The Impact of Artificial Intelligence in Reshaping Education: An Analysis Based on Learning Theories

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Abstract. A change in behavior that results from experience and is relatively permanent in nature can be defined as Learning. Behaviorism, a dominant theory used to explain learning, sought to measure only observable behaviors. In AI training, supervised and reinforcement learning methods can help machines learn from feedback and improve their performance and this process influences or biases the learner when he adopts AI as a tool for learning and when it is in their zone of understanding. Exposure to AI technologies in higher education prepares students for future careers, as they gain experience with tools and skills that are increasingly relevant in the workforce. To identify the implications of AI interaction in learning we have taken the experiences of 38 students and 15 educators from different fields. We have identified different levels of AI interactions in scaffolding, individualization, challenges, and stress. The design and implementation of different learning platforms aligned with the Zone of Proximal Development (ZPD) in higher education can also be associated with several learning theories. therefore, the features of such a platform also correspond to different learning theories.

Keywords. Classical theories of Behavioural learning, Information Processing theory, Artificial intelligence, ZPD, Machine learning, AI biases

1. Introduction

Learning theories are often connected with practical application, where theoretical frameworks influence teaching practices. Different theoretical perspectives give rise to various teaching methods and strategies, with some theories being more directly applicable to classroom practices than others. The primary learning theories that dominate educational settings include behaviorism, constructivism, cognitivism, social interaction theories, and humanistic theories. Notable contributions to these theories have been made by DeCarvalho (1991), Rogers (1994), Roseberry-McKibbin & Hedge (2000), and Huitt (2009), as discussed by Jenny Pange and colleagues in Procedia Social and Behavioral Sciences. Classical learning theories refer to a set of psychological theories that aim to explain how humans acquire new knowledge, skills, behaviors, and attitudes through their experience. These theories emerged during the late 19th and early 20th centuries and have influenced our understanding of human learning. There are three main classical learning theories: Behaviorism, Cognitivism, and Constructivism. Behaviorism, pioneered by B.F. Skinner emphasizes the role of environmental stimuli and rewards in shaping behavior. According to this theory, behavior is learned through the process of operant conditioning, whereby a behavior is strengthened or weakened depending on the consequences that follow it. Cognitivism, on the other hand, focuses on the role of mental processes in learning. This theory suggests that learning involves acquiring, organizing, and using knowledge and that learners actively construct meaning from their experiences. Cognitivism is associated with the work of Jean Piaget and Lev Vygotsky. Lastly, constructivism, which was developed by Jerome Bruner and others, emphasizes the importance of learners actively constructing their own knowledge and understanding of the world. This theory suggests that learning is a process of constructing meaning from experiences and that learners must be actively engaged in this process. Overall, classical learning theories have played a significant role in shaping our understanding of how humans learn and have provided a foundation for further development in the field of education. All these theories have significantly contributed in the field of education and digitalization. However, the application of these theories in artificial intelligence for collaborative learning practices and new technological pedagogy. Cognitive psychology has been extensively used for the development of artificial intelligence learning models. Artificial Intelligence (AI) learning models are computer programs that can learn from data and improve performance over time. These models are designed to mimic how humans learn by processing large amounts of information and using it to make predictions or decisions. There are various types of AI learning models, including supervised, unsupervised, semi-supervised, and reinforcement learning, each with unique characteristics and use cases. These models have revolutionized how we solve complex problems and enabled us to build intelligent systems that can perform previously impossible tasks. In this era of data-driven decision-making, AI learning models have become essential for businesses, governments, and individuals to make sense of vast amounts of data for gaining insights that can inform their decision-making. There are lot of research happening in the field of AIEd, and the majority focuses on Mathematics and language. Incorporating classical learning theories with AI in the learning education field is still developing. Researchers are advising to pay more attention in the field of applying learning theories in education. By offering students personalised and adaptable learning opportunities, artificial intelligence (AI) has the potential to transform the way that education is delivered. Both operant and classical conditioning can be incorporated into AI-based education systems to improve learning outcomes. The application of AI in educational contexts is growing exponentially, such that by 2024 it is predicted to become a market worth almost $6 billion. (Home et al., 2019).

2. AI Learning Models and Learning Theories: A Literature Review

Research has happened in abundance on the theories and ways of learning models and concepts of AI training and how AI impacts or transforms the learning environment, but it is seldom seen that the researchers count the context and the complexities involved in the process of learning by humans before they compare and contrast the same with the machine learning. ML is typically referred to as the most well-liked newest technologies in the fourth industrial revolution (4IR or Industry 4.0), as it gives systems the capacity to learn and improve from experience automatically without being expressly programmed (Sarkar et al,2020). The learning algorithms can be categorized into four major types: supervised, unsupervised, semi-supervised, and reinforcement learning. The applicability of machine learning is splendid in the area of education.

Philosophy of mind that is derived from psychology plays a significant part in the process and progress of advancing artificial intelligence and can be regarded as one of the core supporting theories of AI. For example, the current reinforcement learning theory in AI is inspired by the behaviorist theory in psychology, i.e., how an organism gradually develops expectations of stimuli in response to rewarding or punishing stimuli given by the environment, resulting in habitual behavior that yields maximum benefits (Zhao et al.,2022).

2.1 AI Learning Models

AI learning models refer to algorithms and techniques used in artificial intelligence to enable machines to learn from data and improve their performance on a specific task.

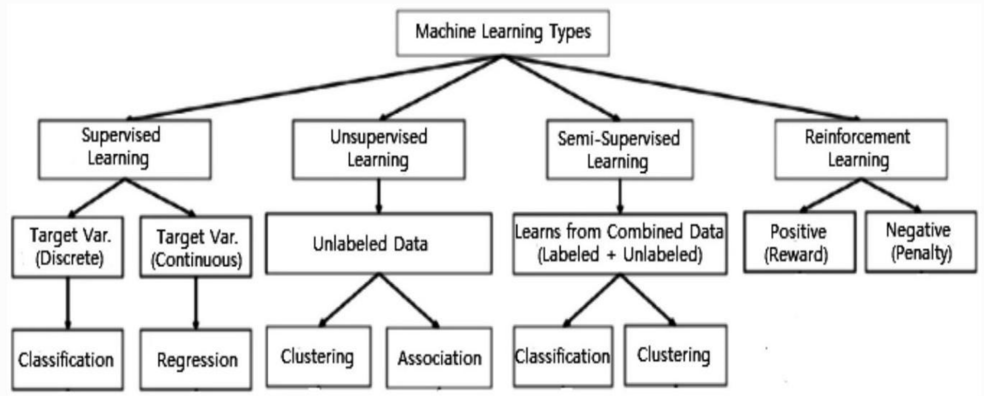

Fig.1. Various types of machine learning techniques (I H Sarker, 2021)

