

## AI-Based Teaching Model: Challenges and Possibilities

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### **Abstract:**

*Teaching and learning approaches have undergone radical transformation as a result of the introduction of artificial intelligence (AI) into the classroom. AI-based teaching models promise to transform conventional pedagogical approaches by providing data-driven insights, real-time feedback, and individualized learning experiences. The digital divide, inadequate teacher preparation, ethical issues, and infrastructure constraints are some of the major obstacles to the adoption of such approaches. The main elements of AI-based teaching models are examined in this research, along with their potential to improve educational results and the obstacles to their successful application. The paper emphasizes the need for a fair and inclusive approach to AI integration in education by examining worldwide trends and placing them inside the framework of the Indian educational system. The results indicate that although AI has enormous potential for the future of education, its effectiveness mostly hinges on legislative backing, human-AI cooperation, and strategic planning*

**Keywords:** AI in education, AI-based teaching model, digital divide, personalized, learning, educational technology, teacher preparation, ethical issues, education policy, and Indian educational system

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### **1. Introduction:**

AI-related themes have been explored by various academic disciplines such as computer science, information science, cognitive science, and social sciences. Important issues surrounding AI, such as conceptual understanding, sustainability, ethics, and social justice, have emerged in connection to school curricula across different disciplines of study. AI education poses an opportunity to educate transdisciplinary generations of citizens who can leverage AI technologies in socially responsible ways.

This presents a new AI curriculum design process undertaken in collaboration with educators and education stakeholders to create a prescriptive AGI curriculum for high school students. AI education and curricular recommendations respond to the VUCA context of the 21st century where popular AI technologies have thriving user bases with little understanding of their societal impact (Aliabadi et al., 2023). The importance of healthy AI education is highlighted as technology with an understanding of social implications is made accessible to younger

audiences. When students have a fundamental understanding of AI technology and how it functions, they can engage with it responsibly and transparently, producing media that aligns with social expectations. AI education inscribes reflections on social implications into the technicalities of AI and allows students to thoughtfully create technology to communicate with others. Accordingly, prior AI education initiatives in K-12 education include AI instruction, research, and curriculum recommendations.

The method of inquiry within this agenda situates education at the intersection of community and curricular needs surrounding youth-aged people's conduct with AI technologies. The AI curricula focus on fine-type ML because meta-prompts to LLMs and diffusion models are too technical for secondary students. Inputs much longer than previous discussions on the limits of LLMs can quickly fall below the threshold of an average person's attention span. Nevertheless, much AI education advocacy work investigates simple types AI technologies, including critics of fitted ML algorithms, filtered advertisements and recommendations, detection of clickbait formulations, and so on. Data self-representation concerns the hygienics of data collection, such as oversharing misinformation and manipulative content. Social implications include the potential errors of bias propagation and misrepresentation of real-world information. Social critique after the fine-type learning/ML process is usually neglected.

## 2. Overview of AI in Education:

Artificial Intelligence (AI) has gained prominence in education for several reasons: It assists in tasks ranging from assessment to scheduling, allowing teachers more time to connect with students. Because students regularly use AI decision and attention algorithms, are society's chief focus for training algorithms, and are points of view on directing attention and handling information transactions, it is imperative that educational institutions explore the myriad hierarchies,

variability, and impact of AI (R. Kshirsagar et al., 2022). Algorithms tailored for teacher attention provide education a valuable lens for understanding risks and privacy concerns for students and educators in a court case with Google due to AI data collection. Access networks trained for education examine algorithmic choices affecting student development, evaluation of reading fluency, detection of cheating, action prediction, fewer assessment choices, and punishment.

The education technology research community has been impacted by algorithm development on mechanical attention, adversarial educational systems, and competitive relationships, assessing risks in attracting students. Four AI systems affecting educational autonomy and mediated environments are explored, along with educational opportunities for districts to evaluate AI systems and a tool to analyse competitive patterns of education technologies designed to combat misuses of AI. Educational institutions are a primary focus for AI in many arenas, a primary target market for a variety of AI providers. K-12 education technology, budget forecasting, and enrolment prediction have seen success with AI systems.

