Smart Learning Environments

REVIEW

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Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review

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Abstract

Sustainable education is a crucial aspect of creating a sustainable future, yet it faces several key challenges, including inadequate infrastructure, limited resources, and a lack of awareness and engagement. Artificial intelligence (AI) has the potential to address these challenges and enhance sustainable education by improving access to quality education, creating personalized learning experiences, and supporting data-driven decision-making. One outcome of using AI and Information Technology (IT) systems in sustainable education is the ability to provide students with personalized learning experiences that cater to their unique learning styles and preferences. Additionally, AI systems can provide teachers with data-driven insights into student performance, emotions, and engagement levels, enabling them to tailor their teaching methods and approaches or provide assistance or intervention accordingly. However, the use of AI and IT systems in sustainable education also presents challenges, including issues related to privacy and data security, as well as potential biases in algorithms and machine learning models. Moreover, the deployment of these systems requires significant investments in technology and infrastructure, which can be a challenge for educators. In this review paper, we will provide different perspectives from educators and information technology solution architects to connect education and AI technology. The discussion areas include sustainable education concepts and challenges, technology coverage and outcomes, as well as future research directions. By addressing these challenges and pursuing further research, we can unlock the full potential of these technologies and support a more equitable and sustainable education system.

Keywords: Artificial intelligence, Sustainable education, Education sustainability, Intelligent tutoring system, Massive open online course

Introduction

The term "sustainable" is intended to describe something that can be maintained or continued over the long term without significant negative environmental, social, or economic impacts. It implies a concept that meets the needs of the present without compromising future generations. To elaborate on the concept of sustainability in education, Sterling and Orr (2001) proposed that sustainable education aims to foster a learning culture that values diversity, creativity, and participation and empowers learners to develop sustainably. To extend the concept of sustainable development to the scope of human life, in 2015, the United Nations adopted a set of 17 global goals called the Sustainable Development Goals (SDGs) (United Nations, 2015) to end poverty, protect the planet, and ensure peace and prosperity for all by 2030. It is worth noting that education is one of the key areas of the SDGs, as it is essential for achieving all the other goals and for building a more sustainable future.

Sustainable education aims to develop the competencies needed to meet the social and environmental needs of present and future generations. Sustainable education is a matter not only of content but also of process and context. It involves rethinking the purpose, methods, and outcomes of education; transforming the culture, structure, and practices of educational institutions; and collaborating and dialoguing among different stakeholders, such as educators, learners, policymakers, communities, and nongovernmental organizations. Sustainable education is an ongoing and dynamic process of learning and change that inspires hope and action for a better world.

The fourth goal of the SDGs, quality education, revolves around the achievement of sustainable education for all humankind. This goal aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. To achieve the goal of quality education, 10 targets covering different aspects of education were proposed in the SDGs, providing detailed guidance for the realization of quality education; these include designing modern information technologies to better implement quality education to achieve sustainable education (United Nations, 2015).

Sustainable education focuses on cultivating learners with sustainable development capabilities, so it is necessary to emphasize personalization and student-centeredness in the learning process to develop the capabilities they need. For this reason, integrating modern information technology such as intelligent tutoring systems (ITSs) into quality education has become the main approach for achieving sustainable education today.

Intelligent tutoring systems (ITSs) are computer-based learning systems that use artificial intelligence (AI) to provide personalized and adaptive instruction for students. The overall concept can be traced back to 1970 (Carbonell, 1970). These systems can model students' psychological states, such as motivation, emotion, and cognition, as well as their prior knowledge, skills, and preferences. They can also monitor students' progress, provide feedback, hints, and scaffolding, and select appropriate problems or tasks for students to practice.

Technology-Enhanced Learning (TEL) (Deng & Benckendorff, 2020) is another approach to education that combines the use of technology with smart approaches designed to support learning. It has the potential to improve teaching and learning and turn them into levers of sustainable learning growth and development. By integrating emerging technologies such as social media, web-based tools, augmented and virtual reality, as well as games in teaching and learning, TEL can enhance the educational experience for both teachers and students. It's becoming a trend in educational system which the remote and hybrid learning become necessary. By leveraging TEL, the students can learn by their own pace and more engaged during the learning. However, it is important to ensure that technology is used responsibly and that its effects are positive and its risks manageable.

Along with the versatile AI machine learning solutions in the recent decade, many ITSs are empowered by AI solutions. For example, the natural language process (NLP) (Liddy, 2001) can be used as a chatbot to interact with students to provide feedback and necessary learning interventions (Lin & Mubarok, 2021). The other example is that of leveraging the powerful data mining capability of machine learning to perform learning analytics activities or performance prediction (Choi & McClenen, 2020; Ouyang et al., 2023). Other areas include leveraging image recognition to identify students' facial expressions, gestures, or emotions to inform teachers' future actions (Leony et al., 2013; Singh et al., 2022).

AI systems can play a significant role in sustainable education. AI-powered algorithms can be used to analyze student data and create personalized learning experiences for each student. This can help students learn more effectively and efficiently while reducing the amount of time and resources required for traditional teaching methods. There are several AI systems that can be used in sustainable education. One example is personalized learning systems that use AI-powered algorithms to analyze student data and create personalized learning experiences for each student. Another example is chatbots powered by AI that can answer inquiries from students and offer them individualized learning experiences. The other typical example is AI-enabled technology can also be used for performance prediction and real-time monitor students' performance so that necessary intervention can be provided to the instructors.