2.1.1 Supervised Learning: In this type of learning, the machine is trained using labeled data, and the goal is to predict a target variable. The algorithm learns by comparing its predicted output with the actual output and adjusting its parameters accordingly.
2.1.2 Unsupervised Learning: In this type of learning, the machine is trained on unlabeled data, and the goal is to find patterns or structures in the data. The algorithm learns by grouping similar data points together and identifying commonalities.
2.1.3 Reinforcement Learning: In this type of learning, the machine learns through trial and error. The algorithm is given a task and must learn to maximize a reward signal while interacting with its environment.
2.1.4 Semi-supervised Learning: This type of learning combines elements of supervised and unsupervised learning. The algorithm is trained on a small amount of labeled data and a large amount of unlabeled data. It uses the labeled data to make predictions on the unlabeled data and adjusts its parameters accordingly.
2.1.5 Transfer Learning: This type of learning involves using knowledge gained from one task to improve performance on another task. The algorithm learns to transfer its knowledge to a new domain or problem.
2.1.6 Deep Learning: This type of learning uses artificial neural networks to learn from data. The algorithm learns by building increasingly complex representations of the data as it passes through multiple layers of neurons.

2.2 Major models of AI learning

- **Generative models** – a model that generates new data that is like the data set it was trained on.
- **Regenerative models** – a model that improves the existing data by predicting the data Gaps. This is more of a reinforced learning
- **Deep reinforcement learning (DRL)** is a machine learning model that maximizes the favourable outcome in a given context acting based on current observations.

2.3 Learning theories

Classical learning theories refer to a group of psychological theories that attempt to explain how learning occurs. These theories emphasize the role of environmental factors in shaping behavior and are grounded in the belief that learning results from the relationship between an individual's behavior and their environment. In this paper we have selected the fundamental theories of learning in which all other theories are built upon these and the other criteria is that most appropriate theories which can be mostly related to learning with technologies, social cognitive aspect and Zone of Proximal Development.

2.3.1 Classical Conditioning Theory

This theory was developed by Ivan Pavlov in the late 19th century. It proposes that learning occurs through the association of stimuli in the environment. Pavlov's famous experiment with dogs demonstrated how a neutral stimulus (such as a bell) could be paired with a biologically significant stimulus (such as food) to elicit a response (such as salivation). Over time, the previously neutral stimulus (bell) becomes a conditioned stimulus that can elicit the same response (salivation) without the presence of the original biologically significant stimulus (food). Classical conditioning is the process of associating two sensory stimuli to achieve an identical response. This process includes sensory and motor neurons. When the sensory neurons receive sensory signals, the motor neurons generate sensory-intensive actions (Ikimi,2022). Classical conditioning is important in humans to learn and predict events in terms of associations between stimuli and to produce responses based on these associations. People are expected to develop classical conditioning when the right condition is presented repeatedly (Novantio et al., 2014). Classical conditioning (or Pavlovian conditioning) [10, p.109–110] [9] is an association of a neutral stimulus that does not elicit a response (called the conditioned stimulus or CS) with another stimulus that elicits a response (called the unconditioned stimulus or US), such that the presence of the CS will elicit the same response that would be elicited by the US, despite the US not actually being present. (Powell et al., 2023). A classical conditioning is different to an operant conditioning. They are both a form of associative learning. However, classical conditioning creates an association between involuntary behaviors and a stimulus before the behaviors are performed, whereas operant conditioning creates an association between voluntary behaviors and their consequences after the behaviors are performed (Chance.p, 2013). The learning process of the dog is somewhat similar to how we train an RL *agent*. According to Poddiachayi (2020), *classical conditioning* corresponds to *prediction* algorithms which predict a *reward* in a given *state*. That's very similar to what happens with the dog (*an agent*). The capacity to detect past connections allows for the construction of both evidence for and against the presence of a particular link, as well as the creation of more sophisticated associations by treating the occurrences of highly related event pairs as separate events (Anirudh, 2019). This also creates a hierarchical model of data.

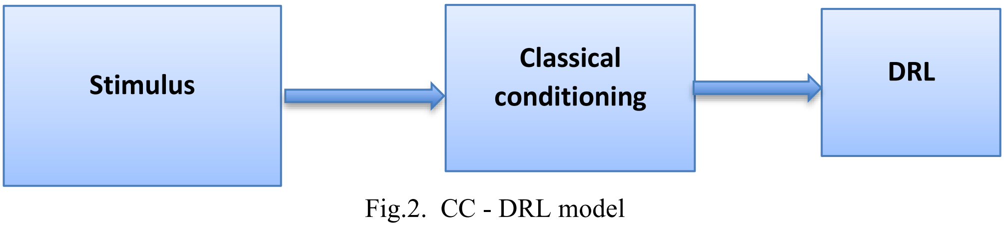

Fig.2. CC - DRL model

2.3.2 Operant Conditioning Theory

This theory was developed by B.F. Skinner in the mid-20th century. It suggests that behavior is shaped by consequences, which can either increase or decrease the likelihood of a behavior

\occurring again. Skinner introduced the concept of reinforcement, which refers to any consequence that strengthens a behavior. Positive reinforcement involves adding a desirable consequence to increase a behavior, while negative reinforcement involves removing an aversive consequence to increase a behavior. On the other hand, punishment involves adding an aversive consequence to decrease a behavior. In biological agents, OC results in behavioral changes learned from the consequences of previous actions based on progressive prediction adjustment from rewarding or punishing signals. In a neurorobotics context, virtual and physical autonomous robots may benefit from a similar learning skill when facing unknown and unsupervised environments. Operant conditioning is a method of learning that employs rewards and punishments for behavior (Cherry, 2020)

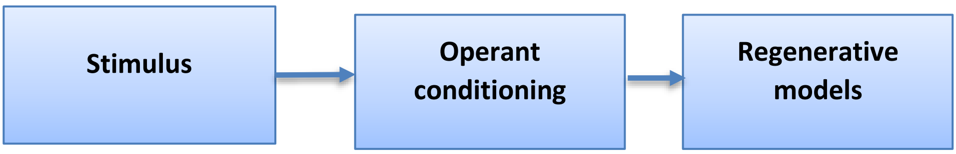

Fig.3. OC - Regenerative model

Through operant conditioning, an association is made between a behavior and a consequence (whether negative or positive) for that behavior. For illustration, when lab rats press a switch when a green light is on, they admit a food bullet as a price. When they press the switch when a red light is on, they admit a mild electric shock. As a result, they learn to press the switch when the green light is on and avoid the red light (Cherry, 2020). OC also consists of a form of associative learning where agents modify their behaviors by associating stimuli and responses, actively changing their behavior from past acquired experiences, by the motivation of rewards or punishments. Hence, agents alter their normal behaviors from acquired knowledge by “evaluating” the acts they previously made and the current changes. (Cyr, 2014).

