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Digital Transformation in Port and Logistics Workforce Training: A Framework and Scoping Review of AI Tools and LMS Adoption

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ABSTRACT: *The digital transformation of maritime port terminals and logistics centers has amplified the significance of flexible human capital enhancement. Port authorities are substituting conventional classroom teaching with digital Learning Management Systems (LMS) enhanced by artificial intelligence (AI) assistants, while also implementing advanced terminal operating systems (TOS) and automated logistics processes. This document presents a theoretical framework and a scoping evaluation to investigate the relationship between AI technologies and personnel digital proficiency in facilitating LMS implementation in ports and logistics. We integrate the interdisciplinary research on technological acceptance frameworks and marine human resource advancement from 2021 to 2026, outlining the primary structural facilitators, operational mediators, and significant obstacles to the execution of digital workforce upskilling.*

KEYWORDS - *Artificial Intelligence, Digital Competency, Learning Management System, Port Logistics, Technology Acceptance Model, Workforce Upskilling*

I. INTRODUCTION

Maritime ports and terminal hubs are the backbone of worldwide supply chains, operating under tight time constraints, complex safety regulations and round-the-clock shift schedules [1]. In this vital operational domain, the development of human capital should not be left to the ad hoc, inflexible training programs [2]. The use of automated yard cranes, digital reproductions and computerised terminal management systems requires a workforce that can think on its feet and adapt quickly to the constant stream of technological innovations. At the same time, corporate Learning Management Systems (LMS) have evolved as the principal digital infrastructure for continuous employee education, compliance tracking, and safety certification [3].

But the switch from traditional education to enterprise digital platforms often finds strong behavioural and structural opposition. There are tremendous differences in digital proficiency, tech-savviness, and technology self-efficacy among the operational personnel, such as berth crane operators, yard drivers, and administrative logistics planners [4]. To overcome these adoption challenges, organisations are progressively integrating AI assistants, conversational chatbots and adaptive tutoring capabilities into enterprise LMS platforms. The potential of conversational AI interfaces is to mitigate the cognitive load associated with navigating corporate software [5]-[7]. But their actual influence on system engagement is substantially mitigated by user digital aptitude and workplace environment characteristics.

The study rigorously explores the confluence of AI assistant capabilities, individual digital skills and learning management system usage patterns in port and business logistics. The research suggests a concrete conceptual framework for methods in educational and corporate training, drawing on contemporary literature from 2021 to 2026.

II. Literature Review and Theoretical Foundations

2.1 Technology Acceptance and Structural Extensions

Research on the adoption of business systems has been primarily influenced by established behavioural frameworks, notably the Technology Acceptance Model (TAM) [8] and the Unified Theory of Acceptance and Use of Technology (UTAUT2) [9]. Conventional models assert that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) directly influence the intention to adopt a technology. In environments enhanced by AI, these traditional frameworks require adjustment [10]. Generative AI co-pilots enhance our understanding in novel ways:

- **Algorithmic Trust:** The user's confidence in the accuracy and fairness of AI-generated feedback.
- **Effort Expectancy Reduction:** The degree to which conversational guidance minimizes manual software navigation.

2.2 Digital Competency in Heavy Logistics Operations

Operational logistics digital competence encompasses far more than mere computer usage [11]. It possesses a multi-faceted capacity framework:

1. **Technical Literacy:** Proficiency with domain-specific terminal management interfaces and mobile industrial devices.
2. **Cognitive Adaptability:** The psychological willingness to unlearn legacy manual routines and embrace automated digital workflows.
3. **Critical Data Evaluation:** The capacity to evaluate AI-generated outputs critically, ensuring that automated operational suggestions align with real-world safety parameters.

In port environments, where operational mistakes may result in major safety hazards or expensive docking delays, a worker's digital self-efficacy will determine whether an AI-supported LMS is adopted as a positive instrument or refused in fear of technology [12].

2.3 Conceptual Framework Development

To map these complex interactions, we present an integrated conceptual model tailored specifically to port terminal and logistics training environments, as shown in Fig. 1.