From educators' perspectives, an ITS can act as a potential tool to enhance their teaching and learning practices rather than as a threat or a replacement. ITSs can offer several benefits for educators, such as providing individualized and differentiated instruction for diverse learners, which is one of the key concepts for shifting from teacher-centered to student-centered processes (Ogunkunle & Qu, 2020; Silva et al., 2022). ITSs can also offload teachers' workload on routine tasks, such as grading feedback and remediation, so that teachers can focus more on teaching itself (Atapattu & Falkner, 2016; Tobarra et al., 2021). Ultimately, teachers will promote lifelong learning and professional development not only to students but also themselves.

There will be some gaps when bringing educators with IT solutions, especially when educators are asked to implement an intelligent tutoring system with modern artificial intelligence features enabled. Some examples of the gaps include lacking the understanding of how IT technology works, the difficulties of integrating ITS into educational curricula, building effective assessments for ITSs, and funding concerns. Even if the ITS is properly built, training instructors to use the system effectively might be another challenge. Thus, we are trying to address the gaps and challenges in this review paper and provide guidance for educators and IT solutions architects by reviewing different approaches to tutoring systems implementation.

In this review paper, we will bridge the perspectives of educators and information technology specialists on sustainable education. Furthermore, we extended the original definition of ITS to be AI and machine learning embedded. Below is the research agenda and questions we will address.

- Background
  - Define the title and focused key areas of the surveyed papers.
  - Define the source of selecting papers.
  - Define the keywords, screening criteria, and year range of the surveyed papers.
  - Review, study, categorize and determine the relevance.
  - Define the target audience of this surveyed paper.
- What are the key challenges to sustainable education?
  - What are the key challenges from sustainable education implementation?
  - What are the key challenges from teachers?
  - What are the key challenges from learners?
  - Are there any other key challenges?
- How are AI and IT incorporated as the ITS to support sustainable education?
  - What are the key factors to consider when building AI/IT systems to support sustainable education?
  - What are the typical AI/IT solutions used to support sustainable education?
  - What and how are pedagogical methods integrated into AI/IT solutions?
  - How are learning statistics data accumulated and analyzed?
- What are the outcomes and challenges of AI/IT embedded as the ITS in sustainable education?
  - What is the outcome measurement mechanism, and what is the outcome?
  - What is the trust and explainable level when using AI/IT in sustainable education?
- What is the future trend of AI/IT-embedded ITS sustainable education?
  - What is a potential area in which we can invest more AI/IT effort?
  - What are the enhancement opportunities of currently existing AI/IT systems?

Thus, based on the research agenda, the following 4 research questions will be addressed and answered.

- RQ1: What are the key challenges of sustainable education implementation?
- RQ2: How are AI and IT incorporated as the ITS to support sustainable education?
- RQ3: What are the outcomes of AI/IT being embedded as the ITS in sustainable education?
- RQ4: What is the future trend of AI/IT embedded ITS in sustainable education?

In the remaining sections of this paper, we will illustrate the overall methodology of how we developed this review study. In section "Methodology", we will perform a literature review and share some typical cases and scenarios about how AI supports sustainable education. In section "Results and discussion", we will detail the breakdown of the information gathered from the reviewed papers, discuss the findings and answer the research questions. In the last section, we will conclude the overall study and discuss future trends.

Literature review

The trend of changing teaching scenarios from traditional classroom style to remote, virtual, and blended is inevitable. There are lots of research focus on how to leverage TEL to make overall learning more efficient and engaged. Xie et al. (2019) reviewed the trend and how and what kind of technologies are applied into the learning environment. There are also review focus on specific subjects like flipping mathematics (Yang et al., 2019) and chemistry (Wu et al., 2021) by leveraging TEL which shows the benefits when embedding technologies into the learning.

With more instructional courses being moved online and becoming remotely accessible, the data generated from the system also become more complicated to manage. Big data mining along with AI has become mainstream when examining information technology in educational systems. Yousuf and Wahid (2021) elaborated different kinds of areas and applications in which AI can support as well as provide good insights for the following research.

There are different perspectives when looking at how AI can support ITSs toward sustainable education. It is reasonable to review different implementations with a standardized framework that can help researchers gain a decent understanding and support sustainable education implementation. To help researchers, Gillani et al. (2023) precisely defined different dimensions of reviewing mechanisms, which were also adopted in this study.

There are two main categories of AI integration with tutoring systems. The first is to not interfere with the tutoring system and to extract log data for further analysis. This kind of approach typically leverages much data mining and clustering to derive learning behaviors (Corrigan et al., 2015b; Ouyang et al., 2023; Weng et al., 2020). When categorizing learning behaviors, unsupervised learning methodology and clustering algorithms are usually used since there is no ground truth data to train the model. The other major approach is for performance prediction (Afzaal et al., 2021; Choi & McClenen, 2020; Serrano-Laguna et al., 2018) and involves extracting features and machine learning algorithms through supervised learning.

The other category of integrating AI with tutoring systems is more difficult to implement. Typically, in this kind of implementation, personalization can be better considered in terms of learning process (Singh et al., 2022; Tobarra et al., 2021) or intervention (Weng et al., 2020). For this kind of integration, the system architecture needs to be considered along with the inflexibility since the AI algorithm is tightly integrated within the system; it is also a kind of adaptive learning (Paramythis & Loidl-Reisinger, 2003) (Paramythis & Loidl-Reisinger, 2003) implementation. AI-embedded ITSs may have better adaptation capability to respond to students' real-time learning status and have a better chance to intervene with students to provide early necessary assistance.

Many studies have focused on engagement and dropout prevention. Leony et al. (2013) leverage students' facial expressions captured by cameras and leverages machine image recognition algorithms to detect students' emotions. Pereira et al. (2019) leverage historic system log data and train a machine learning program to detect if the student will drop out of an online course, which also provides teacher assistance in terms of engagement.

