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Educational futures of intelligent synergies between humans, digital twins, avatars, and robots - the iSTAR framework

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Abstract

With the rapid advances of Artificial Intelligence (AI) and its technologies, human teachers and machines are now capable of collaborating to effectively achieve specified outcomes. In educational settings, such collaboration requires consideration of several dimensions to ensure safe, responsible, and ethical usage. While various research studies have discussed human-machine collaboration or cooperation in education, a framework is now needed that aligns with contemporary affordances. Providing such a framework can help to better understand how human teachers and machines can team up in education and what should be considered while doing so. To address this gap, this paper outlines the iSTAR (Intelligent human-machine Synergy in collaborative teaching: utilizing the digital Twins, Avatars/Agents and Robots) framework. iSTAR represents human-machine collaboration as an ecosystem that goes beyond the simple collaboration between human teachers and machines in education. Therefore, it presents core dimensions of DELTA (design, ethics, learning, teaching and assessments) that should be considered in designing safe, responsible, and ethical learning opportunities.

Introduction

Can machines think? is a simple yet sophisticated question (Turing, 1950). In response to this question, a scholarly event was organized in 1955, where the term "artificial intelligence (AI)" was coined to refer to machines and processes that imitate human cognition and make decisions like humans (McCarthy et al., 2006). The Turing Test was proposed, originally known as the imitation game, as a protocol to determine whether a machine can exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human. Such developments proved pivotal in the emergence of cognitive science and debates about 'what computers could or could not do' that shaped much of the early research in this interdisciplinary field (Dreyfus, 1992). A few decades earlier, the term [ro]bot had also been articulated for the first time in Čapek's (1921) science fiction play; however, it was Asimov (1942; 1950) who visioned that these machines could transform into intelligent forms which led him to introduce the *three laws of robotics* to set the rules that bots should stick to.

Not so long ago, current advancements were depicted as science fiction. With the rapid evolution of computational power and access to massive data, however, such capabilities are being realized through Large Language Models (LLMs). AI machines, such as ChatGPT, are now capable of maintaining conversations like humans. As 'conversational agents', these capabilities represent a major innovation extending beyond the information processing of search engines (Mason, 2023). These technological advancements are finding application in various domains, including education. For instance, Intelligent Tutoring Systems (ITS) have matured as a potent educational tool, harnessing AI technologies to deliver personalized and adaptive learning experiences for individuals or groups of students. By integrating sophisticated algorithms and cognitive models, ITS can assess students' level of knowledge in a given subject domain, monitor their progress over a course of learning actions, and provide targeted instructional interventions (including the recommendation of resources to study and practice, guidance and feedback) (Koedinger & Aleven, 2016).

Alongside ITS, computer-based teaching systems like Plato (Programmed Logic for Automated Teaching Operations), originally developed in 1960 (Dear, 2017), have garnered significant recognition in educational contexts. Plato acts as a comprehensive platform for managing courses, delivering content, and conducting assessments, offering teachers a centralized hub to organize and disseminate instructional materials effectively (Dear, 2017; Jones, 2015). Furthermore, the integration of AI companions in education has demonstrated tremendous potential (Sharples, 2022). AI companions, exemplified by ChatGPT, can engage in conversations with students, offer explanations, address queries, and provide guidance; thereby emulating human-like interactions and supporting learners throughout their educational journey (Tlili et al., 2023a; Adarkwah et al., 2023). These remarkable technological advancements have the capacity to transform education by enhancing personalized learning experiences, fostering student engagement, and providing timely support and feedback.

Such technological advancements also raise questions (e.g., Selwyn, 2023; Tlili et al., 2023a) on how human teachers and machines could work together to achieve an educational objective, as well as the meaningful, transformative changes brought to education (e.g., evolutionary or revolutionary). Schmidtler et al. (2015) observed that the relationship between humans and intelligent machines has shifted from human–machine co-existence and cooperation to human–machine collaboration. In business contexts, the notion of 'collaborative intelligence' has also been used to describe how "(h)umans and machines can enhance each other's strengths" (Wilson & Daugherty, 2018, p. 114). Moreover, Schmidtler et al. (2015) used the term 'synergy' as they believed that education is a complex task that requires more than simple collaboration. Such synergy between the human teacher and the machine (i.e., their combined effect is greater than the sum of their separate effects) is crucial to achieving the desired learning objective.

In this context, several studies pointed out that "humans and machines have complementary capabilities that can be combined to augment each other" (Dellermann et al., 2019, p. 4). Scholars (e.g., Gerber et al., 2020) working on hybrid intelligence or human-machine symbiosis further pointed out that excellent outcomes are possible when the abilities of humans and machines are combined in a mutually beneficial exchange (Dellermann et al., 2019). Consequently, human-machine collaboration is referred to in this present study as 'intelligent human-machine synergy during collaborative teaching'. We define human-machine synergy during collaborative teaching *as the way human teachers and machines interact and work together in several educational settings as a team to achieve a common objective, resulting in enhanced learning outcomes. This synergy combines Human Intelligence (HI) and Artificial Intelligence (AI) to achieve Collaborative Intelligence (CI) in education*. Thus, in this era where IT can be depicted as 'intelligent technology', it is crucial to explore and investigate how human teachers and machines could work together to achieve this synergy and collaborative intelligence for future education.

Similarly, the Beijing Consensus on AI (UNESCO, 2019) calls for using AI to empower teaching and teachers. It suggests that related bodies should dynamically review and redefine teachers' roles and required competences in the context of teachers' training policies and capacity-building programmes for better preparation of teachers to work effectively in AI-rich education settings. Kaber (2018) mentioned that one of the core questions in human-machine collaboration is 'Who does what?'. In the same vein, Vuorikari et al. (2020), through the analysis of eight future-oriented scenarios, highlight 'the ethical considerations (including the balance between human autonomy and machines) and the evolving competence requirements of teaching professionals.' It is, therefore, important to further investigate the different roles that human teachers can take in collaborative teaching with machines.

Furthermore, given the rapid progress in AI development and application, it is most important to address ethical questions and issues on the usage of AI and machines in educational settings and systems (Holmes et al., 2023). In particular, the legal and societal responsibility of human control over AI and machines (that is always a human one) needs to be reflected in introducing and using terms such as human-machine collaboration and synergy. We discuss these urgent and challenging aspects in full detail later.