The predicted growth of AI in academia is roughly proportional to the percent currently used, higher than in any other area measured. Studies on the educational applications of artificial intelligence have been ongoing for over three decades. There is still much to learn, however, about the educational potential of artificial intelligence technologies to assist students with university-level work. Many issues related to the implementation of artificial intelligence systems in postsecondary learning still focus on ethical and legal concerns.

## 3. Benefits of AI in Teaching:

In many diverse pedagogical contexts, teaching intelligence—as specifically articulated in the fields of education, psychology, brain science, and computer science—is a significant expectation. In addition to its fundamental epistemological and pedagogical

concerns, teaching intelligence is relevant to both the problem and the solution of using AI systems to raise a list or number of issues that pertain to understanding and the ethical use of AI. Where intelligence analysis is the focus, it goes beyond cognitive functionality to broaden its scope to consider affective, motivational, social, tribal, and creative dimensions of educational theory and practice.

The generation, proliferation, and competitive-enhancing integration of AI systems have proliferated myriad solutions. International and multidisciplinary efforts are needed to answer a range of questions concerning how intelligent technologies impact education, as well as how they can be ethically and accountably created and used. Educational settings and learning experiences are complex, context-sensitive, and dynamic. They take place in a micro-psycho-epistemic microcosm of class; a meso-macro-socio-cultural ecosystem of institution and nation; and even a global wreck where social justice, equity, and accountability understandings take on starkly different forms. Understanding how implementation of AI technologies to support particular improvements—whether in instruction, education administration, data analysis, or student care—alters the organizational and pedagogical practices and procedures is a daunting task.

In a basic way, designing, deploying, and assessing intelligent educational interventions is an intertwined problem. This presents thorny conceptual, ethical, and methodological challenges. As a micro-hub of intelligence analysis, instruction, identification of learning needs, and trusting negotiation of proper remedial measures, the classroom is the site of the dilemma as well as the best means. Classrooms in which AI systems assist teaching and learning present a nested and distributed unit of analysis as well as a shared micro-world by which to experiment with technology-enhanced scenarios concerning ethical use. AI technologies—specifically, the Deep Neural Networks of recurrent architectures that power them—attached snapshots of depth and degree to

the traditions of educational science with respect to epistemology, theory, cognition, granularity, representativeness, and quality.

### 3.1. Personalized Learning:

Personalization in learning has several dimensions, including personalized materials, learning paths, learning methodologies, and learning interaction. A fully personalized online education system should offer personalized versions of all these aspects. For example, in a personalized learning material scenario, students are provided with materials tailored to their capabilities. Similarly, in personalized learning paths, students' progress through a suitable and personalized set of materials. To illustrate, Reza has just started his probability class and must first learn about the Bayes theorem before reading the materials. With different learning methodologies, students have different ways of learning the same material. For example, some students may learn better with text that covers the mathematics behind the theorem, while others may prefer video material covering a proof of the theorem. Each learning methodology is able to utilize one or more methodologies, including question answering, choosing materials, randomizing materials, and changing the contents of the materials. Finally, in online personalized learning interaction, a teacher is faced with providing a personal response to each student.

Most existing online learning systems are one-size-fits-all systems, treating all students equally, offering them the same teaching and training methodology, and using the same graphical presentation (Tekin & van der Schaar, 2014). On these systems, students blindly view the provided learning materials. This working paradigm provides no personalized interaction, and students are taught with crude techniques. Such techniques include viewing a list of questions one at a time, reporting errors, and automating scoring and time. Unfortunately, while most students are frustrated, a significant number of students are feeling invisible. The measuring and proactive reaction methods are cruel, and as most

students are daily treated this way, dissatisfaction with the online learning experience has grown.