2.3.3 Social Learning Theory

This theory was proposed by Albert Bandura in the 1960s. It suggests that people learn by observing the behavior of others and the consequences of that behavior. Bandura emphasized the role of cognition in learning, including attention, retention, and motivation. He also introduced the concept of self-efficacy, which refers to an individual's belief in their ability to perform a task. According to social learning theory, individuals can learn through direct experience, observation, or instruction. AI systems, as defined above, are inevitably part of larger sociotechnical systems. Thus, both the purpose for which an AI system, the data used and the sociotechnical environment in which an AI system is used are just two of the numerous variables that affect the application for which it is put to use as well as the calibre of the model it produces. Because of this, AI systems do not automatically aid knowledge generation, even when the existing technology allow them to (Mokander, 2022).

2.3.4 Informational Processing Theory

How individuals record, store, and retrieve information in their brains is defines in the Informational Processing Theory. This affects the motivation and the behavior of a person (Hann et al., 2007). It is an approach to cognitive development in which how humans process the information they receive. Basically, this theory says that humans simply respond to stimuli. It also suggests that information is processed in stages, much like the way in which a computer processes data (Orey 2002). The information processing theory is basically transferring the idea of how humans actively process the information they receive from their senses as a computer does. Learning is what happens when our brains receive information, record it, mold it, and store it. According to Truple.C (2016), there are five stages of information processing theory that tutors can take to support students in learning new information Reception – Sensory memory focus.

1. Retrieval – stimulate recall
2. Receive – meaningful organisation
3. Respond – observational learning
4. Reinforce – feedback

2.3.5 Socio-Cultural Theory

Vygotsky's sociocultural theory is a theoretical framework for understanding how social interaction and cultural context shape human cognition and development. According to Vygotsky, learning and development occur through social interaction with others and are deeply influenced by the cultural and historical context in which individuals live. Wang et al., 2011 in their paper suggested that knowledge is socially constructed, and the social nature of cognitive development serves as a powerful dialogic model for understanding how Information Literacy could be integrated into the curriculum in a community of practice and the tools play an important role in these social interactions in curriculum integration also the internalization can serve as a powerful model when data is generated and analyzed using this research approach. Social instability is a deterrence that limits individuals from forming positive identities, giving rise then to consideration for basic short-term objectives and goals in life. Apart from historical and social milieus, there has been research recently that suggested the importance of critical periods in the development of identity (Seijts, 1998; Vázquez & Rapetti, 2006). At the heart of Vygotsky's theory is the idea that social interaction plays a crucial role in cognitive development. Vygotsky believed that children learn through their interactions with more knowledgeable others, such as parents, teachers, and peers. These interactions provide children with new information, perspectives, and skills, and they enable children to develop more complex ways of thinking and problem-solving.Vygotsky also emphasized the role of cultural tools in cognitive development. Cultural tools include things like language, symbols, and other artifacts that are used to mediate thinking and problem-solving. Vygotsky believed that children learn to use these cultural tools through their interactions with others and that they become an integral part of their cognitive functioning. The theory focuses on the social, cultural, and historical artifacts which play a pivotal role in children’s cognitive development as well as their potential performance. Vygotsky revolutionized pedagogy with his thoughtful psychology of child development centered on the sociocultural perspective (Pathan et al., 2017).

2.3.6 The Contextual theory

Contextual theory is a theoretical perspective that emphasizes the importance of understanding behavior and development in the context in which they occur. This theory suggests that human behavior cannot be understood solely in terms of individual characteristics or personality traits but rather must be viewed in the broader social, cultural, and historical context in which it occurs. According to the contextual theory, individuals are influenced by a complex web of factors that includes their cultural background, social and economic status, historical era, and physical environment. These factors interact with one another to shape an individual's experiences, behaviors, and development. One of the key ideas in the contextual theory is the concept of transactionalism, which suggests that behavior and development are the result of ongoing transactions between individuals and their environment. This means that individuals do not simply react to their environment, but they actively shape and are shaped by it. In 'contextual learning theory' three types of contextual conditions (individualization of learning procedures and materials, optimization of development and learning progress, and integrated ICT support) are related to four aspects of the learning process (diagnostic, instructional, managerial, and systemic aspects) (Mooij, 2004). Learning outcomes reinforce the belief that there is a real point to what is being taught and assessed and that there is a reason for what they experience in their courses. Students are less likely to become cynical and dismissive of courses that seem to have a point and more motivated to take them seriously (Potter & Kustra, 2012). The contextual theory also emphasizes the importance of understanding the cultural and historical context in which behavior and development occur. Cultural factors such as values, beliefs, and customs can have a significant impact on behavior, and the historical context in which an individual lives can shape their experiences and opportunities.

2.4 AI in Education and Zone of Proximal Development

2.4.1 AI in education

The rapid growth of application and adoption of technology in the field of education has brought disruptive changes in the system, so there is an urgent need to analyze how academicians and educators and imparting technology in the learning process. The challenges that AI confronts in this field are so complex, and analyzing AI as a third space in education and learning compromises a lot. While merging Human factors and AI techniques, the shift happens in the environment, perception of the learner and the learner himself is changing to an absorber or an observer. In this paper investigation contribution has two parts. First, we are analyzing the significance of the application of AI Techniques in ZPD in the field of education from the literature review and then the Ethical implications that can happen while using AI in education based on Human Intelligent context.

Artificial intelligence (AI) has the potential to revolutionize education by providing personalized and adaptive learning experiences for students. Both operant conditioning and classical conditioning can be incorporated into AI-based education systems to improve learning outcomes. The potentiality of AI is vast to contribute to this education system, and it has become a core of research. We distinguish between academic knowledge as distinct from social knowledge, by which we mean knowledge about the world. This is embodied in Luckin's notion of academic intelligence and is knowledge and understanding that is both multi and interdisciplinary (OECD,2018). From identifying the strength and weaknesses to experiencing real-time life scenarios, AI gives much more to the human education part. It is estimated that effective use of technology could cut the time to just six hours. Even if teachers spend the same amount of time preparing, technology could make that time more effective, helping them come up with even better lesson plans and approaches (Bryant et al., 2020). The bodies of knowledge embedded in AI systems can then be used to help students. They can be presented to students in a variety of modes, for example, as text augmented with pictures or audio or video. The AI system can time the presentation of the knowledge and therefore pace the learner's experience as well as vary the order in which the resources are presented to learners to maximize learning or meet some other criteria which are embedded in the design of the system (OECD,2018). Artificial Intelligence (AI) has been widely applied in educational practices (Artificial Intelligence in Education; AIEd), such as personalized learning, Intelligent Tutoring Systems, Virtual assignments, Adaptive testing, Natural Language Processing, Predictive Analytics, Content creation, etc. Although AI has the potential to transform education (Holmes et al.,2019), good educational outcomes typically do not occur by merely using advanced AI computing technologies (Casta~neda & Selwyn, 2018; Du Boulay, 2000; Selwyn, 2016).