The major contribution of exploiting AI in education probably has not yet been fully discovered. Although Explainable AI (XAI) is becoming popular in the computer science world, it is still being introduced in the education area. Afzaal et al. (2021) used a counterfactual method to explain how an AI algorithm gave instructors predictions to provide students with necessary assistance. In the other research of Pereira et al. (2021), a more recently developed XAI algorithm called SHAP was used to explain the prediction result.

Methodology

This review paper conceptualization process is based on the book "Qualitative Research from Start to Finish" by Yin (2015) with the analytical methodology mentioned in (Chatti et al., 2012). The overall paper review methodology and content framework follows the PRISMA (Page et al., 2021) methodology.

Conceptualization

Based on the analytical model proposed by Chatti et al. (2012), we can put our main topic in the center and consider four different dimensions around the topic, as shown in Fig. 1. We started from the "Why" and focused on the research objectives coming from the research agenda and research questions. We also conducted a brainstorming session with a few researchers to define "Who" are the key stakeholders and what they will be interested to know and what we can contribute from this review paper.

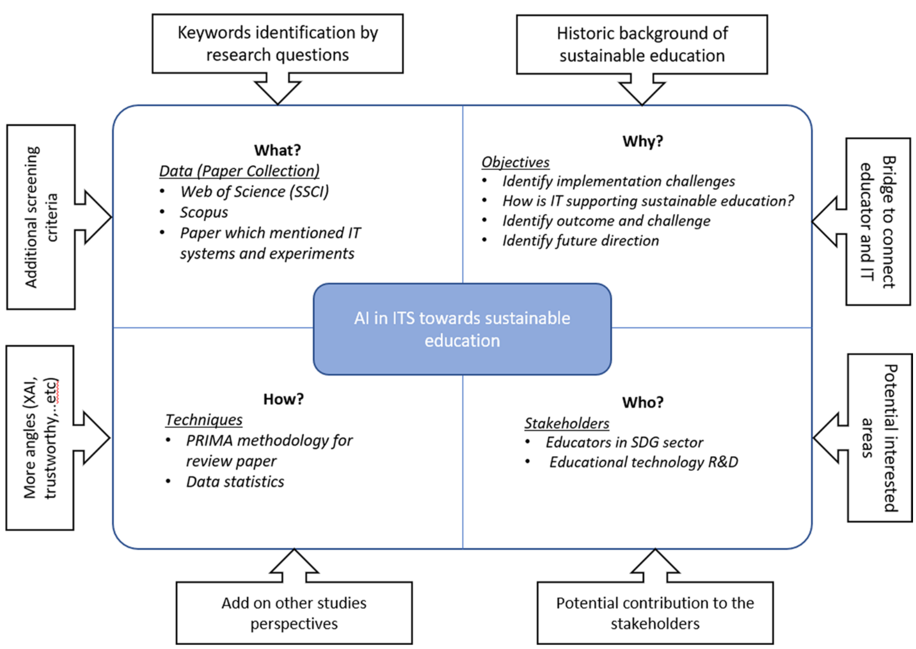

Fig. 1 Analytics model of AI in intelligent tutoring systems

This review paper focuses on educators in the SDG sector and educational technology R&D to provide a systematic review of how AI systems support sustainable education. It may contribute to the understanding and alignment between educators and IT technology in building suitable solutions as well as future potential enhancement toward sustainable education. We discuss the "What" and the "How" in the following section.

Paper selection process

The overall paper selection and screening process is illustrated in the following figure, which follows the PRISMA paper selection process from identification, screening, and eligibility. This process provides researchers with a robust and systematic way of scoping target papers to review. It starts with high-level filtering, abstract screening, and finally content eligibility review. The process and surveyed paper count are illustrated in Fig. 2.

First, the paper search for RQ1 was mainly conducted in Scopus with the keywords "Sustainable Education" and "Challenge". We found 113 articles in total, and then we limited the search results to conference or journal papers written in English only. The query statement can be listed as follows.

(TITLE-ABS-KEY ("sustainable education") AND TITLE-ABS-KEY (challenge)) AND (LIMIT-TO (LANGUAGE, "English") AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p")))

For RQ 2 to 4, we leveraged Scopus and Web of Science (SSCI) to search the surveyed papers. The keywords we used were "Artificial Intelligence" AND ("Education Sustainability" OR "Sustainable Education" OR "Learning Analytics"). Initially we specifically used "intelligent tutoring system" as the keyword but we did not filter out good number of papers and then we later on enlarged the scope to "artificial intelligence" to generally cover "intelligent tutoring system" and "massive open online course". The initial search results were 465 articles from Scopus and 88 from SSCI. Below are the query statements from both.

(TITLE-ABS-KEY ("artificial intelligence") AND (TITLE-ABS-KEY ("education sustainability") OR TITLE-ABS-KEY ("sustainable education") OR TITLE-ABS-KEY ("learning analytics"))) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))

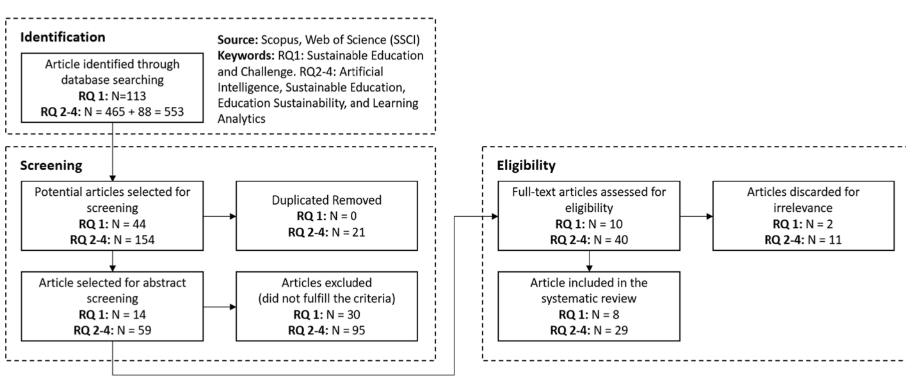

Fig. 2 Paper selection process

Table 1 Article screening inclusion and exclusion criteria

Inclusion	Exclusion
Published between year 2014 to 2023	Published prior to 2014
English language	Not in English
Doc. type: journal or conference paper	Other document types (e.g., books)
Focus on real school educational cases	Focus on methodology or nonschool
Address outcomes and challenges	No outcome or challenges addressed
Must have an IT embedded system	No IT embedded systems