The need for change is urgent, as personalized education is possible due to emerging advances in state-of-the-art digital technologies, personal robot ones, and AI-based teaching methodologies (Aliabadi et al., 2023). As an initial step, researchers focus on how to perform personalized instruction and study what factors affect learning. In more detail, they study personalized measures of engagement, attention, and effectiveness and build learning models. In concert with students' models, these measures guide adaptation. As a first instance, a large-scale intelligent data-driven e-learning system is equipped with an automated assessment program that is able to monitor students' learning states in real-time. Also, using text mining technologies, feedback and hints on the learning process, students' misunderstanding, and reactions can be delivered immediately. In addition, the system is augmented with robots, personalized education addresses how to meet the different needs of each learner by adapting to individual differences. However, how to go beyond a simple matching between characteristics of students and choices of learning materials is an important research challenge in personalized learning.

### 3.2. Efficiency in Administrative Tasks:

Advances in artificial intelligence (AI) promise to transform the field of education. Design decisions that implement AI into educational contexts or programs could impact teaching, learning, curriculum, and policy for some time. AI has enormous transformative potential. However, technologies can also reinforce or exacerbate inequitable practices or beliefs that are already in the world. As efforts to implement AI advance, researchers and educators need information on what is and is not possible (Schiff, 2021). AI could be created and implemented in ways that support students, teachers, schools, and communities. However, AI could also be designed to replace or devalue people and institutions. AI can offset the cost

of education. Within education technology, there are many potentially rapid, and potentially transformative, developments in AI analysis, design, and implementation. Innovation also carries the risk of unintended consequences. AI systems have been developed to augment personal and institutional productivity by providing support for administrative tasks, data management, and non-native interactions, for example. Given existing difficulties in the education ecosystem—many low-paid jobs, chronic job shortages for teachers, data concerns, standardized assessment and data-driven schooling, and equity issues—the implementation of AI in education is both urgent and risky.

AI can support student learning by providing information. AI systems have been developed to augment learning and teaching by providing real-time monitoring of student performance to inform teachers about students' understanding, which content may need attention, and what instructional strategies may need to change during a learning experience. Symbolically interfaced AI-enhanced learning environments can reveal learning, motivation, emotion, and other internally hidden information from student performance data. This information is then shared by the systems and used to assist students, inform teachers, or prompt educator intervention for student support (R. Kshirsagar et al., 2022). This information could inform teachers and instructional designers about what teaching resources to adjust, which content may need practice, and how the topic can be taught better.

### 3.3. Enhanced Engagement:

The Competence-Fostering Instructor Bot prompts students to stay on task by asking self-assessment questions before they select a question to answer, subsequently providing hints. The Social Companion Bot stimulates personal goal reflections through an inquiry about its own contribution and their responses, with the latter shared exclusively with the user. The Career Advising Bot recommends online industries and studies after inquiry about students'

interests, while the Emotional Supporter Bot asks students to express their feelings whenever their emotions fall below a threshold. Despite increased engagement in both realistic and instructive dialogues, learning outcomes did not improve after intervention (Chen Cao et al., 2023).

Nonetheless, this research provides novel pathways that directly target emotional under- and over-engagement. Furthermore, it investigates and compares the roles of multiple chatbots, as well as how bot roles affect interactions and engagement. Introducing multiple roles of multi-modal chatbots presents new opportunities for educational purposes, fostering not only engagement but also inquiry, collaboration, and emotional awareness. Results indicate diverse interactions occurred in three out of four bot roles—Instructor Bot, Career Advising Bot, and Emotional Support Bot—and all bots stimulated dialogue on a broad range of themes (Tan et al., 2023). Leveraging multi-modal capabilities facilitates students generating and responding to inquiry-oriented questions, ultimately enhancing their inquiry-related skills. Phased-based and dynamic directory-enabled multi-modal chatbots will be implemented based on this work, serving as inquiry facilitators and conversation engines.