2.4.2 Zone of Proximal Development

The Zone of Proximal Development (ZPD) is a term used in educational psychology to describe the range of learning that is just beyond a learner's current level of knowledge or ability but still within their grasp with the assistance of a more knowledgeable person or scaffolded learning experience.

Table 1. Stages of learning in ZPD

Stage 1	Aided and assisted by a more knowledgeable person
Stage 2	Assistance provided by oneself
Stage 3	Automatization of knowledge with practice
Stage 4	Deautomization

The concept was introduced by psychologist Lev Vygotsky, who argued that learners make the most progress when they are challenged to reach just beyond their current level of competence, with guidance and support from a teacher or more skilled peer .The ZPD is often represented as a "zone" or "range" of learning, with the learner's current level of understanding and ability at one end and their potential for growth and development at the other. The teacher's role is to help the learner bridge the gap between these two points by providing just enough support to help them reach the next level of understanding or skill. Effective use of the ZPD requires teachers to be able to assess a student's current level of understanding and to provide appropriate levels of challenge and support. By doing so, they can help students to develop their knowledge and skills in a way that is both engaging and effective.

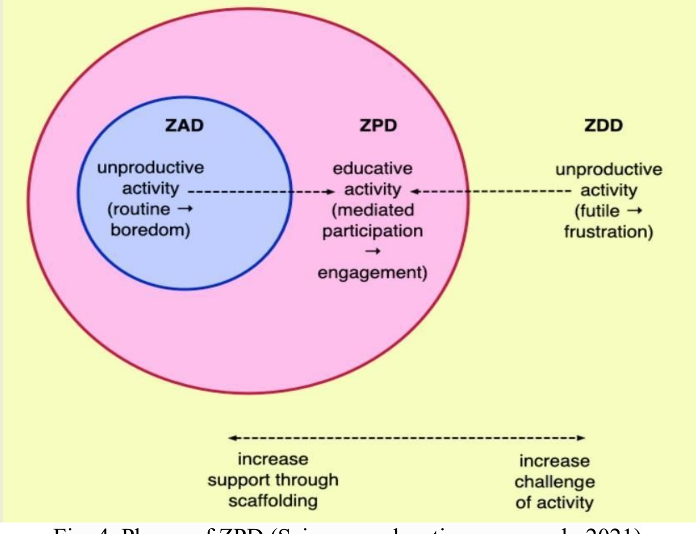

Fig. 4. Phases of ZPD (Science – education – research, 2021)

When a learner is unable to successfully finish an activity without assistance but is able to do so with a level of structured support that enables the learner to gradually master the skill, the activity is said to fall under the ZPD. Activity in the ZDD is, however, "too far away from" the learner's current level of development to benefit from assistance with the task (using the spatial metaphor of zones).The degree of support needed for success on a task that falls within the ZDD is so great that the learner's engagement in the)shared activity would be peripheral and not educative (Taber, 2018). Freund (1990) wanted to investigate if children learn more effectively via Piaget’s or by guided learning via the ZPD. However, recent research has found evidence that Vygotsky’s concept of the ZPD can be beneficial to the design of an adaptive learning system (Zou, 2019). Seita et al., 2019 has proposed an approach that merges the Zone of Proximal Development (ZPD) theory from psychology with modern deep reinforcement learning practices and demonstrates an algorithm for determining which of several teachers should be selected to provide samples for a learner and demonstrated results on Atari environments suggesting that it is not ideal to solely rely on the highest-reward teacher.

AI in Upskilling

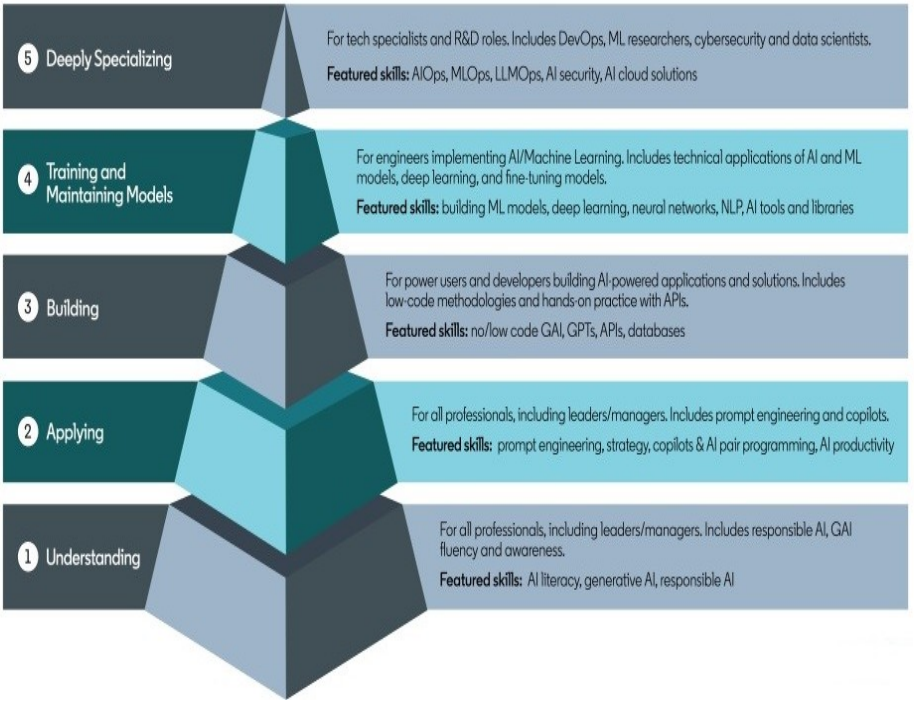

Fig.5. AI Upskilling Framework (Linkedin,2024)

AI Upskilling Framework is a pyramid model that outlines the levels of AI skills development needed across an organization. Even it emphasizes building business-critical AI skills at every level, from foundational understanding to deep specialization, the similar can be applying in learning. It starts with basic AI literacy for all learners, it progresses through applied AI skills, development of AI applications, technical implementation of AI models, and finally, deep specialization for advanced roles. This structured approach ensures that all learners, from students, educators to technical specialists, have the necessary skills to leverage AI effectively in their respective roles and this can be even explained with theories.

Understanding

The foundation of the AI Upskilling Framework begins with a broad understanding of AI for learners. At this level, the goal is to establish a basic awareness and comprehension of AI concepts across the organization. This includes an introduction to AI literacy, learners learn what AI is, how it functions, and its potential applications in various fields. Additionally, generative AI, which involves AI systems that can create content, such as text, images, and music, is also covered. A critical component of this level is responsible AI, emphasizing ethical considerations and the importance of implementing AI in a manner that is ethical and socially responsible.

Learning Theory: Constructivism

Constructivism posits that learners build their understanding and knowledge of the world through experiences and reflecting on those experiences.

- **Active Learning:** Encourage learners to engage in hands-on activities, such as interactive AI tutorials and simulations, where they can explore AI concepts and see them in action.
- **Reflection:** Provide opportunities for learners to reflect on their learning through discussions, journaling, or collaborative projects. For example, after a session on responsible AI, learners could discuss ethical implications in small groups.

