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Review

AI-based adaptive instructional systems for maritime safety training: a systematic literature review

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Abstract
Adaptive instructional systems (AISs) refer to educational interventions designed to accommodate individual learner differences. These systems employ various approaches, such as artificial intelligence (AI), machine learning (ML), and data analytics, to analyze student performance and personalize the learning experience. This article presents a review of the current state-of-the-art of AI methods used in the development of AISs for maritime safety training. The main objective of this systematic literature review is to determine the use of AI/ML techniques in AIS and how they can contribute to the development of AIS for maritime education and training (MET) applications in addressing small data problems. Answering the research questions of the review identifies the fundamental purposes of using AI/ML techniques in developing AIS for MET. Further, the review highlights several crucial research areas, including AI techniques for modelling student and instructor knowledge, as well as ML algorithms for predicting student performance in situations with limited datasets.

Keywords Adaptive instructional systems · Intelligence tutoring systems · AI techniques · Maritime education and training

1 Introduction

An Adaptive Instructional System (AIS) is a type of educational technology that uses algorithms and learners' performance data to personalize the learning process for individual learners. The system collects performance data and uses that information to adjust the level of difficulty and content of the instruction to match the student's needs and abilities. For instance, an AIS can provide immediate feedback to students, allow for self-paced learning, and offer targeted interventions for struggling students. Self-paced learning is important for adult learners because it allows them to learn at their own speed and according to their schedule. The learner receives real-time and personalized feedback to maintain their motivation, challenge their skill development, and improve their learning outcomes. AISs come in different forms, such as intelligent tutoring systems (ITSs), learning management systems, and personalized learning platforms. These systems can be used in a variety of educational settings, including schools, colleges and universities, and online learning platforms.

Our interest is in the application of AIS in maritime safety training. Maritime Education and Training (MET) often takes place at onshore training facilities or vocational schools (e.g., classroom teaching and simulator-based training). Recent advances in technology have expanded MET to train seafarers with cloud-based and online delivery of

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safety–critical training. With the increased demand around the world for online delivery of training, it is important that AIS technologies support the learning needs of seafarers. AISs have the potential to bridge the learning gap as training transitions to remote/online applications.

The purpose of this systematic literature review is to determine what artificial intelligence (AI) or machine learning (ML) techniques are being used in AIS and how they can inform the development of AIS for MET applications. Leading research in AI-based AISs for maritime simulation-based safety training applications are identified. Our goal is that the findings will inform researchers and practitioners in the field of maritime safety training by offering a comprehensive explanation of the AI tools available for AIS development and convey the applicability of the select AI/ML approaches for simulation-based safety training.

1.1 AI/ML techniques for AIS

AISs employ a range of approaches, including AI, ML, and data analytics, to assess student performance and tailor the learning process accordingly. One commonly used approach in developing AISs is learning analytics. Learning analytics are intended to optimize learning by gathering, visualizing, and evaluating student performance data and competence, and by providing learners and instructors with an awareness of the learner's progression through the learning process [1]. Outputs from learning analytics could include a measurable performance score that can be used in comparisons. Another technique employed in AIS development is cognitive modelling, which entails creating a model of the learner's cognitive processes and leveraging this model to personalize the learning experience [2]. Additionally, gamification is a technique that incorporates game-like elements, such as reward structures, to engage learners and foster their motivation to continue learning [3–5]. AI and ML are also widely used techniques in AISs. These approaches employ algorithms to analyze data, allowing for personalized learning experiences by assessing the learner's skill level and offering targeted recommendations regarding content, activities, and resources that align with their learning goals [1].

Advances in cloud-based and online delivery of marine safety training are creating the need for AI-instructors or student-AI interactions. AI-based AISs can be considered a form of human-AI interaction. According to the National Academies of Science, Engineering and Medicine's 2021 report on Human-AI Teaming, there are many forms of AI techniques, such as symbolic approaches (e.g., decision support systems), connectionist approaches (e.g., machine learning applications), algorithmic approaches (e.g., advanced AI algorithms), and hybrid architectures (e.g., multi algorithms approaches) [6]. Some examples of each technique include symbolic approaches (e.g., Case-Based, Expert Systems, and Rule-Based), connectionist approaches (e.g., Decision Trees, Neural Networks, Reinforcement Learning), and algorithmic approaches (e.g., Bayesian Networks, and Markov Decision Processes). This review focuses on techniques applicable to the development of AIS technology.

1.2 AIS for simulator-based safety training

Specific to MET, employing AI and ML techniques in the development of AIS technology can improve maritime simulation-based safety training [7–10]. An AIS can shift simulation-based training from the traditional teacher-centered model of training to a more learner/student-centered approach that is focused on supporting individualized learning and outcomes [7–10]. An ongoing challenge in MET is the effective use of the data collection capabilities of maritime simulation technologies. Marine training simulators are capable of collecting a large volume of information on learners' performance in training. Researchers [11, 12] have discussed opportunities and challenges of using AI and ML techniques for big data to enhance online learning platforms and simulation training. However, in human factors research, collecting large amounts of human performance data for novel applications (e.g., the development and validation of proof-of-concept technology) is difficult. In other words, although simulators can collect a great deal of information from learners' performance in the simulator, it is challenging to collect human performance data in research. This leads to limited data for proof-of-concept technology development. Thus, in this work, we will focus on AI and ML techniques that have been applied in the development of AIS for seafarers with small datasets.

1.3 Structure of the paper

The paper is organized into six sections. Section 2 provides a background explanation of AISs from the perspective of theories, conceptual framework, structure, components and architectures. Section 3 outlines the methods used in the systematic literature review and frames the review in terms of four research questions. Section 4 presents the results of the review in which each research question is discussed. This is followed by the discussion in Sect. 5 that highlights the relevance of the findings. Finally, Sect. 6 provides concluding comments on the paper.

2 Background on AIS

AISs are technology-driven educational systems designed to personalize learning and address differences among learners. A common form of AIS is intelligent tutoring systems (ITSs). ITSs automate the instruction to provide individualized assessment and specific learning pathways [13]. The key features of ITSs are the automation of the student assessment and the reactivity of the feedback to provide real-time interventions [14]. Generally, ITSs meet student needs by identifying gaps in their understanding and responding by delivering content and learning materials to address these gaps. However, some limitations of ITSs are that they lack the sophistication to communicate effectively with students and cannot effectively address student motivation [13], which are two core aspects of learning.

Since ITSs were developed with the application of AI techniques, AI innovations have addressed some limitations with the advancements in natural language processing (NLP). Other research has worked on incorporating insights from human instructors and students in the modelling of ITS/AISs [2].

Figure 1 provides a depiction of an ITS consisting of four main parts: the domain, pedagogical and learner models, and user interface, which will be described more in Sect. 4.4. The design and implementation of an AIS in an ITS involves a range of learning theories, conceptual frameworks, structures, models, components, and architectures, all of which work together to support effective learning.

AISs are built upon various learning theories, such as cognitive load theory, constructivism, and social learning theory. Cognitive load theory suggests that optimizing a student's cognitive load will lead to the most effective learning outcomes [16]. Constructivism emphasizes the importance of the learners constructing their understanding of concepts. These theories inform the system's design, including the content and feedback provided to learners [17]. Social learning theory highlights the social aspects of learning and how this can also inform the design of collaborative features in an AIS [18].

AISs typically incorporate a conceptual framework that guides their design and implementation. One example is the ACT-R (Adaptive Control of Thought—Rational) framework, which models human cognitive processing and decision-making. This framework provides a theoretical foundation for understanding how learners process information and make decisions, helping to guide the design of an AIS [19, 20]. Another example is the open-source Generalized Intelligent Framework for Tutoring (GIFT), which is an architecture designed to create, deliver, manage, and evaluate AIS technologies [21]. Similarly, Evidence-Centered Design (ECD) is another example of a conceptual design framework for AISs [22].