#### **4. Challenges of Implementing AI in Education:**

As AI rapidly transforms the economic landscape, education bears significant implications for economic advancement and societal well-being. Despite the substantial investment in educational AI, improved learning outcomes have not materialized. Designing, implementing, using, and assessing AI-based tools requires interdisciplinary reasoning and collaboration from a diverse group of stakeholders. One prominent factor is the inability to design and implement effective and equitable AI-based education. AI-based education requires high-quality, coherent curricula that systemically integrate domain knowledge and AI technology to facilitate collective and disciplinary understanding. Since the state of current public understanding of AI remains inchoate with many misunderstandings and distrust, improving societal

understanding will require curricula customized to the needs of the public and the interests of the trusted stakeholders from various backgrounds, including education, business, healthcare, advocacy, activism, and policymaking (Aliabadi et al., 2023). Creating an understanding of AI-centered education requires grappling with three salient paradoxes. The first is an educational paradox, intensified by the now ubiquitous and rapid development of AI. The second is a curricular paradox, stemming from rapid developments and ever-accelerating widespread adoption of AI tools with a broader impact than prior technologies. The third paradox is a pedagogical paradox pertaining to numerous AI enhanced pedagogies. Each paradox urgently needs to be studied and addressed in an equitable and ethical way to education's inclusion in the AI age. The paradoxes centre around the urgency of educating the public about AI, the inevitability of unintentional misunderstandings of AI, and the difficulty in reconciling AI tools with pedagogy (Aliabadi et al., 2023). Another factor is the challenges of integrating AI into education. Each technology has societal implications that neither guarantee benefits nor produce detriments. Facial recognition technology, for example, is integrated into school entry systems to streamline access to educational settings while monetizing biometric data, facilitating in-school surveillance, and normalizing police profiles of children. Discussion of the trade-offs these technologies present situates lessons in current events and social realities in ways that engage students. This simultaneously illustrates the negotiation of opportunities, intentions, and implications of technology, prepared by thinking about agency and trust in the context of technology. It introduces responsible JUBI design, addressing how to engage in ethical technology design always over time (Mollick & Mollick, 2023). A benefit of this empowerment is increased trust and agency in technology.

##### **4.1. Data Privacy Concerns:**

Browse the list of questions to locate the topic-related questions of interest. Click on the question to see answers to that question.

The use of big data in commercial AI has raised concerns about privacy breaches from algorithmic systems themselves. In many jurisdictions, healthcare data breaches have been rising, and AI and other algorithms are contributing to a growing inability to protect health information for those impacted. In recent years, a number of studies have surfaced methods by which emerging computational strategies can identify individuals in health data repositories managed by public or private institutions (Murdoch, 2021). This is true even if the information has been anonymized and scrubbed of all identifiers.

An algorithm can be used to re-identify a significant percentage of adults and children in a publicly available physical activity cohort study despite the data being aggregated and direct or indirect protected health information being removed. Furthermore, a "linkage attack framework" (i.e., an algorithm aimed at re-identifying anonymous health information) that tested the efficacy of using 4 or more spatiotemporal check-ins to link online health data to real-world individuals was developed and validated. This method was successful at re-identifying key health data information from different databases, such as that of a national health service. Today, techniques such as support vector machines trained on social media profiles are able to re-identify individual Twitter and Facebook users in health data, even if the individual is not directly involved in the dataset.

As such, the substance of IPH concerns is that knowledge about individual patients is disclosed or inferred from big healthcare datasets, raising questions about the ownership of knowledge about patients arising in this manner beyond the health institutions that own the data. Some have pointed out that today's techniques of re-identification effectively nullify scrubbing and therefore "compromise privacy." The existence of such features in both open-source and commercial products raises

questions about institutional commitment to the ethical management of known privacy risks.

Under the current regime, there may be an increase in the privacy risks of allowing private AI companies to control patient health information, particularly in circumstances in which anonymization occurs. Whether, when, and how a company is liable for inadvertent disclosures of health information is typically discussed only in the most general terms in EULAs, if at all. This is problematic and raises questions of liability, insurability, and other practical issues that differ from instances in which state institutions directly control patient data.

This reality raises questions of liability, insurability, and other practical issues that differ from instances in which state institutions directly control patient data. Carefully constructed contracts delineating the rights and obligations of the parties involved will need to be made.

Regrettably, the equality of resources and legal expertise of the parties will almost certainly favor the commercial agents, who may build in changes of control provisions, arbitration clauses, and extensive indemnities against a wide range of risks that they abrogate responsibility.