Table 2 Coding scheme to analyze included publications

Category	Code	Label	Description
Type of data (what)	Type of data	A1	Refers to any kind of data such as academic data, performance data, interaction data, etc. that are collected by tutoring to support feedback practices in education
Methods (how)	Machine learning	B1	Refers to the machine learning methods such as neural network to learn from data and perform tasks within tutoring systems
	Data mining	B2	Refers to the data mining methods such as clustering, classification, decision tree, regression, etc. that are used to analyze data within tutoring systems
	Gaming	B3	Refers to the leveraging gaming methods within tutoring systems
	Others	B4	Refers to the other methods such home grown systems
Objectives (why)	Monitoring	C1	Refers to tracking students' learning performance
	Prediction	C2	Refers to predicting students' learning behavior and performance
	Assessment	C3	Refers to providing an evidence-based assessment
	Adaptation	C4	Refers to providing an adaptive and flexible learning scenario
	Personalization	C5	Refers to providing individualized training scenarios
	Recommendation	C6	Refers to providing recommendation of what to do next
	Others	C7	Refers to any other goal that can help to support learners
Target Learners and stakeholders (who)	Elementary	D1	Refers to the elementary school students as the learners
	High school	D2	Refers to the high school students as the learners
	University	D3	Refers to the university students as the learners
	Others	D4	Refers to not specifically mentioned who is the learners

ALL = ("artificial intelligence") AND (ALL = ("sustainable education") OR ALL = ("education sustainability") OR ALL = ("learning analytics")) and Open Access and Article (Document Types)

We applied the same limitation as in RQ 1 for RQ 2 to 4, that is, we limited the search result to only journal or conference papers and the language to English only. Furthermore, for RQ 2 to RQ 4 papers, we further defined the inclusion and exclusion criteria in Table 1 so that we could first perform filtering to target the papers we needed.

Then, we conducted a screening and eligibility process for the surveyed papers with the research team. Finally, we selected 8 to support RQ 1 along with other ad hoc selected papers to discuss sustainable education challenges. For RQ 2 to 4, we selected 29 papers that specifically address how AI is leveraged in the ITS with real educational scenarios for further discussion, which will be described in detail and discussed later.

Results and discussion

Out of all the papers selected in this systematic review, there were 8 for the sustainable education challenges review and 29 for the AI with ITS review. The code scheme of all selected papers are shown in Table 2.

For the 29 AI with ITS papers, the distribution of countries and regions with the education levels involved is presented in Table 3.

There are a total of 13 papers (Choi & McClenen, 2020; Hasnine et al., 2018; Jiang et al., 2019; Lee et al., 2021; Lin & Mubarok, 2021; Lu et al., 2018; Niyogisubizo et al., 2022; Ouyang et al., 2023; Silva et al., 2022; Singh et al., 2022; Tzeng et al., 2022; Weng et al., 2020; Yang et al., 2021a, b) from Asia, 9 papers (Afzaal et al., 2021; Corrigan et al., 2015a, b; Guerrero-Higueras et al., 2018; Llurba et al., 2022; Perikos et al., 2017; Ruipérez-Valiente et al., 2021; Serrano-Laguna et al., 2018; Tobarra et al., 2021) from Europe, 5 papers (Montpetit & Sabourin, 2016; Ogunkunle & Qu, 2020; Pereira et al., 2021; Pereira et al., 2019; Xing & Goggins, 2015) from America and 2 papers (Atapattu & Falkner, 2016; Leony et al., 2013) from Oceania. Most of the study experiment targets are university or above (total of 19 papers), which means that the researchers are more interested in higher education, probably because the teaching and learning environment is more diversified for data gathering.

RQ1: what are the key challenges of sustainable education implementation?

When Sterling and Orr (2001) began advocating that sustainable education must be built upon the sustainability of the whole ecological system, he discussed some challenges in his book. Typical challenges such as the paradigm of education are incompatible with the principle of sustainability because it is mechanistic and driven by business. The other aspect of what he mentioned is the foundational challenge in which the whole education system is largely fragmented, isolated, and not collaboratively working well.