To sum up, human-machine collaboration can change how we live and do daily tasks and activities. Aspects of human-machine collaboration have been investigated in several fields, such as economy (Bolton et al., 2018), managerial decision making (Haesevoets et al., 2021), and health monitoring (Muin & Mosalam, 2021). However, very few studies have proposed a viable model or comprehensive framework for human-machine collaboration in education. There is still a lack of information on what types of machines teachers could collaborate with in education and how to ensure an effective collaboration for a safe learning experience and enhanced learning outcomes. To close the various research gaps, this study presents a conceptual analysis and proposes an innovative human-machine collaboration framework, namely the iSTAR framework. The iSTAR framework focuses on intelligent human-machine Synergy in collaborative teaching through utilizing Digital Twins (DT), Avatars, and Robots (iSTAR). It aims to present the different types of machines that human teachers could collaborate with in education, as well as different levels of possible collaboration. Additionally, the iSTAR framework signals how human teachers could work with machines and how their roles can be reformed in the era of so-called 'intelligent technologies', keeping in mind different dimensions for a safe and effective learning environment. The iSTAR framework was developed based on a rapid review, which is defined as "a type of knowledge synthesis in which components of the systematic review process are simplified or omitted to produce information in a short period of time" (Tricco et al., 2015, p. 2).

Theoretical background: Human-machine collaboration

Several theoretical foundations can be identified in the emergence of human-machine collaboration. Hoc (2000) observed that the trend toward increased complexity and coupling of Information Technology (IT) systems required a new conception of human-computer interaction (HCI) that signalled the role of interfacing with automated systems. He argued that a "human-machine cooperation (HMC) approach is necessary to address the new stakes introduced by this trend" (Hoc, 2000, p. 833). This construct can also be found in earlier literature (Vanderhaegen et al., 1994). Likewise, the foundational terminology of 'socio-technical systems' was coined around 1960 in the context of labor studies "to stress the reciprocal relationship between humans and machines" (Ropohl, 1999, p. 186). The terminology of socio-technical systems (STS) and human-machine cooperation (HMC) is now embedded in the literature, and both place emphasis on systems interoperability. Thus, systems science can be regarded as a pivotal foundation of the more recent construct of 'human-machine collaboration'.

Further investigation of the origins of human-machine collaboration are revealed in the development of Man-Machine-Environment System Engineering (MMESE), a fundamental principle of human-centered system design. This principle was initially introduced by Professor Shengzhao Long in 1981, with the influential support of esteemed Chinese scientist Xuesen Qian (Guo et al., 2022). MMESE has developed as a research field that uses system science theory and system engineering methods to efficiently handle the relations between humans and machines with a view to achieving an "optimal combination of man-machine-environment system" (Long & Huang, 2022, p. 3). During the past 40 years, MMESE has been developed and applied to many areas, such as automation systems, shipboard equipment, aircraft systems, finance, etc. Notably, the three goals of the optimization of MMESE are safety, efficiency, and economy (Long & Huang, 2022).

Card (2018) observed that human-machine collaboration as a research field is different from human-machine interaction because it goes beyond interaction and information presentation theories to include team- and group work. Human-machine collaboration has been tackled in the literature from various perspectives, most commonly from the different levels of automation (Vagia et al., 2016), where fully manual implies that humans are fully in control, while fully automated implies that humans, as operators, are completely out of the loop (Parasuraman et al., 2000). However, less consensus exists in the literature about the scales between 'fully manual' and 'fully automated'. Consequently, several taxonomies have been put forward discussing the various automation levels (Saurin & Patriarca, 2020; Simmler & Frischknecht, 2021).

Most of the aforementioned frameworks are technical-focused, neglecting the importance of effective synergy between humans (in this study, human teachers) and machines to achieve a collaborative activity (in this study, collaborative teaching). In the field of Intelligent Tutoring Systems (ITS), however, this consideration is more prevalent (Longo et al., 2017). Dellermann et al. (2019) stated that for effective human-machine collaboration, the machine should not deal with all of the roles in a team but should instead be built to complement human activity and intelligence (collaborative intelligence).

This idea has persisted in education, where Vuorikari et al. (2020) discuss three different approaches, namely, teacher-in-the-loop, teacher-over-the-loop and teacher-out-of-the-loop to deal with the distribution of responsibility between human teachers and an algorithm/machine in educational applications and services that rely on autonomous decision-making (e.g., AI). Han and Huang (2023) further articulated the idea that machines should empower human teachers and collaborate with them to better achieve a given educational goal. In many contexts, this augmentation role requires machines to be designed with human-like abilities, enabling them to act like humans (Nass & Moon, 2000). This vision has led to the development of the *computers are social actors theory* (or social response theory), which highlights that "humans mindlessly apply the same social rules used for human interactions to computers" (Nass & Moon, 2000, p. 669). This theory emphasizes anthropomorphism, attributing human characteristics to non-human actors (Qiu & Benbasat 2009; Watson 2019).

These characteristics could involve several aspects, including appearance, behavior, reasoning, etc. Following on from this theoretical perspective, the present study identifies two human-like machines (that can also be called technologies) that could collaborate with human tutors, namely *(1) physical robots* and *(2) avatars/agents*. The first type of machine (technology) allows collaborative teaching in physical spaces (e.g., classrooms), while the second type of machine (technology) allows collaborative teaching in cyberspaces. Specifically, Han et al. (2023) further point out the importance of providing realistic cyberspaces to enhance human-machine collaboration in education. To achieve this, the present study adopts *digital twins* as another important technology in human-machine collaboration in education.

Importantly, this study is also informed by the literature associated with human-centered design in the development of technology, as it provides guidance on principles for maintaining the preeminence of human agency within complex systems environments (Dart et al., 2019; Giacomin, 2014; ISO, 2019). Moreover, while human-machine collaboration is informed by this work, it also extends the scope. For example, due to advances in the Internet of Things (IoT), Cruickshank and Trivedi (2017) point out that in an IoT environment, a 'user' might be a toaster!