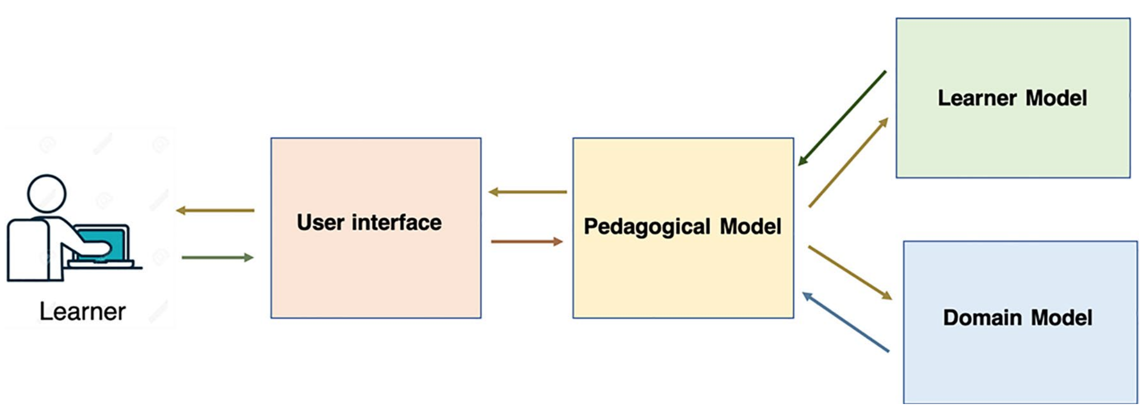

Fig. 1 The architecture of ITS after [15]

AISs can be designed using various architectures, such as Case-Based Reasoning and Rule-Based Systems. Rule-Based Systems use pre-defined rules to make decisions about content and feedback, such as providing feedback when the learner makes an error. Case-Based Reasoning systems use past cases to guide decision-making, such as adapting the content and feedback based on the learner's prior performance [23]. AISs have a variety of structures that support learning, such as knowledge structures, task structures, and user models. Knowledge structures organize the content in a logical way, such as organizing content into modules or topics [23]. Task structures specify the sequence and complexity of the learning tasks, such as determining the order in which concepts should be learned [23, 24]. User models capture information about the learner, such as their prior understanding, learning preferences, and performance, which can be used to adapt the instruction and feedback to the individual student [25].

AISs employ various models to support learning, including domain models, pedagogical models, and learner models. Domain models represent the knowledge and skills to be learned, such as slow speed maneuvering skills in lifeboat operations [26], while pedagogical models specify the instructional strategies to be used, such as providing hints or feedback [27]. The learner model provides student information and an assessment of their performance, such as measuring the learners' behaviors and identifying the collection of behaviours and abilities for completing tasks in a lifeboat training simulator [7–10].

AISs typically consist of several components, including content, feedback, assessment, and adaptation. The content component provides the learning material, such as text, images, or videos [28]. The feedback component provides information on the learner's performance, such as indicating whether an answer is correct or incorrect [22]. The assessment component evaluates the learner's progress, such as determining if the learner has mastered a concept [28]. The adaptation component adjusts the content and feedback based on the learner's needs, such as providing additional material [28].

Overall, these theories, frameworks, structures, models, architectures, and components will be discussed as they relate to select AI/ML techniques in the development of AIS for maritime training applications.

3 Methods

This study follows the guidelines for conducting a systematic literature review [29]. The initial stage of the study involved the planning phase, which encompassed justifying the study, formulating research questions, preparing a search strategy, identifying relevant databases, constructing search strings, and establishing criteria for inclusion and exclusion. Overall, the review was conducted in two phases. The first phase used search terms to focus on answering the first question related to AI/ML techniques being used in AIS for MET. However, the initial results found limited articles relevant to MET. Therefore, a second phase was developed to broaden the review and gather more generalized papers regarding the use of AI/ML in AIS development, specifically looking at AIS development as it relates to similar training applications and small dataset problems faced by the MET domain. As such, new search terms were created and a second search was preformed that aimed to gather literature on AIS and AI/ML techniques to inform MET researchers and practitioners. These elements are elaborated on in the following subsections.

3.1 Research questions

The primary objective of this systematic literature review is to examine the current state of research on AI-based AISs in the context of maritime safety training. The review aims to identify the methodologies, primary purposes, drawbacks and advantages associated with the implementation of such systems for small datasets. As such, this review responds to the following Research Questions (RQ):

- RQ1: What AI/ML techniques have been used in Adaptive Instructional and Intelligent Tutoring Systems for MET?
- RQ2: Which AI techniques have been applied in developing AIS for small data problems?
- RQ3: What are the fundamental purposes of using AI techniques in AIS?
- RQ4: Are AI techniques aimed at supporting and informing the domain knowledge, facilitating pedagogy, user interface model, or developing instructor/student models?

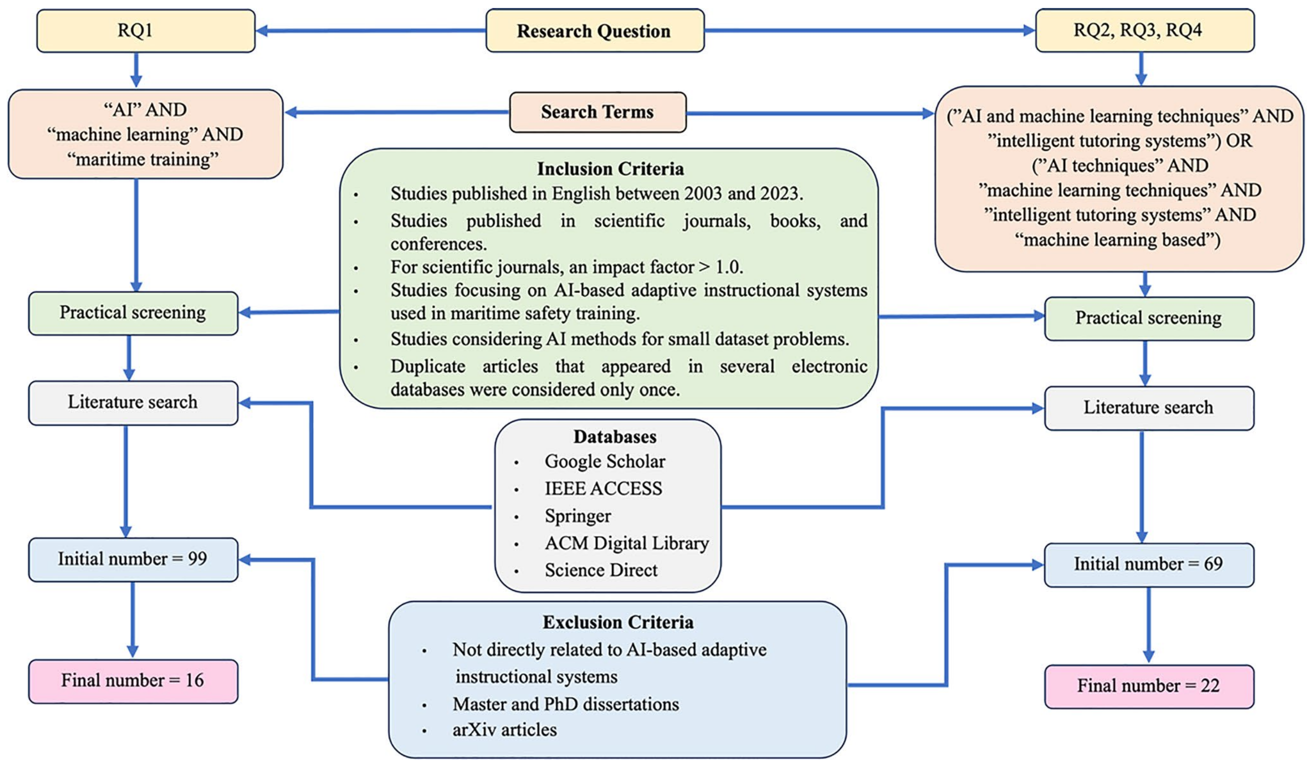

Fig. 2 Systematic literature review process

Table 1 Search term for RQs

Research Question	Search terms
RQ1	"AI" AND "machine learning" AND "maritime training"
First Search for RQ2, RQ3, and RQ4	"AI techniques" AND "machine learning techniques" AND "intelligent tutoring systems" AND
Second Search for RQ2, RQ3, and RQ4	"AI and machine learning techniques" AND "intelligent tutoring systems" AND "machine learning-based"

3.2 Search strategy

Figure 2 presents the diagram of the systematic literature review process. A broad search was used to identify relevant journal papers and conference proceedings. Journal databases and repositories that are commonly used for publication in AISs and AI techniques were selected. We used Google Scholar, IEEE ACCESS, Springer, ACM Digital Library, and ScienceDirect. The keywords searched in this study are listed in Table 1. The search terms, such as "intelligent tutoring systems", "AI techniques", and "ML techniques", were used to identify relevant papers for the systematic literature review. These search terms provided a broad review. These generalized search terms pose limitations to the specificity of the review as they do not include sub-categories such as AI and ML methods, models, and algorithms. The search terms played a crucial role in identifying relevant papers for our systematic literature review. The initial search terms, ("AI" AND "machine learning" AND "maritime training"), yielded some relevant papers as outcomes. However, as few articles outlined the specific implementation of AI and machine learning techniques used in maritime education and training (MET) applications, further refinement of the literature review was necessary. The search terms that directed us to more relevant papers were: ("AI and machine learning techniques" AND "intelligent tutoring systems") OR ("AI techniques" AND "machine learning techniques" AND "intelligent tutoring systems" AND "machine learning based"). Compared to broader terms like "algorithm" or "model," the keyword "technique" presented a larger number of papers that described the specific AI and ML methods used in AIS/ITS for maritime training.

3.3 Inclusion and exclusion criteria

To gather studies for this review, the following inclusion criteria were applied:

- Studies published in English between 2003 and 2023.
- Studies published in scientific journals, books, and conferences.
- For scientific journals, an impact factor > 1.0.
- Studies focusing on AI-based adaptive instructional systems used in maritime safety training.
- Studies considering AI methods for small dataset problems.
- Duplicate articles that appeared in several electronic databases were considered only once.