In the last decade, most governments and educationists have promoted sustainable education in all ways along with the United Nations (2015) SDGs, and the challenges

Table 3 Research selected by country and education levels

Regions	Country	Count	Education level
Asia	Taiwan	5	High school: 1, University: 4
	China	3	University: 1, Graduate: 1, General: 1
	Japan	2	University: 2
	Korea	1	University: 1
	India	1	N/A: 1
	Sri Lanka	1	High school: 1
Europe	Spain	5	High school: 2, University: 2, N/A: 1
	Ireland	2	University: 2
	Sweden	1	University: 1
	Greece	1	University: 1
America	US	2	K-12: 1, N/A: 1
	Canada	1	N/A: 1
	Brazil	2	University: 1, N/A: 1
Oceania	Australia	2	University: 2

have shifted to a different angle, especially after information technology was integrated into the implementation of the whole sustainable education system. Sustainability concepts have gradually emerged as part of education curricula, and the challenges with AI and information technology have become more obvious. There might still be resistance (Smaniotto et al., 2023; Wade, 2012), mindset (Tsegay et al., 2022), and awareness (Khahro & Javed, 2022; Shah et al., 2022; Smaniotto et al., 2023) issues, but eventually, these issues will be improved by deploying sustainability culture through information technology in schools. As we stated earlier in this review paper, the challenges may come from IT perspectives as well as the education system. Below are the key challenges summary from the surveyed paper we selected:

- [C1] More challenges taking care of more students during virtual or blended learning environment (Tsegay et al., 2022; Wade, 2012), it may be because students are from remote especially like under COVID situation, and the instructors are forced to use tutoring systems to deliver courses on line.
- [C2] Unequal global access, lack of devices for connectivity or bandwidth (Simuț et al., 2021; Wade, 2012). The network connectivity becomes a bottleneck when students need to join the training from remote, and it becomes another challenge to ensure the quality of connectivity and healthy bandwidth.
- [C3] Teachers' ICT (Information and Communication Technology, which means the integration of telecommunications and computers, as well as necessary enterprise software, middleware, storage and audiovisual, that enable users to access, store, transmit, understand and manipulate information.) teaching skill, use and acceptance of new technologies (Saudelli & Niemczyk, 2022; Simuț et al., 2021; Tsegay et al., 2022). There will be more training needed to enhance the teachers' internet tools usage skill set to ensure teachers accept the new technologies.
- [C4] Lack of physical and emotional interaction (Simuț et al., 2021). Due to the virtual training environment, the teachers will worry about the lack of students' interaction.
- [C5] Limited students collaborative learning (Acevedo-Duque et al., 2023). The students' collaboration will be limited by the systems since the students cannot see each other with virtual and remote training environment.
- [C6] Engagement and dropout concern in virtual learning environments (Khahro & Javed, 2022; Simuț et al., 2021). It's another challenge that students will dropout due to losing attention without teachers' intervention.
- [C7] Privacy and security concern (Tewari, 2020). This is another challenging area when students need to provide personal identify through internet as well as facial biological features.
- [C8] Fairness and bias correction (Tewari, 2020). When leveraging AI systems, the system will be very challenging to provide fair interactions without the bias.
- [C9] Interpretability and transparency (Smaniotto et al., 2023; Tewari, 2020). Providing comprehensive explanation from the AI system to the teachers is another major challenge, the educators will always need a good explanation to trust the AI system when providing any prediction and intervention.

Based on the challenges listed above, there must be some recommendations and guidance that can be given to educators and IT solution architects when implementing sustainable education solutions. Below are key recommendations summarized from the surveyed papers.

- *Awareness [C1, C3]*: The trend of emerging AI technology in education is becoming unavoidable. Fundamentally, delivering awareness of sustainable education and SDG goals is becoming critical to the whole educational eco-system.
- *Policy and regulation [C7]*: Undoubtedly, government and institutional support is another key for sustainable education implementation to support educators since governments are responsible for effective, accountable, and inclusive SDG implementation. Policy and regulations, which also need to be enacted at the government level, may also cover privacy and security protection.
- *Technology enablement [C3, C4, C5, C6]*: Instructors should be trained in more AI-empowered concepts that can potentially be leveraged in educational systems as well as the new internet Connectivity Tools (ICT) digital skills. Eventually, instructors need to know how to incorporate pedagogical strategies and theories into the AI system to make everything meaningful.
- *Infrastructure readiness [C2]*: Obviously, AI and IT technology can be an accelerator and innovation toward SDGs; thus, considering internet connectivity with decent devices becomes crucial. This may also include consideration of the inclusion or diversity of students who need to engage in distanced learning.
- *Explainable systems [C8, C9]*: One of the key responsibilities of AI and IT solution architecture is to develop quality and inclusive systems that can support explainable data-driven decision-making for teachers and students to improve learning outcomes. Only this way can AI and IT provide an environment with fairness, accountability, trustworthiness, and ethics (Khosravi et al., 2022) for sustainable education.

These challenges require collaborative and collective action from all stakeholders involved in education and IT solution architects, such as policymakers, educators, researchers, parents, and students. We need to work together to find innovative and inclusive solutions that can ensure sustainable education for all in the twenty-first century.

RQ2: how are AI and IT incorporated as the ITS to support sustainable education?

There are different purposes and objectives when considering ITSs in sustainable education implementation. However, one of the major consideration points is the need to be more student centric. Below in Table 4, we list the major objectives from the 29 selected surveyed papers.

There is much research focusing on students' performance prediction based on the systems' logs generated during the interaction between the students and the systems. The typical approach involves using machine learning algorithms with a feature extraction process to predict students' performance (Guerrero-Higueras et al., 2018; Yang et al., 2021a, b). The next major objectives are to identify learners' learning behaviors (Lee et al., 2021; Weng et al., 2020), which will most likely be input into the machine

Table 4 Purposes of using AI in intelligent tutoring systems

Purpose	Description	Count
Performance Prediction	Leverage machine learning algorithms to predict learners' outcome performance	13
Learning Behavior Analysis	Leverage system's log to perform clustering and come out different learning behaviors	9
Engagement and Dropout Prevention	Detection of dropout risks by leveraging machine learning programs	5
Provide Intervention	Provide necessary intervention by learning behaviors identification	3
Adaptation/Personalization	Provide personalized training episodes to improve learners' performance	5
Instructors' Support	Provide information (like emotions) to help instructors adopt actions for helping learners	4
Tutoring Systems Assessment	Evaluation the performance of the tutoring system for future enhancement	2
Self-Regulation Learning Improvement	Evaluate the improvement of Self-Regulation Learning capability by survey	2

One study may have multiple purposes

learning algorithm for further performance prediction. Behavior identification can be part of feature engineering, and educators are highly interested in what learning strategies are adopted during the learning process. The other objectives also focus on students' engagement to prevent boredom and dropout (Niyogisubizo et al., 2022; Pereira et al., 2019) and on personalization (Ogunkunle & Qu, 2020) and provide instructors with the suitable timing to deliver interventions (Lin & Mubarok, 2021) and assistance to students.