To summarize, to ensure human-machine synergy in collaborative teaching, this study proposes the iSTAR framework, which builds on the three identified enablers (technologies), namely (1) digital twins, (2) avatars/agents, and (3) physical robots, that can be intelligently tuned into synergistic relations with human input. The overall framework places a human at the centre of these three enablers, making explicit the relations with the human teacher. Details are presented in the next section.

iSTAR framework

Figure 1 shows the iSTAR framework, which depicts the various dimensions of human-machine collaborations (HMC) based on the three identified machines, namely digital twins, avatars/agents, and physical robots. Particularly, the iSTAR framework places the human teacher at the center. This means that the design of human-machine collaborative teaching should be human-centered, and machines should be used as enablers to augment human teachers (Dede et al., 2021; Dede et al., 2017) rather than replace them.

iSTAR dimensions

The three dimensions of iSTAR are described below.

Digital twins

A digital twin is the digital representation of a physical object, person, or process contextualized in a digital version of its environment. As one of the main technologies associated

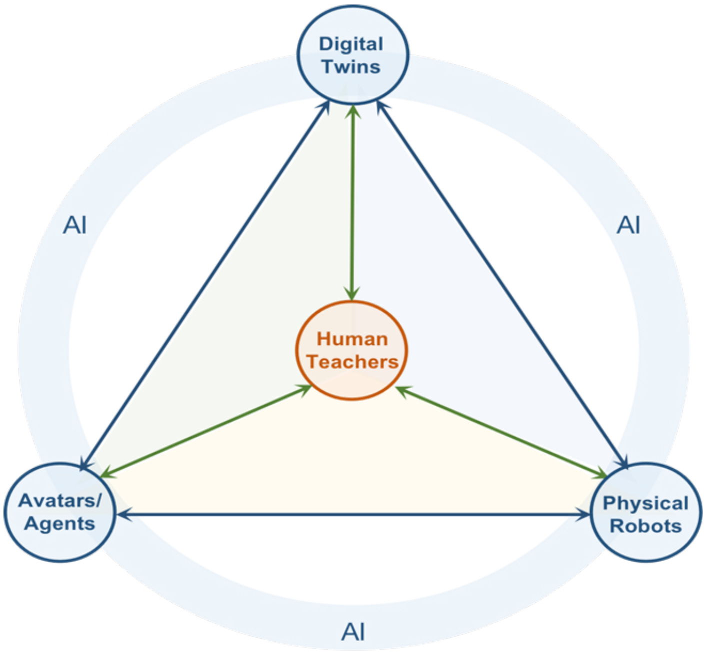

Figure 1. iSTAR framework.

with Industry 4.0, the terminology of 'digital twin' was first proposed by Michael Grieves, to mitigate issues leading to undesirable and unpredicted emergent behavior at the phases of creation and production and realized during the operational phase in complex systems (Sepasgozar, 2020). Prior research highlights that digital twin systems consist of two sub-systems, the physical system and a virtual system, which contain all essential information about the physical system (Liljaniemi & Paavilainen, 2020). Data flows between the physical-digital objects, which are fully integrated in both directions. This enables the virtual system to represent, monitor, and issue commands to the physical system while also understanding, evaluating, and predicting the state of the physical counterpart, generating insights and suggestions to optimize the system's performance throughout the lifecycle. Digital twin systems are becoming more and more common in the areas of manufacturing, finance, aerospace, etc. There are also attempts in education to investigate methods, benefits, and barriers to adopting digital twin technology (Tlili et al., 2023c).

Avatars and agents

Avatars and agents have demonstrated their effectiveness as valuable tools in education (Segaran, 2021). In past research, these two terms have been used interchangeably. Nevertheless, it is crucial to recognize that the two possess distinctive attributes and characteristics. Bailenson and Blascovich (2004) define avatars as "a perceptible digital representation whose behaviors reflect those executed, typically in real-time, by a specific human", while an agent is "a mathematical or computational formula designed to achieve a specific goal" (p. 65). In other words, the controller is one of the main differences between avatars and agents. Avatars are human-controlled representations of persons or other entities, whereas agents are computer-controlled representations. Agency is a broad term, however, and it should be noted that avatars could act as agents, with some control residing in the computer instead of a human. Such variations in control are seen in video games, where these avatars are referred to as Non-Player Characters (NPC). In addition, avatars and agents appear differently. Avatars are typically graphical representations, such as 3D/2D models or images, representing the user's visual persona (Blake & Moseley, 2010). Nevertheless, agents may not have a graphical representation as software programs or systems, such as chatbots, or they may have a graphical appearance to enhance social interaction (Baylor, 2011).

Physical robots

Robots can be used in intracurricular and extracurricular activities (Mubin et al., 2013). They can have different roles, including being used as learning tools/teaching aids (robotics education) or as co-learners, peers or companions, mentors, and tutors (Mubin et al., 2013). The robot's appearance has evidently affected students' responses and interactions with an education robot in different stages, from junior grade to undergraduate level. Junior-grade students prefer a toy-like robot with a cute design; middle-grade students care about the appearance of anthropomorphic robots; senior-grade students will keep interest in a robot if its responses are non-repeating; and undergraduate students will care about the functionalities of an education robot (Sun et al., 2018).

iSTAR scenarios

As shown in Table 1, various levels of human-machine collaboration can be conceived. Level 0 *depicts humans using machines simply as tools* (e.g., calculators) without any collaboration. Level 1 represents *Basic Human-Machine Collaboration (HMC)*, while Level 2 represents *Dual Human-Machine Collaboration (HM^2C)*. The difference between these two levels is in terms of the established collaboration between the human teacher, the machine and the learning space.

Specifically, in basic Human-Machine Collaboration (HMC), collaborative teaching is established between the human teacher and only one machine type, which could be digital twins (HMC1), avatars/agents (HMC2), and physical robots (HMC3). Additionally, the learning space is either physical or cyber. With Dual Human-Machine Collaboration (HM^2C), on the other hand, more complex collaborative teaching activities are enabled, where various types of machines could also collaborate, in addition to the human teacher, to achieve an educational objective. Therefore, M^2 represents two or more types of machines working together and amplifies the level of collaboration between machines. Additionally, it is seen that the learning space is becoming more complex, where a possible real-time collaboration in physical and cyber spaces could occur. Finally, *Complex Human-Machine Collaboration (HM^nC)* depicts the future development of this field, where human teachers could work with several machines in a balanced and safe ecosystem of humans and machines to achieve a specific educational goal.