Exclusion criteria:

- Studies not directly related to AI-based adaptive instructional systems.
- Master and PhD dissertations.
- arXiv articles.

4 Results

Table 2 summarizes the number of articles from the queries for each research question and documents the number of articles excluded and the final number of articles included in the analysis.

4.1 RQ1-what AI/ML techniques have been used in adaptive instructional and intelligent tutoring systems for MET?

The first question of the literature review focused on gaining an understanding of the use of AI and ML techniques in adaptive instructional and intelligent tutoring systems for the domain of MET. The queries to answer RQ1 are represented in Table 2 and resulted initially in 99 articles.

Given that many AI/ML techniques are commonly used to optimize marine operations, the search was revised by adding the term “Maritime Training” to focus the search on education and training applications and to avoid marine operations.

After reading the titles of the articles and applying inclusion and exclusion criteria, the remaining 16 articles were used in the analysis. Table 3 provides an overview of the articles found for RQ1 that described the use of AIS/ITS in MET

Table 2 Number of articles from queries using search terms for RQ1, RQ2, RQ3, and RQ4

Research question	Queries	Initial	Exclusion	Final
RQ1	”AI” AND ”machine learning” AND ”maritime training”	99	83	16
RQ2, RQ3, and RQ4	(”AI and machine learning techniques” AND ”intelligent tutoring systems”) OR (”AI techniques” AND ”machine learning techniques” AND ”intelligent tutoring systems” AND “machine learning based”)	69	47	22

Table 3 Overview of articles found for answering RQ1

Article	Type of article	Application Themes	Specific AI & ML technique
[7]	Journal	Review of Training (MET)	–
[30]	Journal	Training—Virtual Reality, Augmented Reality, Mixed Reality	–
[31]	Journal	Ship Design and Shipbuilding	–
[32]	Conference	Simulation-based Training (MarSEVR)	–
[33]	Journal	Survey: students' perceptions of competence requirements for Autonomous Vessels	–
[34]	Journal	Simulation-based Training	–
[35]	Conference	Autonomous Vessels Review paper	–
[11]	Conference	Simulation-based Training (LAD)	Bayesian Networks, Artificial Neural Networks
[12]	Conference	Review of Simulation-based Training	Artificial Neural Networks, Support Vector Machine, Convolutional Neural Network
[36]	Conference	Shipping Operation Simulation-based Training	–
[37]	Journal	Autonomous Vessels	–
[38]	Conference	Computer-based Training (STEP)	–
[39]	Conference	Performance Assessment Training—Virtual Reality	Artificial Neural Networks
[40]	Conference	Intelligent Vessels Requirement changes for the future	–
[41]	Journal	Simulation-based Training	–
[42]	Journal	Autonomous Vessels Simulation-based Training	–

and provides a brief summary of the main focus of each article. The articles were categorized based on the application, the training technologies, and the source of the publication.

4.1.1 Applications of AIS/ITS in MET

Overall, ten articles in Table 3 (representing 63%) made reference to simulation-based training. This finding was expected based on the prevalent use of simulator technology in MET [11] and that AIS/ITS are common approaches to augment simulation training.

MET is core to the development of qualified seafarers and is often delivered using a variety of different modes. According to [30], in MET there are five fundamental divisions of training, namely: procedural, decision-making, operational, maintenance, and team training. Among each of the MET training divisions, a range of low to high fidelity training simulators are used to teach practical skills [11]. MET simulator configurations are generally categorized based on fidelity into full-mission, multitask, limited, and special tasks [30].

In the context of simulation-based MET, AISs have been applied to various marine operations and training applications to enhance the learning experience and improve operational effectiveness. For instance, adaptive systems have been incorporated into maritime simulators used for training ship crew members. Training technical skills for navigation, ship handling, and emergency response are among the areas where AISs have been employed in marine training.

AISs have been used to train sailors and ship navigators in various navigation scenarios (e.g., practicing passage planning and teaching non-technical skills like Bridge Team Resource Management), helping them improve their decision-making skills and responses to changing conditions at sea [43]. Ship-handling simulators equipped with AISs have been used to replicate real-world maritime situations and adjust simulation parameters (e.g., weather conditions) based on the trainee's performance, creating more challenging scenarios as skills improve [31, 43]. Adaptive systems have also been used to train maritime personnel in emergency response procedures, allowing them to practice responding to various crisis situations in a controlled environment [33]. For example, the system *Maritime Safety Education with Virtual Reality* (MarSEVR) consists of various learning chapters and allows trainees to perform training scenarios in a personalized manner [32].

Overall, the AISs applied to maritime training have been used to modify the level of difficulty and complexity of scenarios according to the trainee's skill level and progress to provide a more personalized training experience [31, 32].

4.1.2 Prospective use of AI and ML in MET

Four articles represented in Table 3 made reference to emerging training technologies for maritime education [40]. For instance, [30] discussed the concepts of Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) for MET applications and future marine operations. Another example, [42] explored the use of maritime navigation training simulators as testbeds for assessing algorithms for autonomous ships with a focus on understanding humans-in-the-loop. In this study, the performance of an algorithm was compared with the performance of an experienced human navigator in a series of navigational tasks in the simulator setting [42].

Of the articles included in the review for RQ1, there was a lack of reference to the application of specific AI and ML approaches. Many articles discussed AI and ML only from a conceptual sense or regarding their prospective utility. To illustrate this point, for example, in [38], the authors describe STEP, a software designed to use AI, VR, and AR to augment personnel training. According to [38], these technologies allowed the training to be more time and cost-efficient and more interactive [38].

Overall, a consistent finding throughout the articles for RQ1 is that few articles described specific AI and ML techniques used in MET, with the exception of one conference paper [39] and two review articles [11, 12].

The conference paper [39] conducted a literature review and proposed the use of Artificial Neural Networks as an objective means of assessing human performance during maritime VR training.

In [11], the authors conducted a review of learning analytic dashboards and their application in maritime simulator training. This review found that researchers have used different approaches and datasets, consisting of eye trackers and simulator training experiments to evaluate training performance in maritime studies. To address the variability of subjective assessments, several studies applied AI or ML techniques such as Bayesian Networks and Artificial Neural Networks to minimize biased evaluations [11].

Similarly, in [11, 12], the authors conducted a systematic literature review of maritime simulator training from the perspective of designing, measuring, and analyzing data and scenarios. In the analysis, [12] outlined how maritime training simulators are evaluated based on factors such as training time, type, and difficulty, as well as data collection and analysis methods. The review found that some data collection tools have included physiological measures, and AI or ML techniques for data analysis (e.g., Artificial Neural Networks, Support Vector Machine, and Convolutional Neural Network) [11, 12].

4.1.3 Modified search for subsequent research questions

The findings from RQ1 have shown that while AI and ML techniques are being discussed prospectively in MET, there were few articles that outlined the implementation of specific AI or ML techniques. Refinement of the literature review was necessary to investigate how specific AI/ML techniques are being used in MET applications. For subsequent questions in this review, the queries were expanded to AI/ML techniques for more general AIS/ITS applications. The search terms used are listed in Table 2.

The revised search terms resulted in a total of 69 articles identified. The articles were screened based on reviewing the abstracts for relevance. The total number of articles included in the systematic literature review was narrowed to 22 references, which are listed in Table 4. These articles have been summarized and are used to address Research Questions 2, 3, and 4.

4.2 RQ2-which AI techniques have been applied in developing AIS for small data problems?

The second question of the review (RQ2) intended to identify the AIS/ITS applications that used AI and ML techniques for small data problems. AISs typically require large amounts of data to personalize each student's learning experience. The use of data to train models for performance predictions is a significant feature of using AI techniques for AIS applications [44]. However, a main challenge associated with using ML approaches for AIS development is identifying and accessing the appropriate data to train the models [45]. For high-risk and high-consequence industries such as MET or the education domain as a whole, it can be difficult to collect sufficient training data for AI algorithms [44]. Also, in human factors