When considering adaptation and personalization in tutoring systems, one of the ways AI is being used in these systems for personalization is through adaptive learning. Adaptive learning is a personalized approach to learning that makes the best out of every student's learning, and the categories and guidelines were recommended in (Paramythis & Loidl-Reisinger, 2003). This means that using AI in adaptive learning involves analyzing students' learning patterns and developing a customized learning process that will assist students in achieving their best academic performance. Through this smart use of AI, tutors can identify students' strengths and weaknesses and then tailor their teaching strategies to meet their individual needs.

If we further examine how AI and information technology are incorporated into ITSs, below in Table 5, we list what technology supports the different objectives in different ways.

Most of the AI technology embedded in ITSs consists of machine learning algorithms, especially when the system architect does not want to interfere with the original ITSs. Typically, an offline process is involved in performing machine learning and providing necessary information and interaction with instructors or students. Gillani et al. (2023) provides a systematic way to map machine learning algorithms with different ITS purposes. In our study, most of the machine learning technology used for performance prediction is supervised learning (Corrigan et al.,) since we need much historic labeled training data to train the model. However, another concern from this kind of approach is

Table 5 AI and technology used in intelligent tutoring systems

Objective	Category	Technology description	Count
Performance Prediction	Supervised Learning	Logistic or Linear Regression: 5, SVM (Support Vector Machine): 5, BayesNet/NB (Nayes Network or Naive Bayes): 4, RF (Random Forest) 3, NN (Neural Network) 4, AB/XGBoost (Adaptive or Extreme Gradient Boosting): 3, CART (Classification and Regression Tree): 2	33
	Unsupervised Learning	KNN (K Nearest Neighborhood): 4	4
	Others	Novel approach or other models	7
Learning Behavior Analysis	Unsupervised Learning	KNN: 4, SVM: 2	6
	Supervised Learning	Regression: 1, RF: 1, NN: 1, XGBoost: 2	5
	Others	Novel approach or refer to other studies	3
Instructors Support	Natural Language Processing Support	LDA (Latent Dirichlet Allocation): 1, DistilBERT (Distilled Bidirectional Encorder Representing Transformer): 1, NLTK (Python Natural Language Tool Kit): 1, PyCharm (Python Development Kit): 1	4
	Decision-Making and Facial Recognition	HMM (Hidden Mokov Models): 1, Azure for ER (Emotional Recognition), OpenCV (Facial Detection Kit)	3
	Others	Novel approach/refer to other studies	1
Engagement & Dropout Prediction	SVM	Support Vector Machine	1
	Supervised Learning	SVM: 1, RF: 1, XGBoost: 1, GB (Gradient Boosting): 1, NN: 1	4
	Others	Novel approach/Refer to other studies	1
Adaptation/Personalization	CNN (Facial)	Convolutional Neural Network	1
	TensorFlow	TensorFlow Object Detection API	1
	Replika API	Chatbot API	1
Learning Intervention	eMail	Sending reminding through email	1
	System Reminding	System reminds instructors	2
Assessment	Guidelines	Guidelines for system architects	2
Explanation	XAI	Counterfactual and SHAP method	2

One study may have multiple AI technologies involved

about bias, fairness and equality due to overfitting issues, which means that researchers may need more and better training data.

On the other hand, when performing learning behavior analysis (Pereira et al., 2021; Weng et al., 2020), most of the technology used turns to unsupervised learning, which also makes sense since there are no ground truth data for model training and the overall concept is for clustering or categorization without any reference. In addition to the objectives and embedded technology, we also need to examine the scenario used by the educator to answer RQ 2 in a more complete way. In Table 6, we list the typical pedagogical scenarios in the 29 surveyed papers.

Table 6 Scenarios of AI used in intelligent tutoring systems

Category	Major scenarios	Targets	Count
AI Not Embedded in the Tutoring Systems	Performance prediction and behaviors analysis	Instructors	18
	Automatic system intervention	Learners	1
	Intervention recommendation	Instructors	1
	Provide outcome/behavior explanation	Instructors	2
	Discussion topics generation	Instructors	1
	Emotional analysis	Instructors	2
	Dropout prevention early notification	Instructors	1
AI Embedded in the Tutoring Systems	Serious games and interaction with learners	Learners	2
	Intelligently learning path decision (Interactive)	Learners	2
	Natural language or chatbot interaction	Learners	3

One study may have multiple scenarios involved

Table 7 Outcome observed from intelligent tutoring systems with AI and IT support

Category	Description	Count
AI not Embedded in the Tutoring Systems	Performance prediction algorithm verified with high accuracy	10
	Learners' behaviors identified	6
	Learners' participation rate improved by early dropout notification	5
	Learning performance improved after intervention provided	2
	Provide explainable result to instructors	2
	Remind instructors to aid learners through emotion detection	2
	Topics generated by AI are verified	1
	Performance improved after personalized diagnostic feedback provided	1
	Performance improved after emotional detection and recommendation	1
	Learners' satisfaction increased	1
AI Embedded in the Tutoring Systems	Performance improved by interaction with the AI system	3
	Knowledge gained and verified	1
	Higher interest with higher engagement	1
	Performance improved by providing personalized learning path	1
	Remind instructors to aid learners through emotion detection	1

One study may have multiple outcomes identified

The key scenario involves instructors predicting learners' performance based on the learning behaviors captured during the learning process. Here, we combine performance prediction and behavior analysis because normally learning behaviors are captured as one of the features for performance prediction (Ouyang et al., 2023; Weng et al., 2020). Some of the scenarios are for instructors to adopt necessary actions for intervention, while some of the scenarios are for learners to have personalized learning experiences (Serrano-Laguna et al., 2018; Singh et al., 2022).