Table 1. Classification of Human-Machine Collaboration.

Level 3	Complex Human-Machine Collaboration (HM^nC)	Humans collaborate with more than two types of machines
Level 2	Dual Human-Machine Collaboration (HM^2C)	Digital Twins & Avatars/Agents
		Digital Twins & Physical Robots
		Avatars/Agents & Physical Robots
Level 1	Human-Machine Collaboration (HMC)	Digital Twins
		Avatars/Agents
		Physical Robots
Level 0	Human-Utilize machine (HUM)	Humans simply use machines as tools

Examples of each human-machine collaboration (Level 1 and Level 2) within the iSTAR framework are described below.

Level 1: Human-machine Collaboration (HMC)

Based on Figure 1, various educational scenarios are found in the literature related to the Level 1 of Human-Machine Collaboration, as follows:

HMC1 (human teachers-digital twins)

Kaarlela et al. (2022) introduce a novel robotics teleoperation platform supported by the emergence of Industry 5.0. The platform described by Kaarlela et al. (2022) is based on digital twins with bi-directional data transmission between the physical and digital counterparts. The proposed system allows teleoperation, remote programming, and near real-time monitoring of controlled robots, robot time scheduling, and social interaction between users. Teachers can use the platform as a teaching tool, cooperating with students to finish robotic programming.

HMC2 (human teachers-avatars/agents)

Mizrahi et al. (2022) presented a novel system for facilitating small group online talks using an avatar during video conferencing, where avatars act as agents to support teaching and learning. The avatar was pre-programmed, whereas the course instructors created the material for the activities. Students from the tenth grade interacted with the system in groups, where Mizrahi et al. (2022) compared avatar-facilitated activities to unfacilitated activities. The findings demonstrate that when compared to activities without avatar facilitation, students felt the activity with the avatar was much more efficient, more understandable, and encouraged more involvement. In addition, students were more likely to speak with avatar facilitation.

To provide inclusive education for deaf students, Brazil teachers collaborated with animated 3D avatars as the latter served as sign language translators. Using the avatar translator, Spanish speech can be translated to Spanish sign language through speech recognition technology. Therefore, it can translate what the teacher is saying automatically, allowing deaf and hard-of-hearing students to follow the instructor as easily as their hearing peers (De Martino et al., 2016).

HMC3 (human teachers-physical robots)

Following the pioneering work of Seymore Papert in the 1960s, there is already an extensive history of robots being successfully used in classrooms to teach programming concepts (Resnick, Ocko, & Papert, 1988). More recently, Kindergarten Social Assistive Robotics (KindSAR) is a practical example of using robots in contemporary education settings (Keren & Fridin, 2014). With the help of this cutting-edge technology, kindergarten teachers now have a creative means of fostering social learning. It has previously been shown that children in a preschool setting gain from using the KindSAR robot to play educational games (Keren & Fridin, 2014). An interactive robot worked as a teacher's aide, reading small groups of kids taped stories while combining songs and motor activities. For instance, KindSAR tracks children's development over time while giving children and the teaching staff detailed feedback on how well they performed in the game or assignment. Then, the kindergarten staff can use the visual and audio task performance data and feedback for further teaching design. The findings indicate that the kids respected the robot's authority and enjoyed engaging with it. This study reveals that implementing KindSAR in preschool education is feasible and will have the desired effects (Keren & Fridin, 2014).

Level 2: Dual Human-machine Collaboration (HM^{2}C)

Based on Figure 1, various educational scenarios are found in the literature related to Level 2 of human-machine collaboration, as follows:

HM^{2}C1 (human teachers-avatars/agents-digital twins)

Virtual Reality Learning Environments (VRLEs) describe a platform that uses digital twins to create a learning environment similar to the physical one, where students and teachers use their avatars to conduct various tasks within the designed virtual laboratories (Lugrin et al., 2016). In VRLEs, teachers and students can communicate and collaborate with peers and engage in educational tasks providing and receiving real-time feedback (ibid). One crucial aspect of the VR learning experience is the utilization of the multi-user VRLEs, as shared spaces or worlds, where students and educators have extensive control over individual 3D avatars. It was reported that the combination of multi-user VRLEs and avatar representation can enhance students' and teachers' engagement and performance in the teaching and learning process (O'Connor et al., 2018; Schild et al., 2018). For instance, in the TeachLivETM platform, teachers are immersed in a real-time 3D simulation of a classroom with a head-mounted display and headphones (ibid). Importantly, their body motion and facial expressions can be captured in real-time and projected onto a high-fidelity avatar. In addition, teachers can carry out the lectures and communicate with students in the virtual environment through the avatars.

HM^{2}C2 (human teachers-avatars/agents-physical robots)

It is better for teachers to build a learning environment using digital reality in conjunction with robots due to the constraints of time and space as well as the restricted interaction capabilities of robots. For example, Al Hakim et al. (2022) developed an interactive situated learning approach to enhance students' learning performances. In their approach, students and robots role-play characters and immerse themselves in digital situated learning tasks and challenges. In addition, robots can provide real-time feedback to guide and assess how well students are applying their knowledge, based on pre-setted agents. The evaluation was conducted during interactions with the robot, virtual objects, and virtual characters based on textbook context and content. This approach encourages human-robot interaction while allowing students to study and engage in any situation relevant to the textbook subject that can be efficiently digitalized.

HM^{2}C3 (human teachers-digital twins-physical robots)

The substantial expense associated with deploying robots and their utilization in widespread educational settings, particularly in underprivileged and distant regions, presents a formidable challenge. There is also a risk of causing personal injury when using robots in teaching. One way to solve this problem is to 'virtualize' robots. For instance, Shahab et al. (2021) developed Virtual Reality Robots (V2R) based on the social robot NAO to conduct music education for children with high-functioning autism. Virtual humanoid robots teach children with autism to play instruments in the virtual classroom. Human tutors act as an operator to control virtual robots and give assessments. For skills such as handwriting, painting, and driving, which require hands-on instruction, it is often difficult to achieve remote teaching. However, a haptic-based training system provides a solution in this scenario.