Applying

The next level focuses on the practical application of AI concepts in daily roles of the learner of any kind. This level is designed to enable the learner to apply AI tools and techniques to enhance their productivity and decision-making processes. Key skills at this stage include prompt engineering, to improve AI outputs, and developing strategies for integrating AI into the learning and Education processes. AI productivity tools are also highlighted, demonstrating how AI can streamline workflows and automate routine tasks, leading to significant efficiency gains. This level ensures that learners are not just aware of AI but can also leverage it effectively in their work.

Learning Theory: Experiential Learning

Experiential learning emphasizes learning through experience and is often described as "learning by doing." Key aspects include concrete experiences, reflective observation, abstract conceptualization, and active experimentation.

- **Real-World Projects:** Assign real-world projects where learners apply AI tools and techniques to solve actual business problems. This could include using prompt engineering to improve chatbot interactions or employing AI productivity tools in their daily tasks.
- **Iterative Practice:** Encourage iterative cycles of applying AI solutions, receiving feedback, reflecting on outcomes, and making improvements. This hands-on approach helps solidify understanding and skill application.

Building

At the third level, the focus shifts to the development of AI-powered applications and solutions. This stage is particularly relevant for power users and developers kind of learners who are responsible for building and integrating AI capabilities within existing systems. Practical skills in this level involve hands-on practice with AI APIs (Application Programming Interfaces), enabling the integration of AI functionalities into various applications. Understanding and utilizing Generative Pre-trained Transformers (GPTs) and managing databases for AI applications are also key components. This level equips learners with the necessary skills to create AI applications that can automate tasks, provide insights, and enhance user experiences.

Learning Theory: Cognitive Apprenticeship

Cognitive apprenticeship involves learning through guided experiences on cognitive and metacognitive processes. It emphasizes teaching the processes that experts use to handle complex tasks.

- **Mentorship Programs:** Pair learners with experienced AI developers for mentorship. This allows novices to observe experts' problem-solving processes and gradually take on more complex tasks with guidance.
- **Scaffolded Learning:** Provide scaffolded learning experiences where tasks start simple and gradually increase in complexity. Use AI project-based assignments that build on each other, enhancing both confidence and competence.

Training and Maintaining Models

For the learners especially in vocational training, focused on AI and Machine Learning (ML), the fourth level gives the technical aspects of implementing, training, and maintaining AI models. This includes building and fine-tuning ML models, which are crucial for developing sophisticated AI applications. Natural Language Processing (NLP), which allows AI to understand and interact with human language, is also a significant focus area. At this level, proficiency with AI tools and libraries that support model development and deployment is essential. By mastering these skills, learners can ensure that AI models are not only accurate and efficient but also scalable and maintainable over time, enabling continuous improvement and innovation.

Learning Theory: Social Constructivism

Social constructivism highlights the importance of social interactions and collaborative learning. Learning is viewed as a social process, where knowledge is constructed through interaction with others.

- **Collaborative Learning:** Implement collaborative projects where engineers work in teams to train and maintain AI models. Encourage peer review sessions where team members critique and improve each other's work.
- **Community of Practice:** Foster a community of practice within the organization where engineers regularly share insights, challenges, and breakthroughs in AI and ML.

Deeply Specializing

The pinnacle of the AI Upskilling Framework is aimed at tech specialists and R&D roles, including DevOps engineers, ML researchers, cybersecurity experts, and data scientists in their learning levels. This level involves deep specialization in advanced AI areas, requiring a thorough understanding of complex concepts and technologies. Key skills include AIOps (AI for IT Operations), which leverages AI to optimize IT operations, and LLMOps (Large Language Model Operations), and optimization of large-scale AI models. The expertise in AI cloud solutions is necessary for deploying and managing AI applications in cloud environments. This level ensures that specialists can push the boundaries of AI innovation.

Learning Theory: Self-Directed Learning

Self-directed learning emphasizes the learner’s ability to take charge of their own learning process, setting goals, finding resources, and evaluating their progress.

- **Specialization Tracks:** Offer specialization tracks with advanced topics in AI, allowing learners to choose their focus areas based on interest and career goals. Provide resources like online courses, research papers, and advanced workshops.
- **Research Projects:** Encourage self-directed research projects where learners explore cutting-edge AI technologies such as AIOps, AI security, and AI cloud solutions. Provide access to advanced tools and platforms for experimentation.

3. Research Questions

Whether there is any significant impact of AI in ZPD on the learning

Hypothesis setting

H0: AI has no impact in ZPD on learning

H1: AI has impact in ZPD on learning

4. Theoretical Framework and Conceptualisation

4.1 Classical Learning Theories of Learning, ZPD, and AI Applications

The Zone of Actual Development refers to the skills and knowledge that an individual can perform independently or with minimal guidance. Behaviorism and Cognitivism are two classical theories of learning that emphasize the importance of reinforcement, practice, and feedback to help individuals acquire and strengthen skills. In AI training, supervised and reinforcement learning methods can help machines learn from feedback and improve their performance. The Zone of Proximal Development (Lower End) refers to the skills and knowledge that an individual can perform with guidance or assistance. Behaviorism and Cognitivism also apply to this zone, and AI training concepts such as transfer learning and curriculum learning can help machines learn new tasks with less data and supervision.The Zone of Proximal Development (Upper End) refers to the skills and knowledge that an individual can perform with expert guidance. Sociocultural Theory and Constructivism are two classical theories of learning that emphasize the importance of social interaction, collaboration, and problem-solving to help individuals learn new skills. In AI training, unsupervised and deep learning methods can help machines learn complex tasks with minimal human intervention. The Zone of Potential Development refers to the skills and knowledge that an individual can potentially acquire with proper guidance and support. Sociocultural Theory and Constructivism apply to this zone, and AI training concepts such as reinforcement learning and generative adversarial networks (GANs) can help machines learn new skills and create new outputs.