RQ3: what are the outcomes of AI/IT embedded as the ITS in sustainable education?

In response to RQ 3, the outcomes of tutoring systems integrated with AI and information technology are listed in Table 7. There are still two main approaches in which

AI is or is not embedded into the tutoring system itself. For AI-embedded tutoring systems, most of the outcomes indicate that the performance prediction accuracy is high (Guerrero-Higueras et al., 2018; Hasnine et al., 2018), which implies an opportunity to aid those predicted low performers. However, most of the research does not focus on explaining why and how machine learning algorithms perform predictions, which means that instructors can only take necessary actions based on their experience. Of the 29 surveyed papers, only 2 focus on the result and try to leverage explainable AI (Afzaal et al., 2021; Pereira et al., 2021) on machine learning prediction. Eventually, this will be more valuable to the whole education system since it can eliminate the concerns of educators in terms of fairness, trustworthiness, and inclusion.

There are also some researchers who have explored different learning behaviors (Ruipérez-Valiente et al., 2021; Yang et al., 2021a, b) through clustering algorithms, which can also provide instructors with information for further intervention as necessary. The relationship between performance and learning behaviors is also one of the major areas where researchers may invest great effort since this may help instructors to understand and improve the overall pedagogical process. Some researchers have also shown that AI machine learning algorithms can provide early notification to prevent student dropout (Weng et al., 2020) and enhance engagement (Ouyang et al., 2023).

For AI-embedded tutoring systems, researchers focus on dynamic learning processes and personalization (Tobarra et al., 2021) experience when a system is designed to provide any necessary intervention or adjust the learning path for instructors. Overall, there are still many potential areas we should address to reflect instructors' resource shortages when they have no bandwidth to take care of every student during the learning process and provide necessary intervention or assistance.

The overall outcome seems reasonable, but it needs to be more explainable for learners and instructors to adopt AI technology. Since machine learning algorithms are normally treated as a black box, an increasing number of studies have focused on explaining the AI machine learning model to gain trust from users so that the true value can be demonstrated and accepted.

Table 8 Limitations and challenges

Description	Count
Need more learner's participation for sampling good quality data	5
Features extraction for machine learning not fully representing the learning process	4
Need longer period of learning data statistics	4
AI solution is not portable to other tutoring systems	4
No strong educational theory	2
Need further actions and recommendation in addition to performance prediction	2
Privacy concern	1
Need more advanced big data analysis technology to support better quality	1
Trustworthy concern (the AI solution not being explainable)	1
Need more courses validation of the AI solution	1
No ground truth for AI solutions improvement	1
Machine learning accuracy challenge (e.g. Face recognition when wearing masks)	1

Not all the studies listed the limitations and challenges, and one study may have multiple challenges

RQ4: what is the future trend of AI/IT embedded ITS in sustainable education?

Before we answer RQ 4 and identify potential future research trends, we list the limitations of the challenges of AI-embedded tutoring systems in Table 8. Since most of the AI technology that is used is machine learning, the first limitation and challenge is the amount of data. Theoretically, the more training data from more participation there is, the better, and some research (Corrigan et al., 2015a; Guerrero-Higueras et al., 2018) demonstrates an ambition to expand the participation scope and expectations of higher performance through obtaining more sampling data. The following key limitations are also related to machine learning and include feature extraction improvement (Hasnine et al., 2018), needing longer period learning data (Guerrero-Higueras et al., 2018), or the solution not being portable to other tutoring systems (Yang et al., 2021a, b).

Based on the limitations and challenges, many future potential research directions were mentioned and discussed in the 29 surveyed papers. Potential future directions are listed in Table 9. Again, the top items tend to be related to machine learning aspects, which gives IT solution architect good opportunities with which to start. Typically, researchers want to have a robust solution architecture that can support more precise performance prediction (Lin & Mubarok, 2021) and hope that the solution can be more portable (Silva et al., 2022) by providing a better sample space and training dataset (Guerrero-Higueras et al., 2018).

There is not much research from the 29 papers addressing more recent ways to train machine learning algorithms, such as leveraging transformer to conduct learning behavior clustering or leveraging reinforcement learning to predict or evaluate students' status by teachers' input. While AI and machine learning are becoming increasingly advanced, there might always be a better way to improve and make prediction and analysis more accurate.

There are also some important potential future research directions brought up in some research. While researchers want to focus more on engagement rate improvement (Silva

Table 9 Future direction

Description	Count
Increase the sample space/training dataset (Invite more learners to participate)	7
Expand or integrate the solution to other areas and courses	6
Identify, extract or create more features/observable events for better prediction	4
Educational context/theory validation through experts	4
Leverage alternative solutions to enhance the prediction/clustering accuracy	4
Enhance learners' engagement rate	2
More personalization	2
Better data quality for AI/ML algorithm training	2
Create a dashboard to support real time monitoring and decision-making	1
Add on additional functions to bring up more learners' interest (IDC)	1
Solution generalization to suit for other tutoring systems	1
Close loop system enhancement based on AI explanation	1
Explore more aspects of emotions (like satisfaction, not just for dropout prediction)	1
Better survey response analysis methodology	1
Better intervention mechanism	1

One study may have multiple future directions identified et al., 2022) or personalization (Lin & Mubarok, 2021), some researchers have started to focus on emerging educational theories (Leony et al., 2013) and boosting students' learning interest. Researchers are eager to prove the phenomena derived from machine learning algorithms by linking to educational theories or seeking educational experts' comments. Some researchers have started to combine all observations and created theories to reflect the foundational change from an examination-focused to an interest-focused instruction style (Chan et al., 2018) or even to build a vision of what the future educational environment will be like.