Table 4 Overview of AI and ML techniques used in this study

Article	AI & ML technique	Type	Description
[5]	NLP	Book	Guide to introduce AI in teaching and learning
[47]	SVM, RNN, ANN, K-NN, NB, RL, DT, FL, BN, GA, Clustering, Ant colony optimization	Journal	Systematic literature review on AI-enabled adaptive learning systems
[48]	ANN, BN, BKT, RBS, CBR, ES, DT, FL, NLP, SVM, DL, Clustering	Journal	Systematic literature review on Intelligent Tutoring Systems
[15]	RL, ANN, BN, FL ES, Clustering, Hybrid	Conference	Review paper on AI/ML techniques in Intelligent Tutoring Systems
[49]	HMM, FL, BKT	Conference	Review paper of techniques, approaches for Intelligent Tutoring Chatbot system
[58]	LR, K-NN, DT, RF	Conference	ML approach for detecting academic fraud in online tests (higher education)
[54]	NLP	Conference	AI approaches in legal education (higher education)
[56]	ANN	Journal	AI and big data e-learning in higher education
[51]	NLP, ASR	Journal	AI in language teaching and learning
[59]	SVM, LR, ANN, DT, BN, K-NN, NB RF, GB, Bp	Journal	Systematic literature review AI/ML in digital education
[55]	NB, SVM, LR, DT, KNN, RF, ANN, RBS, CBR ES, Ensemble models	Journal	Explainable AI and ML in educational data mining
[45]	RBS, DL	Journal	AI applications for K-12 teaching
[46]	NB, DT, NLP, KNN, SVM, LR, CNN, LSTM, ANN	Book	State of the art for AI based adaptive learning
[57]	BN	Journal	AI techniques for assessment
[60]	BN, DT, CBR	Journal	Adaptive e-learning systems for requirement monitoring and diagnosis
[52]	FL	Journal	Automatic personalized assessment for e-learning for computer programming (higher education)
[61]	NLP, ANN, SVM, RF, DT	Journal	Systematic literature review AI for K-12 education
[62]	RF, NB, NLP	Journal	Intelligent math solver
[63]	CBR	Journal	Collaborative tutoring architecture and multi agents
[50]	NLP, NB, FL, DL	Journal	Review paper on detecting emotion from text in learning environments
[44]	RL, SVM, DT, RF, FL ANN, SVM, KNN, NB LR, CNN, LSTM, DL, RNN, GA	Journal	Comprehensive review of data drive AI in education
[53]	NB, DT, KNN, SVM	Journal	Adaptive intelligent system to enhance online learnings performance for business courses (higher education)

research, collecting large amounts of human performance data for novel applications is not always possible. Despite these challenges, there are AI techniques suitable for small datasets.

The results from queries to answer RQ2 are summarized in Table 4. The articles were categorized based on the AI and ML techniques, a description of the type of article, and the source of the publication.

Of the 22 articles included in this review (represented in Table 4) there were two books, eight review papers, and twelve application papers. The two books [5, 46] introduced AI approaches for teaching and learning applications and outlined the state-of-the-art of AI-based adaptive learning. The review papers [47, 48] looked at the use of AI/ML in ITS development more generally in K-12 education, higher education, as well as digital education. Other review papers were in the domain of Natural Language Processing (NLP). While it is acknowledged that NLP is a subfield of AI, for the purposes of this paper, techniques that focused on language processing tasks have been labelled with NLP. Papers involving NLP applications included Intelligent Tutoring Chatbot systems [49] and detecting emotion from text in e-learning [50]. The application papers describe AI/ML techniques at various levels of education including higher education (e.g., applications in language learning [51], Computer Science [52], Business [53], and Legal Education [54]). There were also papers that employed AI/ML techniques to adaptive e-learning applications (e.g., educational data mining [55], AI and big data for e-learning [56], AI for monitoring, assessment and diagnostics [57], and detecting cheating in online tests [58]).

4.2.1 AI and ML techniques used in developing AIS/ITS

Table 5 categorizes the articles based on the AI/ML technique discussed in the literature. Decision Trees (DT) were the most prevalent technique cited with 10 relevant articles. Other common techniques included Artificial Neural Networks (ANN) and Support Vector Machines (SVM) with 9 and 8 relevant articles referring to each of these methods. This was

Table 5 Overview of AI/ML techniques and related references in the literature

Notation	AI/ML Technique	Count	References
–	Ant Colony Optimization	1	[47]
ANN	Artificial Neural Networks	9	[44, 46–48, 55, 56, 59, 61, 64]
ASR	Automatic Speech Recognition	1	[51]
Bp	Backpropagation	1	[59]
BN	Bayesian Networks	7	[44, 47, 48, 57, 59, 60, 64]
BKT	Bayesian Knowledge Tracing	2	[48, 49]
CBR	Case-Based Reasoning	4	[48, 55, 60, 63]
–	Clustering	3	[47, 48, 64]
CNN	Convolutional Neural Networks	2	[44, 46]
DL	Deep Learning	4	[44, 45, 48, 50]
DT	Decision Tree	10	[44, 46–48, 53, 55, 58–61]
–	Ensemble models	1	[55]
ES	Expert Systems	3	[48, 55, 64]
FL	Fuzzy Logic	7	[44, 47–50, 52, 64]
GA	Genetic Algorithm	2	[44, 47]
GB	Gradient Boosting	1	[59]
HMM	Hidden Markov Model	1	[49]
–	Hybrid	1	[64]
K-NN	K-Nearest Neighbors	4	[44, 46, 53, 55]
LR	Logistic Regression	5	[44, 46, 55, 58, 59]
LSTM	Long Short-Term Memory	2	[44, 46]
NB	Naive Bayes	7	[46, 47, 50, 53, 55, 59, 62]
NLP	Natural Language Processing	7	[5, 46, 48, 51, 54, 61, 62]
RBS	Rule-Based Systems	3	[45, 48, 55]
RF	Random Forest	6	[44, 55, 58, 59, 61, 62]
RNN	Recurrent Neural Networks	2	[44, 47]
RL	Reinforcement Learning	3	[44, 47, 64]
SVM	Support Vector Machine	8	[44, 46–48, 53, 55, 59, 61]

followed by 7 relevant articles each on Bayesian Networks (BN), Naive Bayes (NB), Natural Language Processing (NLP), and Fuzzy Logic (FL).

Overall, Table 5 illustrates the diverse AI techniques applied to AIS/ITS. The key insights for each article are summarized in this section.

Bayesian Networks and Decision Trees were some of the most cited AI techniques discussed in the literature. In [47] the authors conducted a systematic mapping of literature related to AI-enabled AISs. The authors in [47] found in their review of 147 articles that Bayesian Networks were identified as the most frequently referenced technique in the studies on AI and data analytic methods for AISs (representing 14 articles). Other common techniques included Neural Networks (11 articles), K-Nearest Neighbor, Genetic Algorithm, and Decision Trees (at 7 articles each) [47].

Similarly, [59] identified the Bayesian generalized linear model as more efficient compared with Artificial Neural Networks and Random Forests in terms of stability and model training time.

Conversely, in [48], the systematic mapping of the literature from 2007–2017 reported the frequencies in which AI techniques were used in ITS. The most common techniques were condition-action Rule-Based Systems (34%), data mining techniques (23%), Bayesian based techniques (21%), intelligent agents (15%), Fuzzy based (13%), Natural Language Processing (11%), Artificial Neural Networks (9%), Case-Based Reasoning (4%) and other techniques (6%). Authors in [44] cited another study [65], that provided a literature review from 2010 to 2018, focusing on AI techniques in educational data mining that included the use of Decision Trees, Random Forests, Artificial Neural Networks, Fuzzy Logic, Support Vector Machines, and Genetic/Evolutionary algorithms.

Other insights gained from the articles included a discussion on issues related to AI-enabled AIS/ITS, the diagnostic and predictive analytic aspects of the AI and ML techniques for AIS/ITS applications, and methods to evaluate the efficacy of AI and ML techniques.

In their review, [47] noted that the effectiveness of AI techniques for AISs has been established in the literature. However, there was a lack of practical implementation. Further, [47] also highlight that there is an issue with existing AISs related to the over use of complex models (i.e., where large generalized human performance data are used and lack specifics to the individual learner).

Several articles discussed the suitability of ML for AIS applications. In [45], applications of ML were described as the best approaches for tasks involving multiple factors and complicated solutions. Those sort of tasks are not solvable with a predefined rules or a simple computation [45]. Further, [55] described how ML models such as Decision Trees and Bayesian classifiers are easier to understand for learners compared with more complicated structures such as Deep Learning models.

4.2.2 Suitability of AI and ML techniques for small datasets

Table 6 describes the size of data of each article from Table 4. Table 6 also briefly summarizes the primary purposes of AI techniques and the ITS/AIS model that AI techniques support for each article. Upon reviewing the articles, determining the optimal technique for addressing small data problems presents a challenge. To better understand this, we will explore the role of data in ML and provide a brief overview of two subcategories of ML (i.e., supervised and unsupervised learning).

The information provided in Table 6 aims to describe the size of the datasets, but the articles do not specify the units used to quantify the dataset sizes.

ML is a field of study in artificial intelligence that involves accessing and learning from data [55]. ML techniques heavily rely on data, as without it, inference and predictive analytics cannot be performed [55]. Collecting data for intelligent systems, especially in real-case scenarios, can be a challenging process [15]. Once data is collected, it needs to be structured, stored, and validated to ensure its suitability for the specific use case. Representative training data is crucial for accurate predictions by the model. Additionally, data quality plays a vital role, requiring preprocessing techniques to handle missing values and align the data with the models. Proper feature selection and extraction are also essential for training the model and contribute to the prediction capabilities of an ML application [15].