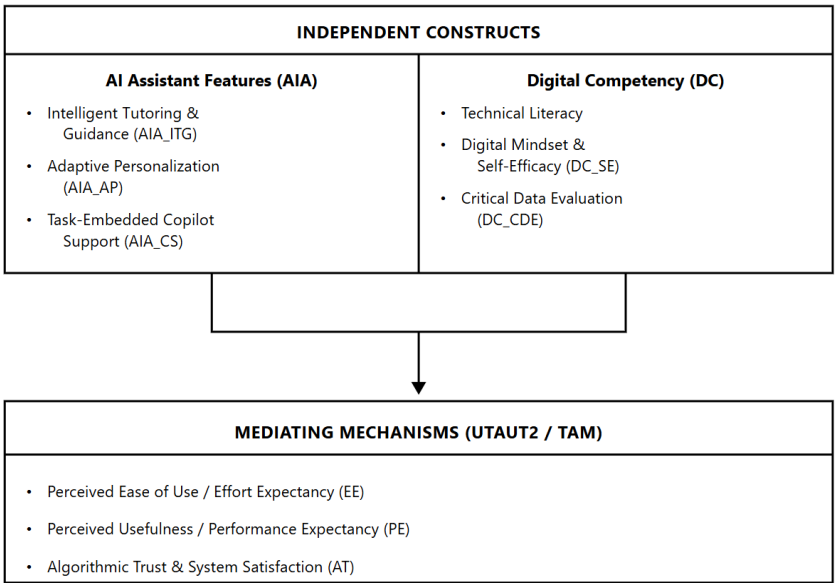


Fig. 1 Conceptual framework

III. METHODOLOGY

3.1 Search Protocol and Eligibility Criteria (PRISMA-ScR)

To map the literature domain systematically, search strings were executed across Scopus and Web of Science (WoS) Core Collection databases. The query targeted three conceptual pillars:

("AI assistant" OR "generative AI" OR "artificial intelligence" OR "intelligent tutoring system*")*

AND

("digital competency" OR "digital literacy" OR "digital readiness" OR "digital capability")

AND

("learning management system" OR "LMS" OR "e-learning adoption" OR "corporate training")*

The inclusion and exclusion criteria applied during screening are summarized in Table 1.

Table 1 Summary of Inclusion and Exclusion Criteria Matrix

Selection Domain	Inclusion Criteria (IC)	Exclusion Criteria (EC)
Publication Window	Published between **2021 and 2026** (capturing post-pandemic acceleration and AI integration).	Published prior to 2021.
Document Type	Peer-reviewed journal articles and indexed conference proceedings.	Non-peer-reviewed editorials, opinion pieces, book reviews, or white papers.
Target Population	Enterprise/industrial workforce, operational staff, port and maritime logistics personnel.	Primary/secondary (K-12) school contexts or early childhood education.
Core Subject Focus	Empirically or conceptually addresses AI tools, digital competency, and LMS adoption.	General AI algorithms without human interaction/training evaluation.
Language	English.	Non-English publications.

3.2 Hypothesized Structural Pathways

Researchers who want to test this framework experimentally through Structural Equation Modelling (e.g. PLS-SEM) might express the structural relationships [13] using the following formal assumptions.

- H_1 **(AI Capabilities → Acceptance Constructs):**
  - H_{1a}: AI Assistant Features (AIA) significantly exert a positive effect on Perceived Ease of Use / Effort Expectancy (EE).
  - H_{1b}: AI Assistant Features (AIA) significantly exert a positive effect on Perceived Usefulness / Performance Expectancy (PE).
- H_2 **(Digital Competency → Acceptance and Trust):**
  - H_{2a}: Employee Digital Competency (DC) positively influences Effort Expectancy (EE).
  - H_{2b}: Employee Digital Competency (DC) positively influences Algorithmic Trust (AT).
- H_3 **(Mediating Effects → LMS Adoption):**
  - H_{3a}: Effort Expectancy (EE) positively predicts Behavioral Intention to Use the LMS (BIU).
  - H_{3b}: Performance Expectancy (PE) positively predicts Behavioral Intention to Use the LMS (BIU).
  - H_{3c}: Algorithmic Trust (AT) positively influences Continuous System Engagement (CSE).

3.3 Operative Definitions and Measurement Matrix

The operative definitions and recommended measurement indicators for each construct are presented in Table 2.