Generative models—models trained on a patient dataset X to develop the ability to generate realistic but synthetic patient data Y with no connection to real individuals—can potentially be used to obviate continuing privacy concerns.

#### 4.2. Bias in AI Algorithms:

While AI can offer many benefits to education, it also brings along the subtle threat of bias. In this respect, a recent statement from the USA's National Education Association is ominous. The NEA warned that Hatch, the Education Department's AI chatbot, is "rife with bias" and the bot "dug its heels in" when pushed (Leavy et al., 2020). Researchers have long warned of potential bias in AI algorithms stemming from historical societal bias embedded in the content on which the algorithms were trained. Bias in AI and

machine learning (ML) models presents multiple challenges for fairness, accountability, and transparency (Englert & Muschiol, 2020). Bias will provide one of the key challenges for the effective deployment of AI models in the classroom.

Syntactic bias is defined as: The bias can be detected by mathematical computation models. Syntactic biases can be further classified into a hierarchy of types, including Invalidation biases: The training data do not cover the input space and thus lead to an incorrect model that does not match the validation sample. Direct structure biases: The training data contain constraints that are not inherent to the function to be modelled, leading to a model that captures the constraints and ignores the target function. Finite approximation biases: The training data define an approximation function class that is too small to represent the target function, leading to a model that maps all inputs to the same value.

Semantic bias is defined as: The bias cannot be detected by mathematical or theoretical computation models as the bias concerns the input-output relation. Semantic bias can be further classified into a hierarchy of types, including: Prejudice biases: In training and validation data, too many samples contain fault-input/fault-output pairs and thus the model is not a correct representation of the input-output relation. Irrelevance biases: In training and validation data, too many input x-components are not informative for determining the output, leading to a model that does not discover (or underestimates) these relevant variables.

Existing bias detection methods have limitations. No specific measure exists to detect syntactic bias. With respect to the most practically relevant and pressing semantic biases, the means for the detection can be computed but not necessarily interpreted as “where to measure it and what value to interpret” (i.e., discriminative attribute inclusion).

#### 4.3. Resistance from Educators:

The rapid rise in AI applications has increased the anticipation of curbing faculty-related costs that account for more than 50% of all university budgets, with the greatest potential savings coming from substituting existing faculty with intelligent tutors (Schiff, 2021). The majority of universities currently already use teaching assistants or adjuncts to teach massive classes with little if any interaction with students. However, the scale, success, and even survival of such classes is often questioned. AI has the potential to offer a compromise with classes of 200–800 students per course that include “face-to-face” sessions along with virtual tutorial sessions with intelligent agents. Intelligent tutoring systems can provide quick assessments of students’ performance and feedback that could predict a student’s success before they fail the course. Therefore, AI could not only personalize education on a one-to-one basis but could also compete fairly successfully with one-on-many educations since it will cost universities essentially nothing compared to adjuncts or teaching fellows while being able to offer 24/7 open admission. However, all such potential advantages must be greeted with cautious optimism, since intelligent tutors are still relatively primitive.

Much of current AI technology has been trained using “clean” databases that have been curated or filtered. However, it is easy to find faults in language models that rely solely on unfiltered data. Over- or under-reliance on chatbots or intelligent agents could lead to catastrophic errors, lack of attention to appropriate subject matter, and dishonest behaviour. Lecturers or industry experts often still make mistakes when relying on presentation tools. Detecting such artifacts or errors is far easier in human-produced material than in AI-generated material, making it difficult for students or administrators to evaluate quality. Further progress in large language models is anticipated that could generate creative novels and films for human consumption. However, such programs have yet to pass an advanced high school chemistry exam and could therefore struggle to answer more technical questions or fields. Since millions of students take

high-stakes competitive exams based on unwritten or unmemorized material these models may not compete with true experts leading to a two-tiered intelligence gap.

## 5. Future Trends in AI Education

As AI begins to dominate our lives, questions related to ethical use, fairness, bias, transparency, and privacy have arisen. Among many other topical needs, AI literacy is essential and needs to be included as part of the curriculum, which currently lacks implementation. There is a critical need for an understanding of AI approaches, effects, and benefits for a wide variety of learners, especially K-12 students around the globe, who will encounter AI in their everyday lives, and for whom there are currently limited teaching resources. Low-cost hands-on robotic artifacts provide a relatable and active way to learn about AI for students of all ages and in diverse environments.