In the field of education, supervised learning is predominantly used for predictive analysis [44]. Supervised learning has two subtypes, classification and regression. Examples of supervised learning algorithms include Support Vector Machine, Decision Trees, Random Forest, and Linear Regression. In supervised learning, the algorithm is trained using labelled data and matched inputs and outputs are used to create target functions [55]. Conversely, unsupervised learning involves analyzing unlabeled data (inputs only) to create a data-driven model [55]. The subtype of unsupervised learning is clustering, and examples of unsupervised learning techniques include K-Means and Hierarchical clustering [55].

Table 6 Overview of datasets, purpose of AI/ML and model supported by AI/ML

Article	Size of datasets	Purpose	Model
[5]	–	Predictive analytics, Remote protected examination, Mobile learning, Gamification	–
[47]	large-scale dataset, big data	To improve users' learning experiences, Predictive analytics	Learner model, Pedagogical model, Domain model
[48]	–	Defining, classification, or updating the learner's characteristics	Learner model
[15]	Data collected from 106 college Students, Uncertain data	To measure and evaluate a learner's educational performance	Learner model, Pedagogical model, Domain model, user interface
[49]	Students during teaching	Enhance capabilities of teachers and the abilities of students	Pedagogical model
[58]	54 volunteer participants that performed online tests = 500 k raw logs	To create new data sets and build new more advanced models	–
[54]	Large amounts of legal data, data privacy	A new paradigm in legal education and practice	–
[56]	Big data, 290 participants	Adaption of the E-learning system for imparting better education facilities	Learner model, Pedagogical model,
[51]	Big data	To examine main trends in AI technologies for second and foreign language learning and teaching	Learner model, Pedagogical model
[59]	Large data	Intelligent tutors, dropout predictions, performance predictions	Learner model, Pedagogical model
[55]	Total number of instances in a dataset is 215	A framework for career counseling of students using ML and AI techniques	–
[45]	Large data	To support k-12 teachers and teaching	Learner model, Pedagogical model, Domain model
[46]	–	Review paper: AI applications in education	Learner model, Pedagogical model, Domain model, user interface
[57]	Large data, Multiple sources of data	To argue that set of issues in traditional assessment and review AI approaches for that	Learner model
[60]	Data gathering from INSPIREus. 21 learners have enrolled into a course	To monitor and diagnose adaptive e-learning systems requirements at runtime and improve their design	Learner model
[61]	Large data	AI applications were categorized into Student performance, Teaching, Selection, and Behavior tasks	–
[62]	Large data, SingleOp dataset	presents arithmetic mathematical word problems solver	–

Table 6 (continued)

Article	Size of datasets	Purpose	Model
[63]	Large data	a response to the problem of learner desertion encountered by e-learning platforms	Learner model, Pedagogical model, Domain model, user interface
[50]	developed a new database for e-learning and smart classroom environments	To analyze the main APIs and tools for emotion detection	–
[44]	Large dataset, a dataset of 32,500 demographics, data obtained from different sources	Comprehensive review of data drive AI in education	Learner model, Pedagogical model
[53]	552 learners	A case study to enhance online learnings performance	–

According to [44], the scarcity of high-quality datasets is considered a main constraint in using supervised learning for AISs in the education domain. To overcome this limitation, semi-supervised learning has been introduced. Semi-supervised learning performs classification tasks by leveraging partly labelled training sets [55]. For example, [44] cited a reference [66] that proposed a semi-supervised learning framework for assessing the performance of secondary school students. Similarly, Reinforcement Learning is another example of a semi-supervised learning approach.

The authors in [15] highlight one common challenge in the development of ITS, which involves the use of uncertain data to estimate and display the current knowledge states and learning needs of students. Addressing the uncertainty in student models poses a significant challenge. Various Artificial Intelligence techniques, such as Bayesian Networks, Fuzzy Logic, Rule-Based Systems, and Neural Networks, have been designed for reasoning with uncertainty [15]. However, these ML technologies require further advancements to address this challenge effectively.

Five references from Table 6 as indicated by [15] used small data. To provide further insight, Table 7 summarizes the AI techniques employed in these references and the respective counts. Decision Tree and K-Nearest Neighbors methods exhibit the highest frequency among the mentioned techniques.

4.3 RQ3-what are the fundamental purposes of using AI techniques in AIS/ITS?

The third question of the review (RQ3) sought to identify the main purposes of employing AI and ML techniques in the development of AIS/ITS. A systematic literature review by [48] was found to pose a similar question and subsequently classified the main purposes into five categories: adaptive guidance, adaptive instruction, learner evaluation, learning model definition and updating, and the classification and clustering of learners. Table 6 briefly summarizes the primary purposes of AI techniques in the ITS/AIS for each article.

For this review, the primary reasons for using AI techniques in AIS/ITS were more broadly described with two categories: (1) improving learner performance evaluation and prediction, and (2) enhancing the overall teaching and learning process with adaptive mechanisms. Each of these topics will be described briefly in this section.

4.3.1 AI to improve learner performance evaluation and prediction

To improve the evaluation and prediction of learner performance in AIS/ITS with AI techniques there are several aspects to consider. For instance, in [48] AI techniques were described to be used to establish and update the learner model, categorize learners according to predefined criteria, and assess the learner's performance and progress throughout the training. In addition to these performance evaluation and learner diagnostic considerations, we also considered the prediction of the learner's future performance to enhance the adaptive functionality of AIS/ITS. Here, we outline the insights gained from the articles in this review.

One of the primary purposes of AI in AIS/ITS is to assess learner performance [15]. Related to understanding the learners' overall knowledge, [15] suggested that to promote learner outcomes, the system should be informed by using Bayesian Networks to assess learners' existing knowledge and to make modifications and updates to the learners' pathway. Several AI techniques were suggested to address problems in diagnosing student skills and backgrounds [47, 48], specifically, Fuzzy Logic, Case-Based Reasoning, and Rule-Based Systems. The authors in [47] indicated that if a student failed to reach the target skill or performance, then predictive analytic methods could be used to address the student's challenge, enhance their performance and encourage engagement and motivation. Predictive analytic methods included Naive Bayes, Bayesian Knowledge Tracing, Fuzzy Logic, Neural Networks, and Bayesian Networks [47]. In addition, in [61], Decision Trees were used for teaching and student performance.

Performance prediction is another core purpose of using AI for AIS/ITS development. According to [44], supervised learning is commonly used for prediction in educational settings to predict student assessments, skill retention, and the likelihood of students dropping out of the course entirely [44]. ML and educational data mining techniques are described as effective means to also predict learner performance. In [55], the authors propose a framework that uses three ML methods (i.e.

Table 7 Overview of AI techniques work with small datasets

AI techniques	Count
DT, KNN	3
ANN, FL, ES, RF, LR, NB, SVM	2
RL, BN, Clustering, HMM, BKT, RBS, CBR	1

Neural Networks, Decision Trees, and Naive Bayes) to predict performance in a case study involving high school students. Similarly, related to success prediction, in [46], the authors investigated predicting learner success through ML algorithms with the objective of assessing performances (i.e., using a Decision Tree algorithm and factors such as the learner's grades, online behaviour, and level of engagement). For dropout prediction in online courses, in [59], the following ML techniques are listed in order of most to least predominant: Support Vector Machine, Logistic Regression, Decision Tree, Naive Bayes, Random Forest, and Gradient Boosting. In addition, K-Nearest Neighbors and Artificial Neural Networks were each applied in three studies [59]. Similarly, [44] cited a reference [67] that students in danger of failing or dropping out were identified using supervised learning algorithms. In this case, the algorithms consisted of Naive Bayes, Decision Tree, K-Nearest Neighbors, and Deep Learning. In general, the most often used algorithms in learning application are built on prior knowledge. Thus, supervised learning is the type that is applied to a wide range of learning aspects [46].

4.3.2 AI to enhance teaching and learning process with AIS/ITS

AI techniques have been beneficial for enhancing teaching and learning processes in AIS/ITS. According to [47, 48] AI techniques have been used to provide adaptive instruction and guidance for AIS/ITS. For example, adaptive instruction could include presenting adaptive material and creating adaptive learning paths [48]. Similarly, adaptive guidance involved generating adaptive feedback, hints and recommendations [48]. Here, we outline the insights gained from the articles in this review.

Related to enhancing the teaching process, many studies have applied AI techniques to the ITS structure [48]. As an example, [15] discussed applying Artificial Neural Networks as they provide a learning pathway that is more adaptive to a student's learning profile.

Another approach that can augment the teaching process is Reinforcement Learning. In terms of learning, the optimum teaching policy can be identified using Reinforcement Learning. In this way, the student's situation is considered as the state and the student's resulting behaviour should be the reward [15]. Reinforcement Learning agent acts according to state and reward to find the best teaching policy [15, 44].

Regarding the learning process, in [15], they presented how cognitive tutors using Bayesian Networks could be used to make efficient decisions. The authors developed an ITS model that leveraged Bayesian Networks to facilitate the learning process. In this work, [15] cited another study [68] that proposed using Fuzzy classification as a new method for tutoring conversation and the basis for predicting and responding to a student's learning style.