In the haptic-based training system, a network connecting two haptic devices plays the role of putting hands together, based on which the algorithms of haptic guidance and correction in real-time are developed for skill transmission between human experts and trainees (Liu et al., 2013). Solis et al. (2002) used haptic interfaces as cooperative systems to reproduce and simulate human actions, such as teaching people to write Japanese characters. The Reactive Robot systems provide the capability of interpreting the human teacher's actions and exert a more intelligent force feedback strategy.

Robots and digital twins can collaborate in effective teaching. In a classroom or at home, the robot sits next to the student. The educational lesson is displayed on a computer screen in front of the student and the robot. Through the online interface, a remote teacher can teach the student from anywhere in the world using a robot. A student who interacts with a robot in this way might behave similarly to kids who read to dogs in the Reading with Rover program (http://www.readingwithrover.org/) (Lee et al., 2008). This program has demonstrated that students do better when they read to a dog rather than a stranger adult because they are less anxious. It is plausible that a friendly robot character may elicit the same reaction. Additionally, because the robot is always under the control of the instructor, the instructor is prepared to respond to a student who is distracted from the course or poses a spontaneous question. The training system does not operate as a fully autonomous robot since current systems are still incapable of effectively managing the intricacies of human behavior.

A new form of teaching is a robot system for English classes, which utilizes a teleoperated robot controlled by a teacher from a remote site. By providing a unique operation interface that incorporates non-contact vision recognition technologies, a teacher can easily control the robot from a distance to provide lectures (Yun et al., 2013).

The development of human-robot interaction strategies, such as promoting trust between humans and machines in high-stakes situations like emergency response, will be greatly impacted by this digital twin (Pairet et al., 2019). Additionally, it will enable the evaluation of task planning algorithms for collaborative inspection and long-term autonomy, as well as human-guided supervision and management of the robotic assets from a remote-control station.

iSTAR considerations

This section introduces and discusses the considerations in relation to Design, Ethics and Learning, Teaching and Assessment (DELTA) aspects that need to be addressed when designing iSTAR implementations. Considering these aspects can support developing responsible and effective human-machine collaboration in education. Each of the DELTA considerations is discussed in the subsequent sections.

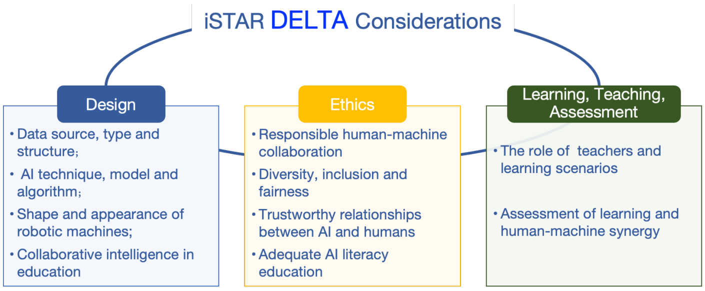

Figure 2. DELTA considerations for designing iSTAR.

Design

Data source, type and structure

The data produced through human-machine synergy is diverse and can support collaborative teaching in various ways. It can be collected from both the human and the machine to enhance the achievement of educational objectives. Human data could include their log data, behaviors, and facial expressions, among others. The machine data could include response accuracy, execution and feedback time, and educational support level, among others. For instance, feedback can be provided to the machine through various inputs such as gestures, behavior, touchscreens, keyboards, and voice commands. This feedback can be used to improve the machine's performance and adapt its behavior to better meet the needs of the users. For example, data from students' gestures or answers could be used to assess their understanding of the material and provide personalized feedback or instruction.

Robots can be equipped with various sensors to collect multimodal data such as audio, visual, and haptic feedback in teaching and learning environments. Cameras, for instance, can capture facial expressions, student gestures, and behavior; microphones can capture speech; eye-tracking devices can capture eye movements; and wearable sensors can obtain various physiological signals such as heart rate and brain waves. In this way, this data can provide valuable information about the interactions between the machine and the students or teachers by providing further data for analysis and improvement of the learning experience (Stracke & Skuballa, 2021).

Data types and structures in human-machine collaboration include multimodal data, which refers to data from different sensors or modes such as text, image, speech, video, notes, logs, gestures, sensors, behavior, and feedback. One of the challenges that come with multimodal data is standardization and interoperability (Yeo & Nielsen, 2020). An approach to aligning multimodal data, therefore, is to map the data from different modalities into a common representation space and then perform alignment in that space. This can be achieved by training a multimodal deep neural network (Summaira et al., 2021; Jabeen et al., 2022).

To ensure an effective human-machine collaboration in education, based on the foregoing discussion, it is vital to analyze what type of educational data from the human or the machine should be collected (e.g., learning navigation behavior, facial expression, etc.) depending on the key educational goals (prediction, personalization, etc.). The use of 'should' here is because there are ethical imperatives to consider when using human data. Additionally, it is important to study how the rich data could be standardized so it can be analyzed to reveal more insights about the educational process (Sampson et al., 2022).

AI technique, model and algorithm

AI technologies such as machine learning (ML), including reinforcement learning (RL), unsupervised learning (UL), and supervised learning (SL), demonstrate a huge potential in their usage and application in education covering many diverse scenarios (Bozkurt et al., 2023) and have been used in various ways to support human-robot collaboration (HRC) (Duan et al., 2019). Among them, unsupervised learning has been used to model human behavior and predict human intentions. Supervised reinforcement learning has been used to improve robot perception and recognition of human actions (Semeraro et al., 2021).

Reinforcement learning (RL) determines a policy for an agent to maximize a cumulative reward through learning by interaction with the environment. RL has been used to optimize task allocation between humans and robots. For example, the system may receive rewards or penalties when students succeed or fail to complete a learning task with robots. By continuously updating the allocation strategy based on this feedback, the system can learn to make better decisions over time and improve its performance. Unsupervised learning (UL) focuses on finding patterns in unlabeled data and can be used to analyze and cluster data to uncover hidden structures or relationships within the data. For example, UL models could be used to cluster students based on their learning preferences, allowing for more personalized instruction. Supervised learning (SL) involves training a model using labeled data. SL can be applied in teaching and learning through the integration in intelligent tutoring systems (ITSs). For example, ITSs use SL algorithms to identify areas where a student is struggling and provide targeted instruction or practice problems to help the student improve.