While there are many low-cost AI teaching resources such as toy robots, online AI simulators, and visual learning agents, few have been applied or appropriately tailored for classroom use by individual instructors. It is clear that widely-adopted low-cost AI teaching resources for K-12 classrooms have yet to be capitalized upon. To address these gaps and tap this potential, pilot studies with a diverse set of teaching materials should be conducted in both formal and informal education environments in parallel to understand specific contextual needs from an instructor's and environment's perspective.

Whether that be a small, relatively isolated informal education environment or a large formal education environment that faces structural and cultural challenges, there are numerous cross-context questions to ask about the effects of diversity on the representation of AI demonstrations, how curricular design influences the incorporation of low-cost artifacts, and how ethical discussions regarding AI literacy are considered and approached in educational strategies. While the ubiquity of AI and diversity of teaching resources means that research

on the cross-context nature of AI education has the potential to be transformative for teaching AI globally, such an endeavour means engaging a significant amount of complexity in how curriculum aligns with the needs of diverse stakeholders and environments. (Schiff, 2021)

### 5.1. Adaptive Learning Technologies

The role of Artificial Intelligence (AI) in Adaptive eLearning Systems (AES) and the different forms of smart tutor are explored. The way learners use eLearning systems can be better understood through classifications of constructive learning which addresses the posed situation and applies prior knowledge and skills. Generative modelling of knowledge representations is pointer in domains where the learners create knowledge rather than receiving it from other people. It was found that self-questioning, commentary, motivation, self-explaining and learning widget generators are activities that can aid rethink this effort (Adamu & Awwalu, 2019).

The challenges of Adaptive eLearning Systems (AES) with particular attention paid to regarding arbitrary individual graphical characters as errors in chemical educational domain. Though classifying the challenges numerous problems in comprehensible form were presented. A comprehensive consideration of challenges involved in formation of AI based Adaptive eLearning Systems (AES) is given the steps involved in formation of AES and the probable challenge in the natural and mathematical sciences domains were highlighted.

With the introduction of online education, students can now access course material at any time, but they are reacting to it differently. Adaptive learning refers to solutions that adapt to students' actions, tendencies, and preferences as they interact with the system. It dictates intrinsic opportunity, incentivization, and nudges while helping an organism prosper, judging the evolution of engagements over time. The advent of new tools, mechanisms, and techniques to improve and

facilitate the learning process through increasingly personalized approaches was introduced (Iyer & Debang, 2023). The basic types of engagement in distant learning was pointed, such as Teacher-content, Content-content, Student-content, Student-Teacher, Teacher-Teacher, and Student-Content Engagement.

Theories that support the use of new technologies in the classroom hypothesize that a productive classroom is one where students are engaged individuals, seeking out and contributing information of relevance and importance to their own context, world, and self. E-learning is the incorporation across devices connected to a network of information, education, resources, and services for the delivery and access of knowledge.

## 5.2. AI Tutors and Mentors

Intelligent tutoring systems (ITS) provide a personalized learning experience, adapting questions, hints, and explanations to the student's knowledge. However, their creation is a daunting task. ChatGPT brings great promise in tutoring and mentoring "on demand," removing the constraints of availability and location. Students can now access their own avatar tutor, a private database of knowledge tailored to their learning preferences and needs. They engage with it through dialogue in natural language (Mollick & Mollick, 2023). However, there are considerable drawbacks and ethical concerns in assigning AI tutors and mentors.

Currently, essays submitted will likely be written by the student, but it is reasonable to fear a shift in the opposite direction, with students submitting historical math equations along with essays written in the style of Shakespeare. It will likely take MIT or Harvard a while to implement the sort of multimodal assessments that might be harder for ChatGPT to get its hands on. However, just like a computer or the internet, AI would eventually become a part of the daily learning process. In this regard, perhaps students would be encouraged to work with it, rather than against it.

