TPM Vol. 32, No. S6, 2025
ISSN: 1972-6325
https://www.tpmap.org/

ROLE OF GENERATIVE AI TOWARDS EDUCATION AND LEARNING: PRESENT & FUTURE

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Abstract
This research paper provides a comprehensive analysis of the role of Generative Artificial Intelligence (GenAI) in education and learning, examining its present applications, theoretical underpinnings, inherent challenges, and future trajectories. With the comprehensive review of recent research work in said domain all over the world, It delves into the integration of GenAI with established learning theories and emerging pedagogical models, highlighting its potential for personalized learning, automated content generation, and intelligent tutoring. Concurrently, the paper critically addresses significant challenges such as academic integrity, data privacy, algorithmic bias, and the impact on human cognitive skills and interaction. Finally, it forecasts the evolving roles of educators and students, discusses future pedagogical shifts, and outlines essential policy and governance considerations to foster an equitable, ethical, and effective AI-driven educational landscape.

Keywords: Generative AI, Education, Learning, Artificial Intelligence, Personalized Learning, Intelligent Tutoring Systems, Academic Integrity, Ethical AI, Pedagogical Models, Future of Education.

1. INTRODUCTION

The landscape of education and learning is undergoing a profound transformation, driven by the rapid advancements in artificial intelligence, particularly Generative Artificial Intelligence (GenAI). This technological evolution is not merely an incremental improvement to existing tools but represents a fundamental shift in how knowledge is created, disseminated, and acquired. According to Baskara [1], the capabilities of GenAI extend far beyond traditional AI systems, which were primarily designed for classification or prediction tasks. Instead, GenAI models possess the unique ability to produce novel and original content, encompassing text, images, audio, video, and even programming code, all derived from the vast datasets upon which they are trained. This generative capacity has quickly moved from a theoretical possibility to a tangible reality, reshaping the very fabric of teaching, learning, and research practices across educational institutions worldwide [8][9][10].
The public introduction of tools like OpenAI's ChatGPT in late 2022 served as a watershed moment, fundamentally altering perceptions and applications of AI in educational settings. Educators rapidly began exploring its utility for tasks such as lesson planning, while students quickly adopted it for homework assistance, igniting widespread discussion and debate about its implications [11][12]. This initial engagement underscored GenAI's potential as a transformative force, compelling a re-evaluation of traditional educational models that may not adequately serve the diverse needs of all learners. Ali et. al [2] concludes the impact extends beyond mere efficiency gains, signaling a deeper paradigm shift where GenAI acts as a catalyst for reimagining the core nature of teaching and learning itself.

1.1. The Transformative Landscape of Generative AI in Education

The integration of Generative AI into education signifies a pivotal moment, moving beyond incremental technological enhancements to a more fundamental redefinition of learning environments. Historically, educational technology aimed to streamline existing processes or provide supplementary resources [13]. However, GenAI's capacity to create original content fundamentally alters this dynamic. For instance, while earlier educational technologies often required children to engage directly with screens, GenAI can operate in the background, assisting educators in preparing creative lesson plans, hands-on activities, or personalized teaching strategies [14][15]. This capability allows for the drafting of science experiments, brainstorming of nature-based math exercises, or generation of storytelling prompts without necessitating direct screen interaction from the child. This distinction highlights that GenAI is not merely a tool for doing existing tasks faster; it enables entirely new possibilities for educational design and delivery [16].
Batista et. al. [3] states that the impact of GenAI on education can be conceptualized as a paradigm shift from focusing solely on efficiency to enabling profound transformation. Traditional AI systems were primarily designed for classification or prediction, offering solutions within predefined parameters. GenAI, by contrast, generates original output, empowering educators to create tailored learning experiences and resources that were previously impossible or prohibitively time-consuming. This moves beyond simply optimizing current practices;

it redefines the scope of what is achievable in teaching and learning. For example, GenAI can provide every student with a personalized tutoring experience on any topic, a level of individualized support that was logistically impossible before its advent [17]. This transformative potential implies a necessary re-evaluation of educational models that may no longer be effective for all learners, prompting a deeper consideration of how education can be reimagined to better serve diverse needs. The ability of GenAI to reduce the creative and cognitive load on educators, for instance, by generating multiple versions of a lesson tailored to different learning levels, allows them to focus on higher-order tasks such as fostering critical thinking, empathy, and curiosity, which remain at the heart of meaningful human interaction in learning environments. This fundamental shift in the teacher's role, from primarily a content deliverer to a facilitator and mentor, is a crucial aspect of GenAI's transformative influence [18][19][20].