Deep learning (DL) is a collection of techniques and methods for using (artificial) neural networks to solve ML tasks, whether SL, UL, or RL. DL based on Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Transformers, and other frameworks is widely employed in HMC. Among them, Recurrent Neural Networks (RNNs) can effectively incorporate temporal dependencies, such as Long Short-Term Memory (LSTM) networks, while Transformers are based on an attention mechanism.

Deep neural networks have been successfully applied to computer vision, natural language processing, recommender systems, speech recognition, and other tasks. Computer vision includes object recognition and semantic segmentation. For example, a standing posture recognition system combined with vision-based techniques and deep learning can be utilized to detect the operator's posture and predict the operator's intended action in human–robot collaboration (Li et al., 2020). Applications of natural language processing (NLP) such as sentiment analysis, question answering, machine translation, and other tasks have been used to improve communication between humans and machines by enabling machines to understand and respond to natural language input from humans. Notably, ChatGPT is powered by a large language model (LLM) which can provide just-in-time feedback based on GPT (generative pre-trained transformer) in Human-AI Collaboration (HAC) (Sharma et al., 2022).

Shape and appearance of robotic machines

Robotic machines can be in different shapes, including humanoid, semi-humanoid, animal-like, etc. The shape and appearance of machines can largely affect their effect on users, as reported by numerous researchers. Differences in gender, skin color, size, and position of facial parts of machines influence the decision-making, impression and judgment by users, which makes the design of their shape and appearance especially important. One theoretical example is the Uncanny Valley Effect (UVE). Uncanny Valley was firstly proposed by Masahiro Mori to hypothesize about people's reactions to robots that looked and acted like humans. According to the theory, a person's response to a humanlike robot would abruptly shift from empathy to revulsion as it approached but failed to attain a lifelike appearance (i.e., robots should be almost just like humans, not only in terms of appearance but also in terms of touch, feelings, movements, etc.).

Given such predictions, the design of humanoid robots should certainly avoid the uncanny valley. Apart from that, the shape and appearance of a machine should be designed according to the educational field and level. For example, a robot-like agent that teaches robot history is more effective than a robot-like agent that teaches humanities (Matsui & Yamada, 2019). Another study (Ringwald et al., 2022) also found that preschool students are more interested in robots that look like animals, such as bees.

Therefore, to ensure an effective learning process, future research direction should investigate the shape and appearance of machines when working with humans, depending on the educational scenario, including educational field, educational level, and educational context.

Collaborative intelligence in education

The notion of collaborative intelligence (CI) can be traced back several decades to early AI theorizing (Selfridge, 1959). Likewise, the related construct of 'collective intelligence' has got the same history with similar semantics (Suran et al., 2020). CI implies that AI and human intelligence complement, or augment, each other in completing a given educational task. Such a conception builds on complementary strengths; the leadership, teamwork, creativity, and social skills of humans, and the speed, scalability, and quantitative capabilities of machines, hence co-evolving together. To realize such collaborative intelligence, the natural capabilities of humans and machines in teaching scenarios require detailed analysis and appreciation of distinctive capabilities, such as humans having a sense of immediate context, humor, and responsibilities, while machines have computing power and physical abilities that humans can't achieve. Note that one relevant practice is Collaborative Intelligent Tutoring Systems (CITS), which are learning systems that integrate AI into collaborative learning environments (Ubani & Nielsen, 2022).

Ethics

With the rapid development and widespread use of intelligent technology, especially AI, educational technologies have moved from the backwaters of academic research to the forefront of the public. UNESCO (2019) indicated that the real AI age must be based on multi-level and all-field human-machine collaboration. It has been suggested that human-machine collaboration has great service to education (Kaarlea et al., 2022; Mizrahi et al., 2022; Tlili et al., 2023a). However, the integration of AI in teaching also raises some fundamental ethical concerns, for example, human dignity, discrimination, inequality, and data privacy issues (UNESCO, 2021; European Commission, 2019; Holmes et al., 2023). The ethical issues should be considered as a prerequisite concern for effective human-machine collaboration. Moreover, it is arguable that the evolution of AI as a branch of computer science has reached a point where ethical and social responsibility imperatives deem it is now multi-disciplinary.

Responsible human-machine collaboration

As the integration of machines into education continues to advance, responsible human-machine collaboration has become increasingly important. In this context, responsible collaboration refers to the alignment of human values with machine capabilities to ensure that machines operate within acceptable ethical boundaries. In this context, three key pillars of responsible HMC should be considered, namely: (1) human dignity, (2) data privacy, and (3) technical robustness and safety.

Human dignity: According to the European Commission (2019), machines should support human autonomy and decision-making and be prescribed by the principle of respect for human autonomy. Furthermore, their usage and application should address and support human rights, democracy, and the rule of law (Holmes et al., 2023). Machines should not be designed to degrade or demean human beings in any way. Instead, machines should act as enablers of a democratic, flourishing, and equitable society by supporting human users' fundamental rights. For example, assistive technologies should be designed to improve the quality of life for learners with disabilities rather than simply replacing them with machines (Alnahdi, 2014). Additionally, machines should not be programmed to discriminate against certain individuals or groups based on factors such as race, gender, or religion.

Data privacy and governance: Intelligent machines, especially AI, usually require a large amount of data, which involves a large amount of confidential information of students and teachers; hence, ethical and security issues will arise when collecting, using, and disseminating (Chen et al., 2021). Therefore, data privacy is a critical aspect of responsible human-machine collaboration. To protect users' privacy, machines must ensure credible data protection and governance systems. This includes implementing strong encryption and access controls, as well as providing individuals with control over their own data. For example, learners should be able to decide what data they want to share with machines and who has access to that data.

Technical robustness and safety: A crucial component of achieving responsible HMC is the technical robustness of machines (European Commission, 2019). It is essential to guarantee that machines operate as intended and do not malfunction or fail unexpectedly. Machines must be designed with appropriate fail-safes and error correction mechanisms to prevent harm to humans or the environment (ibid). Additionally, machines must be thoroughly tested and evaluated to ensure that they meet performance and safety standards.