The "explainable" requirements need to be considered and incorporated into the machine learning algorithm during the design phase in the future. Khosravi et al. (2022) deeply explore XAI in terms of education, which also provides good guidance for educators and IT solution architects. Similar to the 4-year project conducted by DARPA (Gunning & Aha, 2019), the technical teams were requested to provide an explainable model and explanation interface to support users making decisions. In addition, there is another team addressing humans' psychological aspects to define how an explanation can be acceptable. Finally, there is also an evaluation assessment check list to verify whether a system can truly be trusted and adopted by users.

In the XAI review paper, Arrieta et al. (2020) categorized many common machine learning algorithms in detail and described how a model can be explained. Such approaches can be adopted in these AI-integrated educational systems to gain more trust from users. Eventually, designing AI and machine learning algorithms with explanations for users will become culture because this might be the only way to eliminate concerns from learners and instructors and adopt AI as a supportive tool when working toward sustainable education.

However, bringing in more social value and human factors will be one of the key future focuses. Along with explainable AI systems and explainable interfaces to support learners and instructors in decision-making, Human-Centered AI (HCAI) (Auernhammer, 2020) consideration is another future trend in the AI and education integration area. Shneiderman (2020) defined a two-dimensional approach for categorizing and providing guidance on how to produce system designs that are Reliable, Safe, and Trustworthy (RST). In the papers of (Yang et al., 2021a, b, 2023), the authors share the aspects of how AI and HCAI can contribute in different ways to sustainable education with proper social values.

Another potential future trend is to maximize the social value that AI systems can bring. For example, virtualized online courses with AI support can eliminate the distance gap of some students so that their educational equality issue can be addressed. In addition, with AI support, the system can be intelligent enough to consider the minority group or individual by providing an adaptive or personalized learning experience. Eventually, the instructors can focus on pedagogical strategy and improve the overall teaching efficacy, students' learning performance with proper intervention, and sustainable education goals.

Conclusions

In this review paper, we leveraged a combination of learning model analytics and the PRISMA review paper framework to discuss how AI can empower educational systems in many aspects. Starting with RQ1, we listed the typical challenges of sustainable education implementation and the integration of AI and information technology. Following RQ2 to RQ4, we discussed different kinds of AI-embedded technology and how they support sustainable education implementation. We also discussed the typical scenarios that are involved when ITSs are deployed to give educators some reference and guidance when thinking about integrating AI into their tutoring systems. Finally, we discussed future research directions that may also provide IT solution architects and educators some ideas on which to continue working.

In this study, we aimed to help our target audience understand the current state of integrating AI technology into tutoring systems, along with the challenges that come with it. We provided clear guidance for educators and IT solution architects on how to implement and deploy AI-enabled systems. This guidance includes understanding the different types of machine learning algorithms, raising awareness among educators, and the needs of navigating government policies and regulations, among other things. Our hope is that this will bridge the gap between educators and IT solution architects, facilitating the smooth deployment of sustainable education systems.

Many benefits have been explored through the implementation of tutoring systems with big data analysis capabilities. AI-integrated tutoring systems may use natural language processing and machine learning techniques to evaluate student responses and determine individual progress by analyzing their learning behaviors. Additionally, AI-based tutoring systems help bridge the gap between educators and students by providing an innovative platform that makes education more accessible. This means that students can learn at their own pace, from wherever they are, which increases flexibility in the learning process. As a result, AI-powered tutoring systems promote equal access to education, regardless of geographical location or financial status.

However, researchers have started to notice that along with the various benefits, the bias generated from AI and machine learning algorithms may also create harm. This harm may come from “allocational” or “representational” aspects (Mayfield et al., 2019) and may eventually derail the purposes of education. As a result of these potential harms and biases, researchers have also started looking at AI not only in an explainable way but also from fairness and trustworthiness perspectives. This will be one of the major future research directions, and more human-centered (or teacher-centered) factors may need to be considered.

Finally, AI has revolutionized education by promoting sustainable education practices that are more student-centered. Compared to a traditional classroom setting, electronic educational resources significantly share the effort of teachers when individual students’ learning status needs to be considered. With better data analytics and insights provided via AI, tutoring applications can also reduce resource waste and improve sustainable education in the long run.

In conclusion, the incorporation of AI in tutoring systems has resulted in positive outcomes in sustainable education. From personalized education, adaptive learning, automated assessments, and flexible learning environments to eco-friendly practices, AI-powered tutoring systems have emerged as a beacon of a brighter future for education.

Abbreviations

AI	Artificial Intelligence
HCAI	Human-Centered AI
ICT	Information and Communication Technology
IT	Information Technology
ITS	Intelligent Tutoring System
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic review and Meta-Analyses
RST	Reliable, Safe and Trustworthy
SDG	Sustainable Development Goal
TEL	Technology-Enhanced Learning
XAI	EXplainable Artificial Intelligence

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Declaration of AI and AI-assisted technologies in the writing process
During the preparation of this work the authors used ChatGPT to conduct proofreading to improve readability and language of single sentences as some authors are not native English speakers. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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