In addition, in their work [60], the authors cited two references [1, 69], that leverage AI and ML techniques such as Decision Trees, Bayesian Networks, and Case-Based learning approaches. These techniques are employed to analyze learners' data, identify knowledge gaps, and guide learners towards relevant topics as needed. Similarly, in [53], the authors proposed an educational model adopting Support Vector Machine, Decision Tree, Naive Bayes, and K-Nearest Neighbors as classification ML techniques for training.

Lastly, a significant purpose of AI techniques for AIS/ITS is to enhance adaptive learning functionality. In [44], the authors studied how Reinforcement Learning can help create personalized learning materials and paths. They looked at various factors that influence a learner's experience, such as personal, social, and environmental factors. By monitoring and analyzing these factors in different learning environments, they can suggest new learning paths that adapt to individual needs. The smart learning platform they designed recommends suitable learning materials that change as the learners' needs change [44]. Some of the responsibilities of adopting Reinforcement Learning in the education field are to adapt tutorial approaches, provide timely feedback to students, enhance students' problem-solving abilities, and facilitate personalized learning [44].

4.4 RQ4-are AI techniques aimed at supporting and informing core models in AIS/ITS?

The fourth question of the review (RQ4) focused on understanding if and how AI techniques supported core components of AIS/ITS models (e.g., domain knowledge, facilitating pedagogy, user interface model, or developing instructor/student models). This section provides an overview of the ITS architecture models and discusses the role of AI techniques in each model. Table 6 summarizes the ITS/AIS model that AI techniques support for each article. As depicted in Fig. 1, the architecture of ITS includes four primary elements: the learner model, pedagogical model, domain model, and user interface [48]. As presented on Table 6, the frequency of reviewed studies for the learner model, the pedagogical model, and the domain model is 11, 10, 5 articles respectively. Below, we provide further details on each component.

The features and states of individual learners are presented in the student or learner model. As an example, the model incorporates what the student knows, what they have completed in the course, and how they learn [15]. The learner model will provide the AIS/ITS with required student information, and the AIS/ITS's duty is to provide a suitable response to students' needs using the other three elements of the system [48].

The best teaching policy that facilitates and promotes the learner's path will be provided by the tutor, pedagogical, or instructor model [15]. For instance, the model incorporates how the material is taught, the expected steps of the learning process, and possible questions a learner might ask. The pedagogical model's duty is to manage the system's response to the students' actions [48].

The expert, domain, or knowledge model includes the subjects, materials, procedures and skills needed to teach the students [15]. The model also consists of information about aspects of the material in which students make common mistakes or misunderstandings. This is included so that the ITS can respond by providing qualified assistance [48].

Finally, the user interface communicates between an AIS/ITS system and the learner [15]. This model can include graphical, social, emotional, and natural language communication, as well as the system's interface [48]. The authors of [48] discovered that the majority of ITS utilized web-based interfaces, allowing users to access them through computers or mobile applications.

Overall, the papers listed in Table 6 mostly mention the specific details of the learner and pedagogical models in ITS/AIS. Thus, in this review, we will focus on describing the AI techniques that support the learner and pedagogical models. Each of these topics will be briefly discussed in the following section.

4.4.1 AI techniques that support the learner model

The main features of the learner model are the learner characteristics, such as cognitive abilities, motivation, and personal background [48]. The development of an ITS student model can focus on simply one learner characteristic or multiple characteristics. According to [48], most ITSs use a combination of learner characteristics. Here, we outline the insights gained from the articles in this review.

Several studies in this review created learner models using Bayesian Networks [47, 48]. According to [15], the advantages of Bayesian Networks are the ability to support the learning process, the relationship between a student's state of knowledge and their corresponding performance, and the ability to overcome uncertain and scarce information to make decisions. Bayesian Networks use predefined variables and conditional probabilities to provide a graphical representation of relationships [15]. In the case of AIS/ITSs, a student's learning behaviour and profile can be defined as variables, and the Bayesian Networks can update a student's state of knowledge based on their performance and the conditional relationships linking the variables [15]. The resulting outcome is that the Bayesian Networks offer a means to inform the AIS/ITS of the interactions between student behaviours and teaching strategies to determine suitable adaptations.

[15] cited a reference [70] that introduced a mole in ITS, which incorporates an instructional model with a knowledge base learner model. In this study, Neural Networks was applied to develop student skills. Another reference cited by [71] employed Expert Systems and Artificial Neural Networks to acquire skills in student models. Reinforcement Learning can also be used in learner modelling [15]. Another popular AI technique that is applied to expand the learner model is Fuzzy Logic, which assesses student education performance. After identifying the students' knowledge level, a Fuzzy set theory transfers an input to a Fuzzy output [15]. [59] cited a reference [72] that in a smart classroom, Deep Learning was applied to discuss and analyze audio and video information to capture hand gestures and body language exhibited by the presenter [59].

Overall, the AI techniques that support the learner model in this review are Bayesian Networks, Artificial Neural Networks, Expert Systems, Reinforcement Learning, Fuzzy Logic, and Deep Learning. However, it could be considered that all AI techniques mentioned in SubSect. 4.3.1 are applied in learner modelling.

4.4.2 AI techniques that support the pedagogical model

To implement an intelligent instructor, ITSs have used AI techniques that can better assist learners and the learning process [47]. For example, [47] cited a reference [73] that represented adaptive feedback by a combination of three models: pedagogical, domain and learner. This feedback works for a cognitive knowledge approach. Similarly, [51] discussed the roles and duties of the pedagogical model and any technical needs to support the teaching strategy.

In [59], ML techniques like Bayesian Networks and Case-Based Reasoning were applied to implement intelligent teachers for personalized learning. Students are supported by suggesting proper educational material and resources and by providing feedback on their oral presentations and written assignments [59]. Furthermore, the author in [59] presented an e-learning tool based on a Bayesian Network. Bayesian Networks are able to suggest instructional methods for the teachers to evaluate the state of knowledge of a user's preferences [59].

Another ML technique is Reinforcement Learning, which can be used in the pedagogical model in the ITS framework. The best teaching strategy can be identified in the learning process by applying Reinforcement Learning [15].

Artificial Neural Network is another ML technique used in the pedagogical model. The knowledge and learner modules in ITS are used in the learning process [15] to provide information about student performance.

In summary, the AI techniques supporting the pedagogical model were Case-Based Reasoning, Artificial Neural Networks, Reinforcement Learning, and Bayesian Networks. However, it could be considered that all AI techniques mentioned in SubSect. 4.3.2 are applied in pedagogical modelling.

5 Discussion

5.1 Key findings from the research questions

Most articles identified to answer RQ1 were related to simulation-based training and did not consider the AI/ML approach in AIS for MET. The lack of articles on AI and ML approaches in MET was the main limitation of the first phase of the review. Only 3 articles out of 16 discussed particular AI/ML techniques: specifically, a conference paper [39] and two review articles [11, 12]. Many articles discussed AI and ML only conceptually or in terms of their prospective utility, as shown in Table 3.

Due to the limited findings in RQ1, the review changed to look more broadly at AI/ML techniques for general AIS/ITS applications. A specific challenge for MET research and development of AISs is the lack of data. As such, RQ2 focused on AI techniques for handling small data problems. The search terms were revised to AI/ML techniques for more general AIS/ITS applications for subsequent questions. Related to RQ2, of the articles based on the AI/ML technique in the literature, Decision Trees were the most common technique in AIS/ITS. Finding the optimal techniques that work with small datasets is a persistent challenge. However, Decision Tree and K-Nearest Neighbors methods represented the highest frequency among the techniques suitable for small datasets mentioned in the articles [46, 53, 55] as shown in Table 7.

Given that AISs are used in many fields, RQ3 focuses on the primary reasons for using AI/ML techniques in AIS/ITS as this information would be informative to MET. Lessons learned from RQ3 are that AI/ML techniques are predominately used for the student and instructor models of AIS: specifically, for the student model to enhance the performance evaluation and prediction [15, 48], and for the instructor model to adapt the delivery of training [47, 59].

Finally, the architecture of ITS includes the learner model, pedagogical model, domain model, and user interface [48]. RQ4 aimed to identify AI techniques specific to AIS sub-models. However, the articles included in this review only elaborated on the learner [15, 47, 48, 59] and pedagogical models [15, 47, 51, 59]. These results showed that AI techniques were predominantly used to support the development of the student model (e.g., learner performance evaluation) and the pedagogical model (adaptive mechanisms). These findings can be useful for future work to develop an AIS for MET applications.

5.2 Limitations and challenges of AI techniques for AIS/ITS

Several limitations and challenges to AI/ML approaches were identified in this review process, such as the scarcity of training data, uncertainty in learner models, issues diagnosing learner skills, and collecting data from real situations.

Scarcity of Training Data: The effectiveness of AI methods heavily relies on the accessibility of sufficient training data, which significantly influences their prediction capabilities [44, 45], particularly in supervised learning methods. To overcome this limitation, semi-supervised learning has been introduced [55]. However, acquiring adequate training data in reactive environments like maritime education and training can be extremely challenging.