Diversity, inclusion, and fairness

Diversity, inclusion, and fairness are critical aspects of intelligent human-machine synergy in collaborative teaching. The European Commission (2019) emphasizes that ensuring diversity and inclusion in AI development and use is necessary to avoid bias and discrimination. This is because AI systems can perpetuate and even amplify existing societal biases if they are trained on biased data or developed without considering the diverse needs of users. Therefore, in the intelligent human-computer synergy in collaborative teaching, diversity, inclusiveness and fairness in the development and use of artificial intelligence should be considered.

To achieve diversity, inclusion, and fairness in intelligent human-machine synergy in collaborative teaching, it is essential to integrate these concepts into all levels of education and professional development (UNESCO, 2021). This integration should include technical aspects of AI, such as how to design and test AI systems for fairness and how to mitigate bias in data, as well as ethical and social aspects, such as the impact of AI on marginalized communities and the need for inclusive design. One approach to promoting diversity, inclusion, and fairness is through using diverse and representative data sets.

Buolamwini and Gebru (2018) noted that AI systems should be trained on diverse and representative data sets to avoid bias and discrimination. Therefore, it is essential to educate individuals on the importance of using diverse and representative data sets in AI development. Another approach is interdisciplinary collaboration. The European Commission (2019) states that interdisciplinary approaches to AI education can help individuals develop a holistic understanding of AI technologies and their potential implications. Such approaches can involve experts from computer science, ethics, law, social science, and humanities, working together to design and develop AI systems that are fair and inclusive.

Trustworthy relationships between AI and humans

For humans to effectively collaborate with machines, they must trust that the machine will behave ethically, accurately, and transparently. These are the foundations of trustworthiness and a focus of international standardization in the field of AI (ISO/IEC, 2020). Therefore, AI systems must be designed to be transparent, explainable, and accountable (Felzmann, 2020). AI systems must be transparent in their decision-making processes to ensure that humans can understand the rationale behind their decisions. This transparency is particularly important when AI systems are used to make decisions that directly impact human lives, such as in healthcare or legal contexts (Floridi et al., 2019; Tlili et al., 2023d). Additionally, AI must respect human values and not undermine human dignity (Coeckelbergh, 2017). Therefore, AI must be designed to enhance human capabilities rather than replacing them.

Moreover, accountability is another important ethical consideration in the social relationship between AI and humans. AI systems must be accountable for their actions and decisions, and mechanisms must be in place to hold them responsible for any harm that they cause (Scherer, 2016).

There are potential risks associated with the social relationship between AI and humans, which must be addressed ethically. For example, AI systems can reinforce existing biases and discrimination if not purposely designed with ethical considerations in mind (Mittelstadt et al., 2016). Additionally, AI can be used to invade learners' personal privacy, monitor and manipulate behavior, and promote unethical practices (Zuboff, 2019). Therefore, ethical considerations must be addressed in the design and implementation of AI systems to avoid these risks.

Adequate AI literacy education

Adequate AI literacy education in intelligent human-machine synergy in collaborative teaching is a critical aspect of preparing individuals for the increasing integration of AI into various aspects of society. As noted by the European Commission (2019), AI literacy education involves developing a comprehensive set of knowledge, skills, and attitudes necessary for individuals to interact with intelligent machines effectively and ethically in a collaborative context. Such AI literacy includes understanding AI technologies, their capabilities and limitations, and the ethical and social issues related to their use. Besides, Tlili et al. (2023a), based on different human-machine collaboration scenarios, specifically with ChatGPT, revealed that not only are ICT competences now required but also general skills, such as critical thinking and question-asking competences to get the best results of the machine. This 'old' need for generic horizontal competences in our digital era is becoming more demanding due to the introduction of AI (Stracke, 2011, 2014).

The need for adequate AI literacy education in intelligent human-machine synergy in collaborative teaching cannot be overstated. UNESCO (2021) emphasizes that individuals need to have the necessary skills to work effectively with intelligent machines. Without this education, individuals may be reluctant to adopt new AI technologies or may misuse them, resulting in unintended consequences. Moreover, the European Commission (2019) emphasizes that adequate AI literacy education is crucial for ensuring the ethical and socially responsible development and use of AI technologies.

To achieve adequate AI literacy education in intelligent human-machine synergy in collaborative teaching, it is essential to integrate AI literacy education into all levels of education, as well as in professional development and lifelong learning, as pointed out by UNESCO (2021) and the European Commission (2019). This integration should include technical aspects of AI, as well as ethical and social aspects, such as bias and discrimination, privacy and security, and the impact of AI on employment and social inequality. Additionally, to ensure effective AI literacy education, innovative and engaging education methods are necessary, as suggested by the European Commission (2019) and UNESCO (2021). Project-based learning that involves the development of AI applications, for instance, can help individuals develop a deeper understanding of AI technologies and their potential uses. At the same time, the European Commission (2019) stated that interdisciplinary approaches to AI education, which bring together experts in computer science, ethics, law, social science, and humanities, are also crucial to the use and evolution of AI as well as society in general. Such approaches can help individuals develop a holistic understanding of AI technologies and their potential implications.

In conclusion, adequate AI literacy education in intelligent human-machine synergy in collaborative teaching is critical for individuals to interact with intelligent machines effectively and ethically. Integrating AI literacy education into all levels of education, innovative and engaging education methods, and interdisciplinary approaches to AI education are necessary for achieving this goal.

Learning, teaching and assessment

Role of teachers and learning scenarios

In human-machine collaboration, the machine could take various roles and tasks to effectively complete a given educational objective with the teacher. Kaber (2018), in this context, mentioned that one of the core questions in human-machine collaboration is "Who does what?". In a study investigating the effects of humans collaborating with machines, Nass et al. (1996, p. 669) revealed that the "effects of being in a team with a computer are the same as the effects of being in a team with another human". In the same vein, de Vreede and Briggs (2019, p. 103) stated that, in the future, "artificial agents will become fully functional members of teams"; therefore, there is an urgent need to investigate which roles automated agents can fulfill and perform. This implies that machines should not replace humans and take over every role within a team. Rather, they should be designed to fulfill certain activities which are most fitting and effective and, thus, complement or augment the advantages of humans (Dellermann et al. 2019). In this context, Tlili et al. (2023b) also pointed out after conducting a meta-analysis on the effects of Intelligent Tutoring Systems (ITSs) on learning achievement that machines should not replace humans in education. They should, however, complement them to effectively achieve given educational objectives.