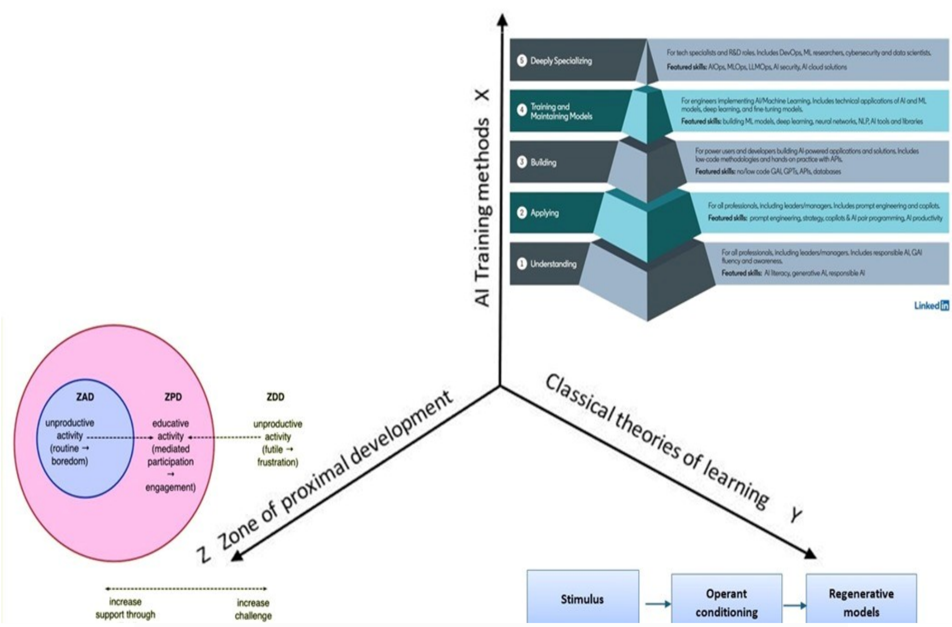

Fig. 6. The triple strands of ZPD, education phases, and AI training model

Table 2. ZPD-OC-AI Collaboration chart

ZPD	**Operant Conditioning**	**AI collaboration using Regenerative models**
Identifying competency level	Trial and Error method	Automated assistance, Personalized learning pathways, Adaptive learning, Competency mapping Learning analytics
Reinforcement pos/neg	Reward / Punishment	AI Powered feedback, personalised rewards, real-time reinforcement, Gamification, Predictive analytics Personalised consequences Immediate feedback and correction
Gradual progression	Dividing the entire task and reinforcing at each progression level	Mindset and wellness applications, personalised learning platforms Simulation and virtual assistance, reflective platforms
Scaffolding	Feedback and adjust	personalized, immediate, multimodal, peer, and data-driven feedback

Table 3. ZPD - CC - AI Collaboration chart

ZPD	**Classical conditioning**	**AI collaboration using DRL models**
Identifying competency level	Stimulus – Response measurement	Biometric data analysis, Natural language processing, Image and video analysis, Machine learning algorithms
Reinforcement pos/neg	Reward / Punishment	AI-Powered feedback, personalized rewards, real-time reinforcement, Gamification, Predictive analytics Personalized consequences Immediate feedback and correction
Gradual progression	Dividing the entire task and reinforcing at each progression level	Mindset and wellness applications, personalized learning platforms Simulation and virtual assistance, reflective platforms
Contextualization	Environment conditioning	AR/ VR, real time feedback, Simulation models, contextual intelligence and adaptive learning

While AI systems can be programmed to simulate aspects of human learning and decision-making processes, they do not possess the same level of self-awareness as humans. The ability to reflect on one's own learning process and level of competence requires a level of self-awareness and metacognition that is not currently present in AI systems. That being said, there is ongoing research in the field of cognitive AI that aims to develop AI systems that can simulate more aspects of human cognition, including self-awareness and metacognition. However, this is a complex and challenging area of research that is still in its early stages, and it is not yet clear how closely AI systems will be able to replicate the full range of human cognitive capabilities. Several parallels can be drawn between learning theories and AI concepts or methods.

Table 4. Learning theory concepts Vs. AI Concepts

Learning theory Concepts	AI Concepts
Behaviorism	Rule-Based Systems
Constructivism	Machine Learning
Social Learning Theory	Natural Language Processing
Cognitive Load Theory	Deep Learning
Connectivism	Neural Networks

Participants

For this study, we have conducted a pilot study between 38 students and 16 educators from Higher education institutions who are using AI as part of learning. The collected responses underwent a Confirmatory Factor Analysis to analyse the underlying structure and patterns if using AI in learning. Factor analysis hinges on several pivotal concepts underpinning its functionality and application across diverse domains. The majority of the participants are in the field of applied sciences which count ups to 53.6% humanities ie almost 33.9%. Majority of the respondents comes between the ages group of 21-25 and are Post graduate level.

Table 5. Demographic information of CFA

Demographic Information for CFA	(%)
Educational achievements	
Undergraduate	33.9%
Postgraduate	58.9%
PhD	8.9%
Age Group	
18-21	3.6%
21-25	53.6%
25-30	14.3%
Above 30	28.6%
Field of Study	
Humanities	7.1%
Social Sciences	1.8%
Natural Science	Nil
Formal Science	3.6%
Applied Science	87.5%

Instrument

To study participants' interaction with AI a five-point Likert scale was employed, ranging between two extremes and one middle point. The scale consists of two sections to collect the information. The first part is to collect basic and demographic data such as participants's age, academic qualification, and field of study. The second part is comprised of the questions to collect the information regarding the participants interaction with AI in learning. To assess the reliability of the scale, we conducted a pilot study and tested the Cronbach's alpha coefficient of 0.84, which exceeded a required minimum of 0.70 for accepted reliability suggested by Field (2013).

Data Collection

A pilot study is conducted among 38 students and 16 educators from higher education side. A questionnaire was circulated among them. Secondary data was collected from quality peer reviewed journals to identify major factors and theories of learning.

Data Analysis

We have done a Confirmatory Factor Analysis is used for analysing the underlying relationships of the variables. The scree plot was used identify the most predominant factors. The spearman Correlation matrix is used to analyse the correlation significance and additionally, Kaiser-Meyer-Olkin (KMO) measure is taken to evaluate the adequancy of sampling and the proportion of variables. Additionally, Cronbach's alpha is used to assess the onternal consistency of the questionnaire. The observations and analysis is done through Python and XL stat.

4.2 Results and Discussion

KMO and Cronbach's alpha test results

Table.6. KMO and Cronbach's alpha test results

Kaiser–Meyer–Olkin Measure of Sampling Adequacy	0.781
Cronbach's alpha	0.845

Factor Analysis

In factor analysis, the values associated with each factor loading typically represent the estimated factor loading and the associated p-value.

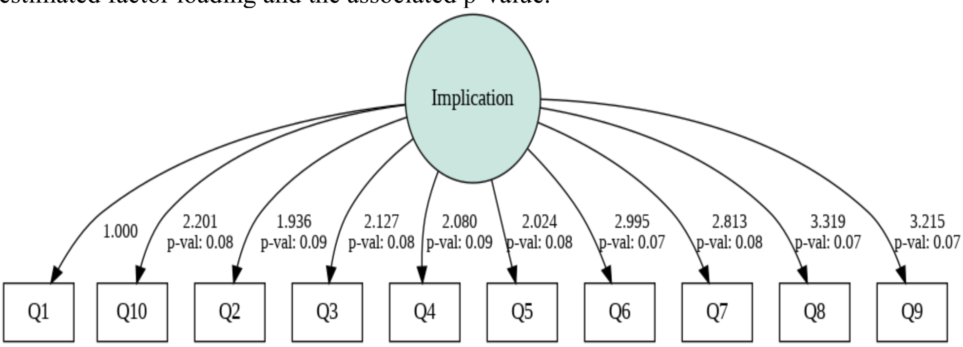

Fig.7. CFA of the identified factors

Table 7. Factors analysed

Questions	Factors analysed
Q1	Frequency of AI encounter
Q2	Effectiveness about learner level
Q3	Meaningful support
Q4	Teaching practices
Q5	Personalised support
Q6	Professional development
Q7	Identification of strength and weakness
Q8	Adjustments to pace
Q9	Comfortability during learning struggle
Q10	Learning Optimization

The factor which that AI can adjust with the learners pace is having the highest magnitude and therefore it can be considered as most contributing factor. From the analysis we can identify that, for learning AI can be leveraged as an effective tool in pedagogies for higher education teaching, which can be effectively contributed to both educator and learner.

