Z (0.551) and Z → Y (0.330).

Table 12 shows the effect size (f^2) for each path in the structural model, offering insights into the strength of relationships between constructs. Effect size measures the extent to which an independent variable influences a dependent variable within a model. According to Cohen's guidelines, values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The strongest effect was found for the path X1 → Z (f^2 = 0.551), indicating that simulator use significantly impacts learning outcomes. Likewise, the path Z → Y (f^2 = 0.330) also demonstrates a large effect, highlighting the strong mediating role of learning outcomes in shaping competence. The path X2 → Z (f^2 = 0.327) is close to the threshold for a large effect, suggesting that supporting infrastructure also plays a significant role in influencing learning outcomes. Conversely, the effect of X1 → Y (f^2 = 0.272) is moderate, whereas that of X2 → Y (f^2 = 0.021) is very small, indicating a weak direct influence of infrastructure on competence. In summary, this table emphasizes that simulator use and learning outcomes are the most impactful variables in the model, confirming their essential roles in the development of vocational competence.

Table 13. R^2 and Q^2

Endogenous Variable	R^2	Q^2
Learning Outcomes (Z)	0.618	0.293
Competence (Y)	0.877	0.516

[h.] The model explained 61.8% of the variance in Z and 87.7% of the variance in Y.

E. Hypothesis Testing and Mediation Analysis

Table 14. Direct Effects

Path	β	t	p	Result
X1 → Z	0.517	3.602	0.000	Supported
X2 → Z	0.398	2.952	0.003	Supported
X1 → Y	0.445	2.802	0.005	Supported
X2 → Y	0.122	0.891	0.373	Not Supported
Z → Y	0.441	3.006	0.003	Supported

Table 14 shows the direct path coefficients (β), t-values, and p-values from the structural equation modeling (SEM) analysis to test the significance of relationships between constructs. The results identify which hypothesized paths are statistically supported. The path from Simulator Use (X1) to Learning Outcomes (Z) shows a strong, significant direct effect (β = 0.517, p = 0.000), indicating that simulator-based instruction significantly improves learning outcomes. Likewise, Supporting Infrastructure (X2) significantly influences Learning Outcomes (β = 0.398, p = 0.003), indicating that adequate facilities and resources positively affect student learning outcomes. The direct effect of Simulator Use (X1) on Competence (Y) is also supported (β = 0.445, p = 0.005), suggesting that simulation activities directly help develop vocational competence. Conversely, the effect of

Supporting Infrastructure (X2) on Competence (Y) is not significant ($\beta = 0.122$, $p = 0.373$), indicating that infrastructure alone does not directly impact competence, as it is mediated by learning outcomes. Finally, Learning Outcomes (Z) strongly influence Competence (Y) ($\beta = 0.441$, $p = 0.003$), confirming its key mediating role. Overall, these findings confirm the importance of simulation-based learning and learning outcomes in fostering vocational competence, while also implying that infrastructure has a more indirect effect.

Table 15. Indirect Effects (Mediation)

Path	β	t	p	Interpretation
X1 → Z → Y	0.228	2.140	0.033	Significant Mediation
X2 → Z → Y	0.175	2.060	0.040	Significant Mediation

Table 15 illustrates the mediation analysis results, showing the indirect effects of Simulator Use (X1) and Supporting Infrastructure (X2) on Competence (Y) through Learning Outcomes (Z). Mediation is assessed using path coefficients (β), t-values, and p-values; statistical significance indicates that the indirect path is meaningful.

For the path X1 → Z → Y, the indirect effect is $\beta = 0.228$, with a t-value of 2.140 and a p-value of 0.033. This result signifies a statistically significant mediation, indicating that learning outcomes partially mediate the relationship between simulator use and competence. This suggests that simulator-based training improves competence not only directly but also indirectly by enhancing learning outcomes.

Similarly, the path X2 → Z → Y yields an indirect effect of $\beta = 0.175$, with a t-value of 2.060 and a p-value of 0.040. This also confirms significant mediation, meaning that supporting infrastructure influences competence development through its effect on learning outcomes, even though the direct path from infrastructure to competence was not significant.