Table 2 Operative Definitions and Measurement Matrix

Construct Name	Code	Operative Definition	Recommended Measurement Indicators
AI Assistant Features	AIA	The degree to which automated tutoring, personalized feedback, and conversational query tools are integrated into the LMS.	• Real-time query responsiveness • Customization of learning speed • Ease of conversational prompt interaction
Digital Competency	DC	The employee's self-assessed capability to navigate digital interfaces, evaluate AI outputs, and adapt to new software without technology anxiety.	• Digital self-efficacy • Problem-solving adaptability • Critical evaluation of system feedback
Performance Expectancy	PE	The degree to which an employee believes that using the AI-augmented LMS will improve their operational job performance or safety compliance.	• Training completion speed • On-the-job task performance improvement • Reduced operational errors
Effort Expectancy	EE	The degree of ease associated with navigating the LMS platform and interacting with its AI assistant.	• Intuitiveness of user interface • Ease of accessing micro-learning modules • Low cognitive burden during interaction
Algorithmic Trust	AT	The user's confidence in the accuracy, reliability, and fairness of AI-generated training feedback and assessment recommendations.	• Confidence in AI output accuracy • Perceived fairness of system evaluations • Willingness to rely on automated guidance

Construct Name	Code	Operative Definition	Recommended Measurement Indicators
LMS Adoption	LMS_A	The observed rate of initial usage, sustained voluntary engagement, and module completion on the enterprise learning platform.	• Daily/weekly login frequency • Course completion rates • Active usage of mobile/ruggedized terminals

3.4 Data Extraction Template for Scoping Synthesis

To guide qualitative charting across screened studies, the standardized data extraction matrix in Table 3 is implemented.

Table 3 Data Extraction Template for Scoping Synthesis

Field No.	Category	Parameter	Description / Coding Instructions
1	**Study Identification**	Article ID and Reference	Author(s), Year, Title, Journal Name, DOI.
2		Geographic Context	Country/Region where data collection took place.
3	**Methodology and Context**	Industrial/Sector Setting	Port/Maritime, Logistics, Manufacturing, Corporate Enterprise, Higher Education, etc.
4		Study Design and Sample	Sample size (*n*), quantitative/qualitative/mixed-methods, survey instrument used.
5	**Theoretical Foundation**	Underlying Models	UTAUT/UTAUT2, TAM, Technology Readiness Index (TRI), DigComp Framework, etc.
6	**Core Construct: AI Assistants**	AI Operationalization	Specific AI features studied (e.g., automated tutoring, personalized learning paths, generative query assistants, workflow copilots).
7	**Core Construct: Competency**	Digital Competency Scope	Dimensions measured (e.g., technical digital skills, digital mindset, adaptability, problem-solving).
8	**Core Construct: System/LMS**	System Metrics	Target platform type (e.g., Enterprise LMS, Moodle, custom e-learning) and adoption metrics (intention to use, continuous engagement, skill gain).
9	**Key Findings**	Direct and Mediating Effects	Main statistical outcomes (e.g., β-coefficients, *p*-values, structural pathways).
10	**Gaps and Future Directions**	Literature Gaps Identified	Gaps noted by authors regarding operational worker adoption, shift work constraints, or maritime/port context.

IV. Preferred Reporting Items for Systematic Reviews and Meta-Analyses

The PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework serves as the methodological foundation for the identification, screening, and selection of literature in systematic and scoping reviews. The PRISMA framework aims to promote methodological precision, clarity, and reproducibility [14]. It offers a standardised multi-phase process for Identification, Screening, Eligibility, and Inclusion that mitigates selection bias and monitors the dissemination of information throughout the review [15]. In rapidly advancing interdisciplinary fields like digital transformation and human-technology integration [16], the PRISMA-ScR (Extension for Scoping Reviews) protocol offers a methodical approach to refine extensive bibliographic collections into a concise, high-caliber body of essential empirical literature [17].

The PRISMA methodology has been employed in this study to delineate the intersection of research domains concerning artificial intelligence (AI) technologies, employee digital proficiency, and the implementation of corporate Learning Management Systems (LMS) within industrial logistics from 2021 to 2026.

The PRISMA methodology guarantees that just peer-reviewed research pertinent to the concept aids in the proposed structural framework [18], following a transparent evidence trail from the initial database retrieval via Scopus and Web of Science to the comprehensive qualitative mapping [19]. The subsequent segment delineates the incremental filtration metrics, selection parameters, and exclusion justifications for every phase of the PRISMA methodology [20].