Factor Loading Coefficient:
The first value represents the estimated factor loading or loading coefficient. This value indicates the strength and direction of the relationship between the observed variable (indicator) and the latent factor.It's typically between 0 and 1, although some datasets might result in factor loadings greater than 1 when calculating multiple variables. Higher factor loadings indicate greater association with the latent variable.. A positive loading indicates a positive relationship (as the latent factor increases, the observed variable tends to increase), and a negative loading indicates a negative relationship (as the latent factor increases, the observed variable tends to decrease). The magnitude of the loading indicates the strength of the relationship. Larger absolute values suggest a stronger relationship. Here we have all the positive loadings on the factors.

P-value
The second value is the p-value associated with the factor loading estimate. The p-value helps assess the statistical significance of the factor loading. A low p-value (commonly used 0.05 but is selected by the analyst based on significance level)) suggests that the factor loading is statistically significant, and you may have evidence to reject the null hypothesis that the loading is zero.
A high p-value suggests that there is insufficient evidence to reject the null hypothesis. Here p-value is set 0.1(10%) based on significance level ‘α’ equal to 0.9.

Since Coefficient value is positive and p values less than 0.1,, . We reject the null hypothesis at the given significance level, indicating that there is sufficient evidence to support the alternative hypothesis. So, reject H0.. Therfore, AI has significant impact in ZPD on learning.

AI Interaction and Learning

Table 8. AI Interaction and Learning

AI Impact on Zones		Factors analysed
AI impact on actual development		• Educators are teachers are encountering with AI powered tools often • AI Tools helps to identify the current level of understanding • AI tools are helpful in understanding the strength and weakness of the learner
AI impact in ZPD	• Scaffolding • Individualisation • Challenges and stress	• AI provide meaningful and personalised support to the learner • AI Support in professional development of educators and students based on knowledge and practice • AI can contribute to optimized learning within ZPD
AI impact in PD		• Overall development

Different AI platforms aligned to Active Development area and Zone of Proximal Development which can be leveraged in Higher Education can be also associated with several learning theories.

Table 9. ZPD and learning theories

Cognitive Constructivism	Adaptive learning algorithm Personalized learning path Intelligent Tutorial System
Socio cultural	Collaborative learning Discussion platforms
Contextual	AR, VR, Gamification, simulations

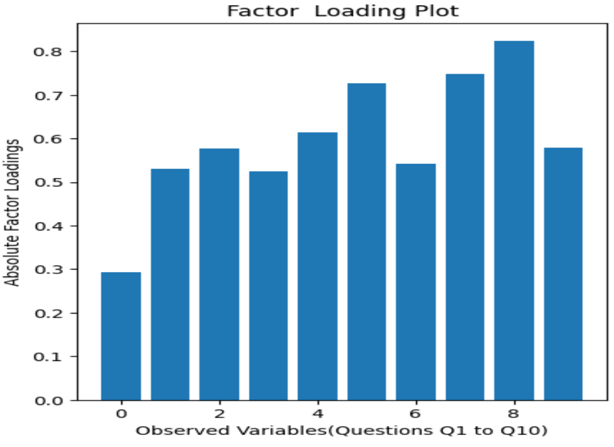

Fig.8. Factor loading plot

Gives absolute factor coefficients of Observed variables (Q1 to Q10) corresponding to the underlying latent variable (Implication of AI in education).

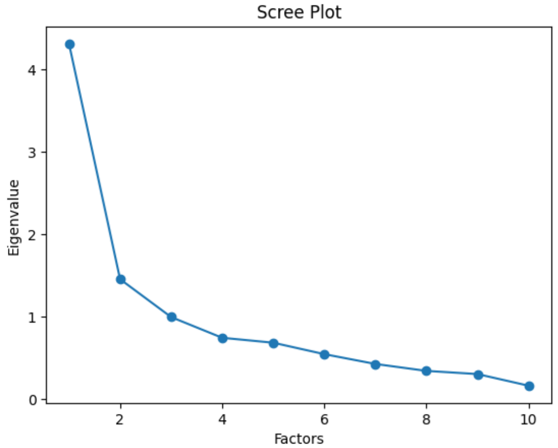

Fig.9. Scree Plot

In Confirmatory Factor Analysis (CFA), a scree plot is a graphical representation used to determine the number of factors to retain in a factor analysis. The scree plot displays the eigenvalues of the factors (latent variables) in descending order.

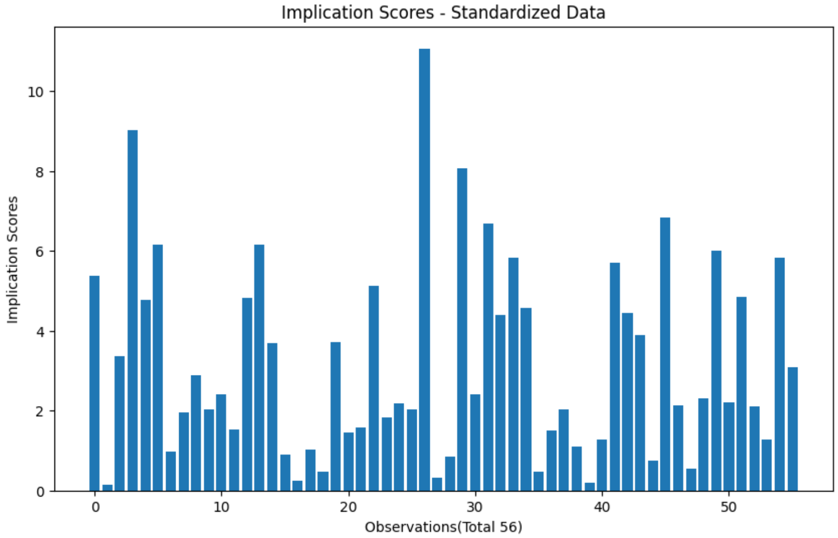

Fig.10. Implication scores of standardised data

Zone of Proximal Development (ZPD) explains the learning levels such as, Current Development Level*: What learners can do independently*. The Potential Development Level: *What learners can achieve with guidance.* And Scaffolding: *Support provided to help learners achieve their potential development level.*
Therefore, after proper analysis we are suggesting the following strategies which integrates the AI Upskilling Framework with higher education, and with various learning theories.