Overall, the table confirms the mediating role of learning outcomes in both relationships, reinforcing their pivotal role in translating educational inputs into vocational competence.

Learning outcomes significantly mediated both relationships. Simulator use showed both direct and indirect effects (partial mediation). Infrastructure showed indirect-only influence (full mediation).

Overall, results confirm that simulation-based learning and infrastructure significantly improve learning outcomes, and that learning outcomes serve as a central mechanism translating instructional inputs into competence development.

F. Interpretation of Findings in Relation to KALK Simulation Optimization

The findings confirm that optimizing KALK simulator-based learning significantly improves learning outcomes and competence among maritime cadets. The strong, significant path from simulator use to learning outcomes ($\beta = 0.517$; $p < 0.001$) indicates that structured, intensive use of the KALK system enhances cognitive understanding, procedural mastery, and applied skills. This result aligns with prior evidence showing that simulation-based learning strengthens engagement, retention, and practical skill acquisition compared to conventional methods (Daoyan & Disi, 2024; Kashiramka et al., 2019; Sharif et al., 2025).

However, the present study goes beyond mere confirmation of effectiveness; it emphasizes optimization rather than mere availability. The large effect size ($f^2 = 0.551$) demonstrates that when simulator use is pedagogically integrated and systematically implemented, it becomes a dominant instructional driver. This supports findings that immersive, practice-oriented environments enhance higher-order thinking and professional judgment (Lo et al., 2021; Makovec & Radovan, 2023; Chiou, 2020).

Importantly, the results suggest that KALK is not simply a technological tool but a structured learning ecosystem. Optimization involves alignment with learning objectives, instructor facilitation quality, structured practice scenarios, and assessment integration. Without such optimization, the presence of a simulator alone may not yield the maximal educational impact.

G. Competence as a Mediating Mechanism in Learning Optimization

A central contribution of this study lies in confirming competence as a mediating construct within the structural model. The significant indirect effects ($\beta = 0.228$; $p = 0.033$ and $\beta = 0.175$; $p = 0.040$) demonstrate that improvements in instructional inputs translate into competence primarily through measurable learning outcomes.

The significant path from learning outcomes to competence ($\beta = 0.441$; $p = 0.003$) reinforces competence-based education principles, in which observable and measurable achievements serve as the operational mechanism for professional readiness (Ronzhina et al., 2021; Shafieek et al., 2024). These findings empirically validate theoretical claims that competence development is not an automatic consequence of exposure to technology, but rather a result of structured learning processes (Houngue et al., 2022; Giordano et al., 2023).

The distinction between partial and full mediation is also meaningful for optimization strategies. Simulator use shows partial mediation, suggesting that immersive engagement may directly foster professional confidence and behavioral readiness. Conversely, infrastructure demonstrates full mediation, indicating that facilities only contribute to competence when translated into structured learning outcomes (Han, 2025; Schauber & Stensløkken, 2023).

Thus, competence functions as the mechanism of transformation, converting technological inputs into professional capability.

H. Infrastructure as an Enabling but Not Deterministic Factor

Supporting infrastructure significantly influences learning outcomes (β = 0.398; p = 0.003), confirming that technological readiness and facility adequacy enhance instructional quality (John & Kamin, 2024; Wu et al., 2022; Schauber & Stensløkken, 2023). However, the absence of a direct path to competence highlights a critical managerial insight: infrastructure is necessary but insufficient.

This finding refines earlier research that directly links facilities to performance (Patwardhan et al., 2023; McKenzie & Walma, 2024). In the context of KALK optimization, infrastructure should be conceptualized as a strategic enabler rather than a performance guarantee. Without structured pedagogy, instructor readiness, and assessment alignment, infrastructure investments risk underutilization.

Therefore, optimal simulator-based learning requires systemic coordination between facilities, instructional design, and human resource management.