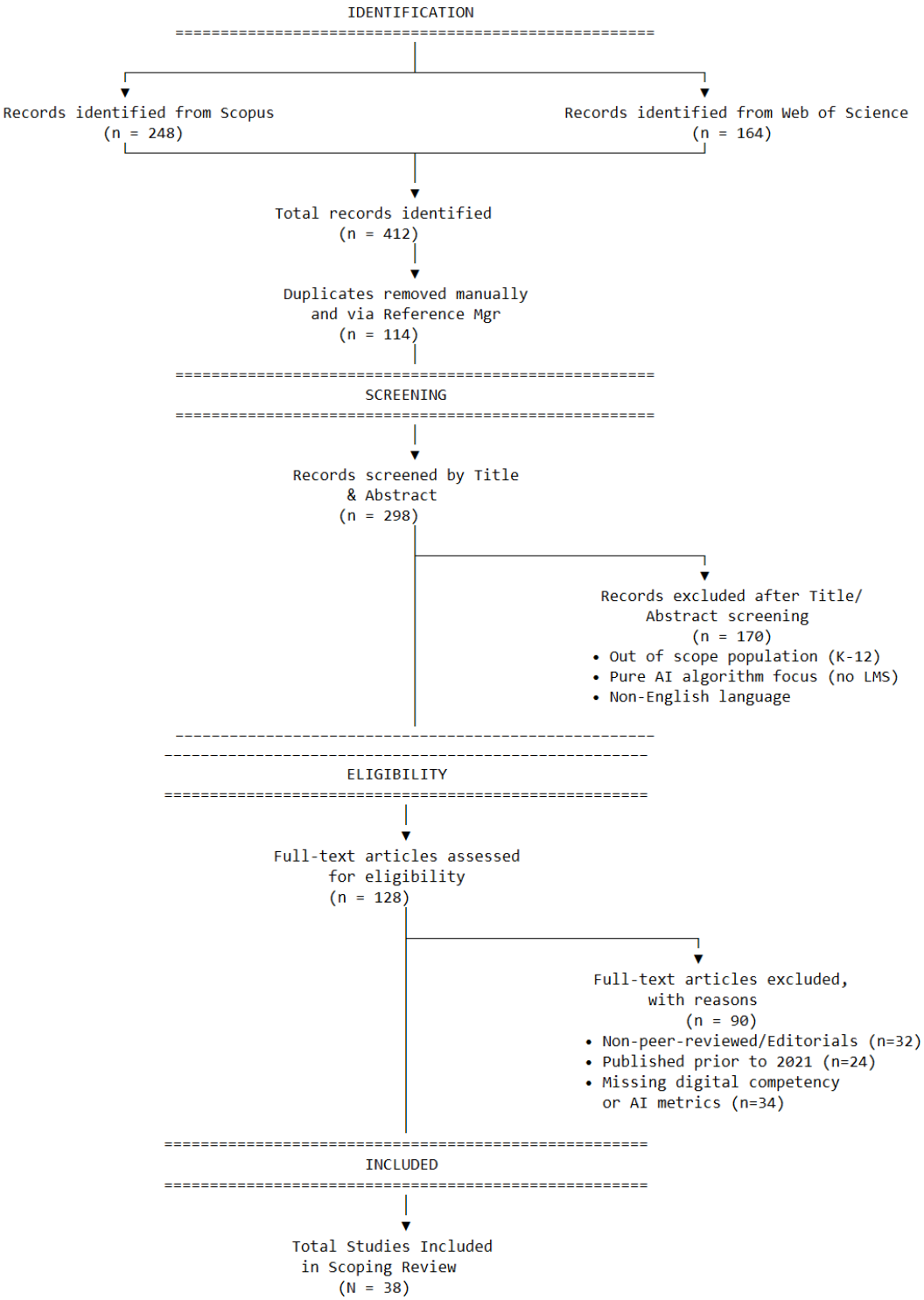


Fig. 2 Reporting items for systematic reviews and meta-analyses (PRISMA 2020) flow diagram

Fig. 2 illustrates the Items for Systematic Reviews and Meta-Analyses (PRISMA 2020). A systematic literature selection strategy according to the PRISMA 2020 requirements resulted in 38 basic empirical and conceptual investigations for qualitative scope synthesis. The PRISMA flow diagram shows that the preliminary electronic database search in Scopus (n = 248) and Web of Science Core Collection (n = 164) yielded a total of 412 entries published between 2021 and 2026. After the removal of 114 duplicate entries, 298 unique articles were evaluated on title and abstract; 170 studies were excluded as they were irrelevant for the review (mostly due to their focus on K-12 educational contexts, purely technical artificial intelligence algorithms without human-technology interaction metrics, or non-English publications). The phase-by-phase selection is summarised in Table 4.