Learner model's uncertainty: ITS development requires accurate evaluation and updating of students' knowledge, however tackling uncertain data is a challenge for developing learner models [15]. Although AI techniques have been applied to solve uncertainty issues, further development is needed to effectively address this issue [15].

Difficulties in diagnosing learners' skills: AI techniques that leverage learning analytics should aim to enhance existing adaptive learning models. Case-Based Reasoning, Fuzzy Logic, and Rule-Based Systems can be employed to address the challenges related to diagnosing learners' skills. Future research should focus on implementing and testing more systems, frameworks, and models to determine their efficacy in overcoming the learning challenges faced by students [47].

Collecting data in real scenarios: Collecting data for intelligent systems, especially in real scenarios, poses significant challenges. The process involves structuring, storing, and validating the data to ensure its suitability for the intended use case. It is crucial for the training data to be representative to enable accurate predictions by the model. Data quality is also essential, necessitating preprocessing steps to handle missing values and align the data with the models. Additionally, proper feature selection for model training is crucial for the success of machine learning applications [15]. Applying ML techniques for developing ITS is costly, particularly when it comes to data collection [15], which is a concern in the context of maritime training.

6 Conclusion

The main purpose of this systematic literature review was to consider the current state of research on AI-based AISs in the field of maritime safety training. Our review pointed to recognized methodologies, as well as advantages and deficiencies related to the implementation of such systems for small datasets.

Overall, the systematic literature review was conducted in two phases. Each phase involved a planning stage, formulating research questions, preparing a search strategy, determining relevant databases, establishing search terms, and constructing criteria for inclusion and exclusion. The study focused on addressing four research questions related to AI-based adaptive instructional systems for maritime safety training. Specifically, the first phase investigated RQ1. Based on the initial findings, the second phase broadened the scope of the review for RQ2, RQ3, and RQ4. It is recognized that this approach deviates from a standard systematic literature review and also has limitations when it comes to the search terms used.

In summary, the key findings are as follows. In response to the first research question regarding the AI/ML techniques used in adaptive instructional and intelligent tutoring systems for MET, only a few articles (Table 3) discussed the specific applications of AI and ML techniques in MET. Most articles focused on simulation-based training, such as navigation and ship handling. The remaining articles explored emerging training technologies for maritime education.

The second research question focused on AI techniques for handling small data problems. Determining the optimal technique for addressing small data problems posed a challenge. According to Table 5, Decision Trees, Artificial Neural Networks, Support Vector Machines, Bayesian Networks, Naive Bayes, Natural Language Processing, and Fuzzy Logic are the most prevalent techniques applied to AIS/ITS, whether for small or large datasets. However, based on the review findings in Tables 6 and 7, the Decision Tree and K-Nearest Neighbors methods were observed to have the highest frequency of use among the AI techniques applied to small data sizes.

The third research question delved into the primary reasons for using AI techniques in AIS/ITS. These reasons were broadly categorized into two areas: 1) enhancing learner performance evaluation and prediction, and 2) improving the overall teaching and learning process through adaptive mechanisms. Subsequently, the fourth research question explored the AI techniques that support the development of learner and pedagogical models. The review provided a description of these techniques and their role in supporting the models. The challenges identified throughout the study were summarized, shedding light on the difficulties and implications discussed in the paper.

Overall, the findings offered a comprehensive explanation of the AI tools available for AIS development and conveyed the applicability of select AI/ML approaches for simulation-based safety training. Further, the insights gathered in this review can be used to inform MET researchers and training practitioners of the capabilities of AIS systems and the augmented potential of pairing these systems with AI tools to offer personalized instruction and feedback to learners. This has the potential to improve learning outcomes and enhance the efficacy of maritime education and training.

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Declarations

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References

1. Baker RS, Martin T, Rossi LM. Educational data mining and learning analytics. Hoboken: John Wiley & Sons, Inc.; 2016. p. 379–96. https://doi.org/10.1002/9781118956588.ch16.
2. Emond B, Zeinali-Torbati R, Smith J, Billard R, Barnes J, Veitch B. Cognitive simulations for adaptive instructional systems: exploring instruction strategies with simulated tutors and learners. Cham: Springer; 2023. p. 123–36. https://doi.org/10.1007/978-3-031-34735-1_9.
3. Casano JD, Fuentes M, Paguio CJ. Directions for the design of an adaptive in-game re-engagement dashboard for teachers using WHIMC. Cham: Springer; 2023. p. 97–108. https://doi.org/10.1007/978-3-031-34735-1_7.
4. Harpstead E. learning within gameplay loops: considering adaptive educational technology from a game design lens. Cham: Springer; 2023. p. 137–47. https://doi.org/10.1007/978-3-031-34735-1_10.
5. Kurni M, Srinivasa KG, Mohammed MS. A beginner's guide to introduce artificial intelligence in teaching and learning. Cham: Springer International Publishing AG; 2023.
6. Committee on Human-System Integration Research Topics for the 711th Human Performance Wing of the Air Force Research Laboratory, et al. Human-AI teaming: state-of-the-art and research needs. National Academies Press: Washington, D.C. 2022; https://www.nap.edu/catalog/26355
7. Demirel E. Maritime education and training in the digital era. Univers J Educ Res. 2020;8:4129–42.
8. Ichimura Y. Evaluating the impacts of digitalization on ship operation: examining how to enhance maritime safety. World Maritime University: Sweden; 2021; https://commons.wmu.se/cgi/viewcontent.cgi?article=2700&context=all_dissertations
9. Fraulini NW, Marraffino MD, Garibaldi AE. Identifying individual differences that predict usage of an adaptive training system in a United States Marine Corps course. Cham: Springer; 2023. https://doi.org/10.1007/978-3-031-34735-1_16.
10. Zeinali-Torbati R, Smith J, Billard R, Emond B, Barnes J, Veitch B. Towards application of adaptive instructional systems in simulation-based lifeboat training using Bayesian networks. Cham: Springer; 2023. https://doi.org/10.1007/978-3-031-34735-1_24.
11. Munim ZH, Kim TE. A review of learning analytics dashboard and a novel application in maritime simulator training. AHFE. 2023; https://openaccess.cms-conferences.org/publications/book/978-1-958651-85-8/article/978-1-958651-85-8_13
12. Munim ZH, Krabbel H, Haavardtun P, Kim TE, Bustgaard M, Thorvaldsen H. Scenario design, data measurement, and analysis approaches in maritime simulator training: a systematic review. MIS4TEL. 2023; p. 39–47. https://link.springer.com/https://doi.org/10.1007/978-3-031-42134-1_4
13. Ong J, Ramachandran S. An intelligent tutoring system approach to adaptive instructional systems. U S Army. 2005.
14. Lee J, Park OC. Adaptive instructional systems. In: Handbook of Research on Educational Communications and Technology. 3rd ed. 2007. p. 16.
15. AlShaikh F, Hewahi N. AI and machine learning techniques in the development of Intelligent Tutoring System: A review. 3ICT. IEEE; 2021. p. 403–10.
16. Sweller J. Cognitive load theory, learning difficulty, and instructional design. Learn Instr. 1994;4:295–312.
17. Piaget J. To understand is to invent: the future of education. New York: Grossman Publishers; 1973. p. 148.
18. Bandura A, Walters RH. Social learning theory. New Jersey: Englewood cliffs Prentice Hall; 1977.
19. Anderson JR. How can the human mind occur in the physical universe? Oxford: Oxford University Press; 2009.
20. Sternberg RJ. Metacognition, abilities, and developing expertise: What makes an expert student? Instr Sci. 1998;26:127–40.
21. Sottilare RA, Brawner KW, Goldberg BS, Holden HK. The generalized intelligent framework for tutoring (GIFT). Orlando FL US Army Res Lab Res Eng Dir ARL-HRED. 2012;
22. Mislevy RJ, Almond RG, Lukas JF. A brief introduction to evidence-centered design. ETS Res Rep Ser. 2003. https://doi.org/10.1002/j.2333-8504.2003.tb01908.x.
23. VanLehn K, Siler S, Murray C, Yamauchi T, Baggett WB. Why do only some events cause learning during human tutoring? Cogn Instr. 2003;21:209–49.
24. Conati C, Vancouver M, Vanlehn K. Toward computer-based support of meta-cognitive skills: a computational framework to coach self-explanation. IJAIED. 2000; 389–415.
25. Brusilovsky P. Adaptive hypermedia. User Model User-Adapt Interact. 2001;11:87–110.
26. Billard R, Musharraf M, Veitch B, Smith J. Using Bayesian methods and simulator data to model lifeboat coxswain performance. WMU J Marit Aff. 2020;19:295–312.
27. VanLehn K. The behavior of tutoring systems. Int J Artif Intell Educ. 2006;16:227–65.
28. Azevedo R, Aleven V. Metacognition and learning technologies: An overview of current interdisciplinary research. Int Handb Metacognition Learn Technol. 2013;20:1–16.