To investigate the different roles that machines could take when collaborating with a human teacher, Bittner et al. (2019), for instance, developed a taxonomy focusing on team composition and the role of machines within teams. They recognized various roles, such as facilitators (e.g., instructors), peers (e.g., teammates), and experts (e.g., analyst or evaluator). They further called for more investigation of the different roles within the taxonomy. Therefore, it is important to investigate how machines can work with human teachers to effectively achieve a given educational objective. Effective collaboration, in which the function of machines is no longer merely that of a tool but rather a team member, can only result from a perception of equal roles (Nass et al., 1996).

Assessment of learning and human-machine synergy

Assessment of learning and human-machine synergy, as well as human-machine collaborative teaching, is crucial for improving teaching and learning. The appropriate assessment results can drive students' learning and promote teachers' professional development. Assessment results can provide a clear picture of goal attainment. In addition, assessment results can shed light on how to improve teaching and learning to illuminate how to align instructional design and enactment.

To examine the effectiveness of human-machine synergy, many methods could be employed in practice. For example, automatic speech evaluation can be employed to investigate the effectiveness of human-machine synergy. In addition, a collaborative human-machine evaluation framework and tools can be developed to examine the effectiveness of human-machine synergy. Furthermore, whether learners have achieved personalized learning or not can be used to evaluate the effectiveness of human-machine synergy since human-machine synergy can empower personalized learning.

To examine the effectiveness of human-machine collaborative teaching, many methods can be employed in practice. For example, it is possible to use explicit methods, such as tests (pre- and post-tests). It is also possible to use implicit methods, for instance, by analyzing students' learning behaviors within the teaching practice (i.e., a human teacher and a machine teaching together), to draw conclusions accordingly. In addition, teachers or researchers can investigate learners' perceptions through questionnaires or semi-structured interviews to get an understanding of the effectiveness of human-machine collaborative teaching.

Quasi-experimental methods can be adopted to examine the effectiveness of collaborative teaching between the human teacher and the machine compared to the teaching practice without the machine (i.e., in the absence of human-machine collaboration). Furthermore, learners' learning engagement, cognitive and metacognitive skills, emotions, motivations, and behaviors can also be examined to measure the effectiveness of human-machine collaborative teaching. For example, Han et al. (2023) proposed a technology-enhanced Edu-Metaverse framework to promote learner engagement with human-machine interactions. Finally, existing standards and frameworks that are already used for technology-enhanced learning designs and their impact assessment can be applied such as the international ISO standard for digital learning ISO/IEC 40180 (2017, revision of the original standard ISO/IEC 19796-1 (2005)) and the Quality Reference Framework (QRF) for online learning developed and evaluated by more than 10,000 learners, designers and facilitators (Stracke et al., 2018).

Generally, it is most important to assess and evaluate the impact of human-machine synergy and human-machine collaborative teaching on all three educational levels: the micro, meso and macro level (Stracke, 2019). Table 2 provides an overview of the key leading questions and perspectives that must be addressed and differentiated for a complete impact assessment at all educational levels.

At the micro level, students and teachers make their own choices and the best ways to learn respectively to educate when involving and using machines. At the meso level, teams and organizations responsible for designing and providing courses and education need to reflect on how they can effectively use machines within their syllabus and learning opportunities. This also raises the question if future curricula should be revisited and redesigned to meet the new needs of this teaching practice (i.e., human-machine collaborative teaching). At the macro level, policy developers and politicians must think critically and decide how machines can be safely implemented in educational systems and curricula to achieve a positive societal impact for the commons. It is important that policymakers make clear guidelines and regulations to safely adopt certain technologies in education (e.g., the use of ChatGPT in schools and universities rather than simply banning it). Within all three levels, the learning processes (i.e., facilitated through human-machine synergy), as well as the learning designs (i.e., facilitated through human-machine collaborative teaching), should include objectives, realizations, and achievements in their impact assessment for a holistic evaluation (Stracke, 2017).

Table 2. Impact assessment on educational levels.

	Human-machine synergy in education	**Human-machine collaborative teaching**
Macro level	How can educational systems and institutions safely adopt and exploit machines?	How can society take advantage of machines for the common good?
Meso level	How can courses and curricula benefit from machines?	How can learning design integrate machines for effective and human-centered teaching practices?
Micro level	How can teachers and students interact or learn with machines?	How can teachers team-up with machines to achieve an educational objective?

All these relevant perspectives and examples demonstrate the potential applications and benefits of human-machine collaboration as well as the need for careful design. It also makes salient to the learning and teaching scenarios and processes involving AI and human-machine interactions. The relevant research has just started to reveal conditions and effects of effective and successful introduction of AI and human-machine collaboration in education.

Limitations

This study has a couple of limitations that should be acknowledged. For instance, this study is descriptive in nature and all the reported findings are mainly based on a review of the literature. Stated another way, no experimental studies were conducted to validate the components of the framework. In addition, as generative AI technologies evolve during the coming decade and other educational technologies emerge, the iSTAR framework will likely need further refinement and validation.

Conclusions and future directions

This study has discussed human-machine collaboration in education, and presented iSTAR as a reference framework. iSTAR presents a simple visual representation of the different types of entities that a human teacher can collaborate with to achieve a given educational objective, as well as the different levels of collaboration. It also highlights the different dimensions that should be considered for an effective and safe human-machine collaboration in education.

The study can contribute to the literature from different perspectives. From a theoretical perspective, this study contributes to the ongoing debate and progress of human-machine collaboration in the field of education, especially with the rapid development of AI technologies. From a practical perspective, this manuscript highlights different dimensions that various stakeholders (e.g., designers, developers, educators, policymakers, etc.) should pay attention to for a safe and effective learning experience; hence, helping ensure enhanced learning outcomes.

This study further suggests the significance of constructing an ethical framework to govern the domain of human-machine collaboration in the educational context. Notably, it suggests that future policies should encompass privacy protection, algorithmic transparency, accountability and human-machine teaming up together. In addition, fostering transparency, explainability, and user control assumes paramount importance in establishing trust and enabling fruitful collaborations. Therefore, future research could also focus on this line of research.

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