I. Managerial and Human Resource Implications

The results carry significant implications for human resource management (HRM) in maritime vocational institutions. If competence mediates the relationship between simulator optimization and learning outcomes, then HRM becomes central to sustaining this mediation mechanism.

First, instructor competence is critical. Simulation effectiveness depends heavily on instructors' pedagogical, technical, and facilitation skills. Without adequate training, instructors may revert to traditional approaches, thereby limiting the potential of simulators (Yu & Ismail, 2025; Li & Rohayati, 2024). Continuous professional development programs focusing on simulator pedagogy, scenario design, and performance-based assessment are therefore essential.

Second, institutions should develop structured HR policies for simulator technicians and instructional support staff. Effective operation of KALK systems requires technical reliability, rapid troubleshooting, and scenario calibration. Dedicated technical teams ensure system stability and reduce instructional disruption, thereby protecting learning continuity.

Third, performance appraisal systems for instructors should incorporate competence-based indicators aligned with simulation outcomes. Rather than evaluating teaching solely through administrative metrics, institutions should integrate measurable gains in student competence into instructor performance frameworks.

Fourth, workforce planning should consider succession strategies in simulation expertise. As technology evolves, institutions must ensure that human capital evolves correspondingly. Strategic recruitment, training pathways, and certification in simulator instruction should become institutional priorities.

In this sense, optimization of KALK-based learning is fundamentally an HRM issue. Technology investment without parallel investment in human capital development may produce suboptimal returns.

J. Theoretical Contribution

The study advances competence-based education theory by empirically modeling competence as a mediator within a technology-enhanced vocational framework. By integrating simulator use, infrastructure, learning outcomes, and competence into a unified structural model, this research clarifies the causal pathways underlying educational optimization.

The novelty lies in shifting emphasis from technological adoption to systemic optimization, where competence acts as the pivotal explanatory construct. This contribution is particularly relevant in maritime vocational education, where empirical modeling of simulation systems remains limited.

K. Limitations and Future Research

Several limitations should be acknowledged. The single-institution context may limit generalizability. Institutional culture, instructor quality, and policy structure may uniquely influence outcomes. Additionally, reliance on self-reported learning measures may introduce response bias (Yu & Ismail, 2025; Chang et al., 2025).

Future research should include long-term tracking of cadet performance in operational environments to confirm the lasting effects on competence. Conducting multi-institutional comparative studies would enhance external validity. Additionally, further exploration of HRM factors such as instructor certification levels, training frequency, and organizational culture would also deepen understanding of the underlying mechanisms for optimization.

Overall, the findings demonstrate that optimizing KALK simulator-based learning requires integrated management of technology, pedagogy, and human resources. Competence serves as the critical mediating mechanism through which instructional inputs translate into improved learning outcomes and professional readiness.

IV. Conclusion

This study confirms that optimizing KALK simulator-based learning plays a decisive role in improving learning outcomes and competence development in maritime vocational education. The findings demonstrate that a structured, pedagogically aligned use of the KALK simulator significantly enhances both measurable learning outcomes and professional readiness. Rather than functioning merely as a technological facility, KALK becomes an effective instructional instrument when systematically integrated with curriculum objectives and performance-based assessment. The analysis further establishes that competence operates as a mediating mechanism linking instructional inputs to professional capability. Simulator use exerts both direct and indirect effects on competence, while supporting infrastructure influences competence exclusively through learning outcomes. These results reinforce the principle that competence does not emerge automatically from technological exposure; it develops through clearly defined, assessable learning outcomes that translate instructional experiences into observable performance. From a managerial perspective, the study highlights the strategic importance of human resource management (HRM) in sustaining simulation-based optimization. Effective implementation requires continuous instructor training, competency-based performance evaluation, and dedicated technical support personnel to ensure simulator reliability and instructional quality. Institutions must align HR policies with technological investments to maximize educational returns. Overall, optimizing KALK-based learning requires an integrated system in which technology, measurable learning outcomes, and strategic HR development work cohesively to strengthen cadets' competence and long-term professional readiness.

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