Table 4 PRISMA 2020 Selection Summary

PRISMA Phase	Selection Step	Records Retained (n)	Primary Action / Reason
Identification	Database Searches (Scopus and WoS)	412	Initial Boolean query execution (2021–2026).
	Duplicate Removal	298	Duplicate record filtration via reference manager software.
Screening	Title and Abstract Screening	298	Initial assessment against basic inclusion criteria.
	Excluded Records	170	Removed K-12 contexts, non-English studies, and purely technical AI papers lacking human interaction metrics.
Eligibility	Full-Text Eligibility Assessment	128	Detailed evaluation of full-text articles (also utilized for VOSviewer bibliometric mapping).
	Full-Text Exclusions	90	Excluded editorials/gray literature (n = 32), pre-2021 publications (n = 24), and studies lacking competency/AI constructs (n = 34).
Inclusion	Final Qualitative Synthesis	38	Empirical and conceptual studies meeting all IC criteria for detailed charting and scoping synthesis.

The leftover 128 complete papers were evaluated for eligibility. At this point, 90 records were omitted as they failed to conform to the specified inclusion criteria. The grounds for deletion included: 32 non-peer-reviewed white papers or editorials, 24 publications dated before 2021, and 34 research that failed to address specific digital competency or AI interaction dimensions. A concluding selection of 38 pertinent studies that fulfilled all rigorous PRISMA-ScR criteria was gathered for comprehensive qualitative analysis, structural hypothesis formulation, and conceptual framework creation. The 128 qualifying full-text documents were preserved for macro-level bibliometric mapping using VOSviewer.

V. Scoping Synthesis and Discussion

Synthesizing findings across digital transformation and enterprise learning literature yields three critical insights for industrial training implementation.

5.1 AI Features as Interface Friction Reducers

Traditional LMS platforms tend to have clunky navigation structures in complex operational logistics, alienating non-desk operational staff. Conversational AI helps reduce cognitive friction by letting employees ask about safety rules or operational processes using natural language voice or text inputs. This change immediately boosts EE.

5.2 Digital Competency as the Ultimate Adoption Gatekeeper

AI tools reduce obstacles to first entry, but a worker's core Digital Competency (DC) drives continued engagement. Employees with low digital self-efficacy are more likely to experience automated prompts as intrusive surveillance rather than constructive counsel [21]. Thus, enterprise digital transformation plans should focus on baseline online literacy onboarding prior to the implementation of complicated AI-driven LMS frameworks.

5.3 Operational Mobility and Micro-Learning Integration

Industrial facilities such as port terminals have rigorous shift schedules that limit the availability of desktop PCs. The literature shows a strong positive association between mobile/ruggedized gear uptake and LMS participation levels [22]. AI-driven personalised micro-learning modules delivered in 3-to-5-minute bursts straight to mobile devices tackle the common issue of time that frequently hinders learning in the workplace.

VI. Managerial and Strategic Implications

For port executives, HR directors, and logistics training managers, implementing this framework requires a coordinated strategy across three operational domains:

- **Infrastructure Alignment:** Ensure that enterprise LMS platforms are fully optimized for mobile devices and ruggedized terminal hardware utilized across berth and yard areas.
- **Targeted Digital Upskilling:** Conduct pre-implementation assessments of employee digital self-efficacy. Implement introductory digital literacy workshops for operational staff showing high technology anxiety.
- **Transparent AI Integration:** Design AI assistant features with high algorithmic transparency, clearly communicating to workers that AI feedback is intended for professional development rather than performance penalty tracking.

VII. Conclusion and Research Agenda

The digital revolution of port and logistics workforce education requires a transition from conventional e-learning repositories to dynamic and highly responsive learning ecosystems. The proposed conceptual framework establishes a robust foundation for forthcoming empirical studies and strategic business applications by examining the structural interactions among AI assistant functionalities, employee digital skills, and operational moderating environments.

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