AI mentoring might create emotional kitsch, as the student grows attached to their created AI chatbot tutor. The greater the personalization, the deeper the attachment. This is both an opportunity and a danger. On one hand, such a trusted confidante might help struggling students. On the other, it could become a dangerous dependence on a tutor that is untruthful and unaccountable.

## 6. Conclusion:

The possibilities of an AI-based teaching model appear promising. It is possible that the emergence and advancement of automation, Artificial Intelligence (AI), and smart technologies may someday revolutionize teaching. Nevertheless, a jarring reality is wondering about the accuracy and suitability of the predictions that AI influences in teaching models will be revolutionary. Without the blueprint and instructional design of how teaching or pedagogical agents should be structured based on theoretical and applied models in combination with contextual settings and content structure, the best of automation and intelligent technology in education would be mere idols of gold, and teaching models would remain at the trial-and-error stage.

To ensure the prospect of an AI-based teaching model, efforts must continue in three parallel but interrelated domains. Bridging the two theatre levels of human intelligence, (Schiff, 2021) proposed evidence-based design and evaluation of individualised tuition by pedagogical agents. His planned four-prong structure was belief system, formal general interpretation, operational principles, and development and testing of an implementation. While's pronouncements were agreed upon, desired action was urged to lift and comprehend how a theory-based teaching model should be structured through its design and internal operation at a parcel level.

The teaching process should be unpacked theoretically, mathematically, and logically through modelling. In this manner, both the actors of personalisation and the controlling system could be

built, which, combined with the beliefs and principles of pedagogy, architecture for implementation, development of agents, AIEd with mathematical subject matter education should necessarily converge into an advanced approach. Theory, context, content, instructional design, and delivery will thus combine and engage supportively as necessary and sufficient to an AI-based teaching model flexibility and adaptability.

## References:

1. Aliabadi, R., Singh, A., & Wilson, E. (2023). Transdisciplinary AI Education: The Confluence of Curricular and Community Needs in the Instruction of Artificial Intelligence.
2. R. Kshirsagar, P., B. V. Jagannadham, D., Alqahtani, H., Noorulhasan Naveed, Q., Islam, S., Thangamani, M., & Dejene, M. (2022). Human Intelligence Analysis through Perception of AI in Teaching and Learning. [ncbi.nlm.nih.gov](https://www.ncbi.nlm.nih.gov)
3. Tekin, C. & van der Schaar, M. (2014). eTutor: Online Learning for Personalized Education.
4. Schiff, D. (2021). Out of the laboratory and into the classroom: the future of artificial intelligence in education. [ncbi.nlm.nih.gov](https://www.ncbi.nlm.nih.gov)
5. Chen Cao, C., Ding, Z., Lin, J., & Hopfgartner, F. (2023). AI Chatbots as Multi-Role Pedagogical Agents: Transforming Engagement in CS Education. [PDF]
6. Tan, K., Pang, T., Fan, C., & Yu, S. (2023). Towards Applying Powerful Large AI Models in Classroom Teaching: Opportunities, Challenges and Prospects.
7. Mollick, E. & Mollick, L. (2023). Assigning AI: Seven Approaches for Students, with Prompts.
8. Murdoch, B. (2021). Privacy and artificial intelligence: challenges for protecting health information in a new era. [ncbi.nlm.nih.gov](https://www.ncbi.nlm.nih.gov)
9. Leavy, S., O'Sullivan, B., & Siapera, E. (2020). Data, Power and Bias in Artificial Intelligence.
10. Englert, R. & Muschiol, J. (2020). Syntactic and Semantic Bias Detection and Countermeasures. [ncbi.nlm.nih.gov](https://www.ncbi.nlm.nih.gov)
11. Adamu, S. & Awwalu, J. (2019). The Role of Artificial Intelligence (AI) in Adaptive eLearning System (AES) Content Formation: Risks and Opportunities involved.
12. Iyer, P. & Debang, M. (2023). The Future of Adaptive E-Learning: Trends and Directions. [osf.io](https://osf.io)

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