Table 10. Implemetantion strategies for AI in higher education

Framework Stage	**Higher Education Application**	**Learning Theory**	**Implementation Strategies**
Understanding	Offer foundational AI courses, Utilize interactive learning platforms	Constructivism	• Use simulations and tutorials. • Implement group discussions and reflection exercises • Incorporate case studies
Applying	Integrate project-based learning, Establish industry partnerships	Experiential Learning	• Assign real-world projects • Provide internships and co-op opportunities. • Encourage iterative feedback and improvement
Building	Provide advanced AI courses, Require capstone projects	Cognitive Apprenticeship	• Create mentorship programs • Use scaffolded assignments to build confidence. • Encourage collaboration with industry experts
Training and Maintaining Models	Offer specialized electives, Promote participation in research projects	Social Constructivism	• Form team-based projects • Conduct peer review sessions • Ensure access to high-performance computing resources
Deeply Specializing	Develop graduate programs focused on AI, Establish AI research labs	Self-Directed Learning	• Create specialized learning tracks. • Support self-directed research projects • Offer continuous professional development

4.3 Ethical issues of AI in Education

Socio cultural theories of learning combined with the ZPD and contextual theories bring out the complexity of Human learning and any system that mimics human learning will face similar complexities. The decision making based on the human intelligence works much on the biases and belief systems which is reinforced by learnings and experiences but also influenced by the contexts. Similarly the AI systems are prone to the biases and limitations or skewness of the data set, training orientation and extent, the biases of the trainer and rule that defines their relationship. Contextual theories, such as feminist theory and critical race theory, raise concerns about the potential for this data to be used in ways that perpetuate systemic biases and discrimination. There are also concerns about how this data is stored and protected, and who has access to it. The significance of a human agent in AI adoptions in education is critical due to these contextual factors in education. There are examples of rule based systems that are biased towards communities. The Guardian Aug 13th 2020, "*Pupils*

*from disadvantaged backgrounds have been worst hit by the controversial standardisation process used to award A-level grades in England this year, while pupils at private schools benefited the most".*Though the AI tools make a good instrument to enhance the learning process the judicious and well guided use of such instruments are equally critical for getting the desired results.
Ethical issues surrounding AI in education are multifaceted and complex, involving considerations of bias, equity, privacy, and the role of human agency. Here are some additional points to consider:

1. Bias in Data and Algorithms
2. Equity and Access
3. Privacy Concerns
4. Transparency and Accountability
5. Human Agency and Oversight
6. Social and Cultural Context
7. Power Dynamics

AI systems in education rely heavily on data, which can be inherently biased due to historical inequalities and societal prejudices. For example, if historical data used to train an AI model reflects gender or racial biases in educational outcomes, the AI system may perpetuate these biases when making decisions or recommendations.
AI-powered educational tools have the potential to exacerbate existing inequalities in education. Students from disadvantaged backgrounds may have limited access to technology or may not benefit from AI systems in the same way as students from more privileged backgrounds. This could widen the educational achievement gap rather than narrowing it. As AI systems collect vast amounts of data on students, including their learning habits, preferences, and performance. There are concerns about how this data is stored, who has access to it, and how it might be used. Students' privacy rights must be carefully safeguarded to prevent misuse or unauthorized access to their personal information. Another major concern regarding the application, AI algorithms can be opaque, making it difficult to understand how decisions are made or to identify and correct biases. There is a need for transparency in AI systems used in education, including clear explanations of how algorithms work and mechanisms for accountability if they produce unfair or discriminatory outcomes. While AI can assist teachers and students in the learning process, it should not replace human educators entirely. Human oversight is always essential to ensure that AI systems are used ethically and effectively, and to intervene when necessary to address biases or inaccuracies in AI-generated recommendations or assessments.
Socio-cultural theories of learning emphasize the importance of social interactions, cultural backgrounds, and contextual factors in the learning process. AI systems must consider the diverse cultural perspectives and individual differences among learners to be truly effective and equitable. The adoption of AI in education can shift power dynamics within educational institutions.
Addressing these ethical issues requires collaboration among educators, technologists, policymakers, and other stakeholders to develop guidelines, regulations, and best practices for the responsible use of AI in education. It also involves ongoing reflection and critical examination of the impact of AI on teaching and learning to ensure that it aligns with educational values and goals.

5. Conclusion

It is evident from the analysis of studies above and the experiences we have that there is a significant impact of AI on education especially when one tries to understand the learning process from a classical and contemporary theoretical framework. The Zone of Proximity of Development holds good for the learning in humans and in machines alike as the contextual factors have a major influence in getting a behaviour or outcome for a particular stimulus. This factor that the contextual factors influence the decision making also means that the system will be subject to the biases or frame of reference defined for each context. and hence the issue of ethics in AI in terms of discriminatory, skewed or unequitable decisions being taken or proceeded with is a probability. and Adoption of such a system into education without a proper role for a human agent could be disastrous. In a broader way, AI has a positive impact on learners' outcome, and act as a significant role in solving major education challenges but AI on education still poses some ethical issues AI raises on learners such as bias, discrimination, autonomy and we need to confront the issues using an established ethical guideline. AI in education need to be guided by ethical principles and these values.

By aligning the AI Upskilling Framework with Vygotsky's ZPD and learning theories, higher education institutions can create robust educational programs that effectively support students at different stages of their learning journey. This approach ensures that students receive appropriate scaffolding, gradually building their skills from basic understanding to advanced specialization. Implementing strategies such as blended learning, continuous feedback, and real-world applications will help students move through their ZPD, enhancing their learning experiences and preparing them for the AI-driven job market.

6. Future Directions

There is a need for research to explore the ethical implications of AIED and to develop ethical guidelines for the development and deployment of AIED systems. This requires interdisciplinary collaboration between education, computer science, philosophy, and other relevant fields. The research should be also focused to check the spiral curriculum models and the iterative models which are even now in use for development of AI tools with respect to the Zone of proximity of development for a learner. The Zones can be an upward spiral and with every turn of the spiral the complexity of AI tool could be increased so that the adoption of AI is smooth and within the zone of proximity of the learner. The idea of spiral curriculum means that the teacher will revisit a concept repeatedly while teaching another. During this revisit the teacher will incorporate the old information with what is being learned now. This process allows the student to begin learning the new concept as well as applying the old one to something different and learning it in greater depth. One of the key challenge in AIED is building trust and transparency between educators, students, and AI systems and the future research in this area could focus on developing mechanisms for explaining how AI systems work, why they make certain recommendations or decisions, and how they can be trusted. There is a need to understand how humans interact with these systems and how these interactions can be designed to be more effective, ethical, and equitable.

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