29. Kitchenham B, Brereton OP, Budgen D, Turner M, Bailey J, Linkman S. Systematic literature reviews in software engineering–a systematic literature review. Inf Softw Technol. 2009;51:7–15.
30. Mallam SC, Nazir S, Renganayagalu SK. Rethinking maritime education, training, and operations in the digital era: applications for emerging immersive technologies. J Mar Sci Eng. 2019. https://doi.org/10.3390/jmse7120428.
31. Sanchez-Gonzalez PL, Díaz-Gutiérrez D, Leo TJ, Núñez-Rivas LR. Toward digitalization of maritime transport? Sensors. 2019. https://doi.org/10.3390/s19040926.
32. Markopoulos E, Lauronen J, Luimula M, Lehto P, Laukkanen S. Maritime safety education with VR technology (MarSEVR). CogInfoCom. IEEE; 2019. p. 283–8.
33. Jo S, D'agostini E, Kang J. From seafarers to e-farers: maritime cadets' perceptions towards seafaring jobs in the industry 4.0. Sustainability. 2020. https://doi.org/10.3390/su12198077.
34. Wiig AC, Sellberg C, Solberg M. Reviewing simulator-based training and assessment in maritime education: a topic modelling approach for tracing conceptual developments. WMU J Marit Aff. 2023;22:143–64.
35. Campos C, Castells-Sanabra M, Mujal-Colilles A. The next step on the maritime education and training in the era of autonomous shipping: a literature review. in: Maritime Transport Conference; 2022.
36. Emad GR, Shahbakhsh M. Digitalization transformation and its challenges in shipping operation: the case of seafarer's cognitive human factor; 2022.
37. Emad GR, Ghosh S. Identifying essential skills and competencies towards building a training framework for future operators of autonomous ships: a qualitative study. WMU J Marit Aff. 2023;22:1–19.
38. Novellino A, Bonogiglio L, Cimmino V, Napoletani L. Step-smart education platform. IMCIC; 2022.
39. Tusher HM, Nazir S, Mallam S, Munim ZH. Artificial Neural Network (ANN) for performance assessment in virtual reality (VR) simulators: from surgical to maritime training. IEEM 2022; p. 0334–8. https://ieeexplore.ieee.org/document/9989816/
40. Alop A. Smart shipping needs smart maritime education and training. Cham: Springer; 2021. p. 131–42. https://doi.org/10.1007/978-3-030-64088-0_12.
41. Jamil MG, Bhuiyan Z. Deep learning elements in maritime simulation programmes: a pedagogical exploration of learner experiences. Int J Educ Technol High Educ. 2021;18:1–22.
42. Vagale A, Osen OL, Brandsæter A, Tannum M, Hovden C, Bye RT. On the use of maritime training simulators with humans in the loop for understanding and evaluating algorithms for autonomous vessels. J Phys Conf Series. 2022. https://doi.org/10.1088/1742-6596/2311/1/012026.
43. Hanzu-Pazara R, Barsan E, Arsenie P, Chiotoroiu L, Raicu G. Reducing of maritime accidents caused by human factors using simulators in training process. J Maritime Res. 2008;5:3–18.
44. Ahmad K, Iqbal W, El-Hassan A, Qadir J, Benhaddou D, Ayyash M, et al. Data-driven artificial intelligence in education: a comprehensive review. IEEE Trans Learn Technol. 2023;17:1–20.
45. Murphy RF. Artificial intelligence applications to support K-12 teachers and teaching. Santa Monica: Rand Corp; 2019.
46. Ezzaim A, Dahbi A, Assad N, Haidine A. AI-based adaptive learning-state of the art. AI2SD. 2022. p. 155–67.
47. Kabudi T, Pappas I, Olsen DH. AI-enabled adaptive learning systems: a systematic mapping of the literature. Comput Educ Artif Intell. 2021. https://doi.org/10.1016/j.caeai.2021.100017.
48. Mousavinasab E, Zarifsanaiey N, Niakan Kalhori RS, Rakhshan M, Keikha L, Ghazi SM. Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. Interact Learn Environ. 2018;29:142–63.
49. Ashfaque MW, Tharewal S, Iqhbal S, Kayte CN. A review on techniques, characteristics and approaches of an intelligent tutoring chatbot system. ICSIDEMPC. IEEE. 2020. https://ieeexplore.ieee.org/document/9299583/
50. Bustos-López M, Cruz-Ramírez N, Guerra-Hernández A, Sánchez-Morales LN, Alor-Hernández G. Emotion detection from text in learning environments: a review. New Perspect Enterp Decis-Mak Appl Artif Intell Tech. 2021;483–508.
51. Son JB, Ružić NK, Philpott A. Artificial intelligence technologies and applications for language learning and teaching. J China Comput-Assist Lang Learn. 2023. https://doi.org/10.1515/jccall-2023-0015/html.
52. Chrysafiadi K, Virvou M, Tsihrintzis GA. A fuzzy-based mechanism for automatic personalized assessment in an e-learning system for computer programming. Intell Decis Technol. 2022;16:1–16.
53. Guerrero-Roldán AE, Rodríguez-González ME, Bañeres D, Elasri-Ejjaberi A, Cortadas P. Experiences in the use of an adaptive intelligent system to enhance online learners' performance: a case study in Economics and Business courses. Int J Educ Technol High Educ. 2021. https://doi.org/10.1186/s41239-021-00271-0.
54. Vučić F. Changes in legal education in the digital society of artificial intelligence. MoStart. Springer. 2023; p. 159–76.
55. Guleria P, Sood M. Explainable AI and machine learning: performance evaluation and explainability of classifiers on educational data mining inspired career counseling. Educ Inf Technol. 2023;28:1081–116.
56. Khan MA, Khojah M, Vivek. Artificial intelligence and big data: the advent of new pedagogy in the adaptive e-learning system in the higher educational institutions of Saudi Arabia. Educ Res Int. 2022;2022:1–10.
57. Swiecki Z, Khosravi H, Chen G, Martinez-Maldonado R, Lodge JM, Milligan S, et al. Assessment in the age of artificial intelligence. Comput Educ Artif Intell. 2022. https://doi.org/10.1016/j.caeai.2022.100075.
58. Volarić T, Martinović G, Ljubić H. Detecting academic fraud at online tests during COVID-19 using machine learning-based methods. In: MoStart. Springer. 2023; p. 144–58.
59. Munir H, Vogel B, Jacobsson A. Artificial intelligence and machine learning approaches in digital education: a systematic revision. Information. 2022. https://doi.org/10.3390/info13040203.
60. Dounas L, Salinesi C, El Beqqali O. Requirements monitoring and diagnosis for improving adaptive e-learning systems design. J Inf Technol Educ Res. 2019;18:161–84.
61. Zafari M, Bazargani JS, Sadeghi-Niaraki A, Choi SM. Artificial intelligence applications in K-12 education: a systematic literature review. IEEE Access; 2022.
62. Mandal S, Naskar SK. Classifying and solving arithmetic math word problems—an intelligent math solver. IEEE Trans Learn Technol. 2021;14:28–41.

63. Ennaji M, Machkour M. Collaborative tutoring architecture: a generic case based reasoning multi-agent. IJIST; 2021.
64. AlShaikh F, Hewahi N. AI and machine learning techniques in the development of intelligent tutoring system: a review. 3ICT. IEEE; 2021. p. 403–10. https://ieeexplore.ieee.org/document/9582029/
65. Charitopoulos A, Rangoussi M, Koulouriotis D. On the Use of soft computing methods in educational data mining and learning analytics research: a review of years 2010–2018. Int J Artif Intell Educ. 2020;30:371–430.
66. Livieris IE, Drakopoulou K, Tampakas VT, Mikropoulos TA, Pintelas P. Predicting secondary school students' performance utilizing a semi-supervised learning approach. J Educ Comput Res. 2019;57:448–70.
67. Nagy M, Molontay R. Predicting dropout in higher education based on secondary school performance. INES. IEEE; 2018.
68. Crockett K, Latham A, Whitton N. On predicting learning styles in conversational intelligent tutoring systems using fuzzy decision trees. Int J Hum-Comput Stud. 2017;97:98–115.
69. Wang X, Yang Y, Wen X. Study on blended learning approach for English teaching. In: 2009 IEEE SMC. 2009; p. 4641–4.
70. Venkatesh R, Naganathan ER, Maheswari NU. Intelligent tutoring system using hybrid expert system with speech model in neural networks. Int J Comput Theory Eng. 2010. https://doi.org/10.7763/IJCTE.2010.V2.108.
71. Malpani A, Ravindran B, Murthy HA. Personalized intelligent tutoring system using reinforcement learning. FLAIRS. 2011; p. 561–2.
72. Kim Y, Soyata T, Behnagh RF. Towards emotionally aware AI smart classroom: current issues and directions for engineering and education. IEEE Access. 2018. https://doi.org/10.1109/ACCESS.2018.2791861.
73. Bimba AT, Idris N, Mahmud RB, Al-Hunaiyyan A. A cognitive knowledge-based framework for adaptive feedback. CIIS. Springer. 2017; p. 245–55.