1.2. Defining Generative AI: Core Principles and Evolution

In accordance of Monib et. al. [4], Generative AI (GenAI) refers to a class of machine learning models distinguished by their ability to produce novel content, including text, images, audio, video, and code, based on the patterns and structures learned from their vast training datasets. This capability sets GenAI apart from traditional AI systems, which are typically designed for analytical tasks such as classification, prediction, or pattern recognition. Prominent examples of GenAI tools include Large Language Models (LLMs) like ChatGPT for text generation, DALL·E for image creation, and Codex for code synthesis [21][22]. The rapid evolution of these models, particularly LLMs, which have processed an immense volume of written data, has enabled them to create highly interactive and diverse content, ranging from domain-specific problem sets to immersive simulations [23].

Liang & Bai [5] describe that the core principle underpinning GenAI's application in education is its potential to deliver highly personalized learning experiences. When provided with deliberately designed and structured prompts, GenAI can offer individualized tutoring on virtually any subject, a level of tailored support that was previously unattainable at scale. This personalization extends to generating customized lesson plans and resource materials that cater to individual student learning needs, often without requiring direct screen interaction from children. This capacity to act as a "planning partner" for educators is a significant aspect of GenAI's unique utility [24][25]. It allows teachers to offload repetitive and time-consuming tasks, such as drafting rubrics, tracking student progress, or creating differentiated task cards, thereby reducing their overall creative and cognitive load. By automating these administrative and content creation burdens, GenAI frees up educators' valuable time, enabling them to concentrate more on fostering critical thinking, empathy, and curiosity—qualities where human interaction and guidance remain indispensable. This fundamental rebalancing of responsibilities, where GenAI handles the generative and administrative heavy lifting, allows human educators to deepen their focus on the relational and higher-order cognitive aspects of teaching [26][27].

1.3. Scope, Objectives, and Structure of the Research Work

This research paper is designed to offer a comprehensive and generalized overview of the multifaceted role of Generative AI in education and learning. Its scope deliberately encompasses both the theoretical foundations that underpin GenAI's integration and the practical applications that are currently reshaping educational environments. To maintain a broad and universally applicable perspective, this paper explicitly refrains from delving into domain-specific case studies. The primary objectives guiding this comprehensive analysis are fourfold:

1. To delineate and analyze the theoretical frameworks that provide the conceptual underpinnings for GenAI's application within educational contexts. This involves exploring how GenAI interacts with established learning theories and contributes to the emergence of new pedagogical models.
2. To identify and systematically examine the current practical applications of GenAI across various facets of education, illustrating how these technologies are being deployed to enhance learning and teaching processes.
3. To critically evaluate the significant challenges and inherent limitations associated with the widespread integration of GenAI in educational settings, including concerns related to academic integrity, data privacy, and the impact on human cognitive skills.
4. To explore future trajectories, forecasting the evolving roles of educators and students, discussing anticipated pedagogical shifts, and outlining essential policy and governance considerations necessary for navigating an AI-driven educational landscape.

Figure 1: Conceptual Diagram of Generative AI's Interconnected Role in the Modern Learning Ecosystem

2. THEORETICAL FOUNDATIONS OF GENERATIVE AI IN LEARNING

The effective and responsible integration of Generative AI into educational practices necessitates a deep understanding of its theoretical underpinnings. This section explores how GenAI interacts with and builds upon established learning theories, introduces novel pedagogical models, and underscores the critical importance of developing robust ethical and governance frameworks to guide its adoption [28][29]. Figure 1 shows the Conceptual Diagram of Generative AI's Interconnected Role in the Modern Learning Ecosystem. By grounding GenAI applications in educational theory, practitioners and policymakers can ensure that technological advancements genuinely enhance learning outcomes rather than merely automating existing processes [30][31].

2.1. Integration with Established Learning Theories

According to Bozkurt et. al. [6], Generative AI's capabilities offer new dimensions for applying and evolving various classical and modern learning theories, providing innovative pathways for educational design and delivery [32].

2.1.1. Behaviorist and Cognitivist Perspectives

Behaviorism, a foundational learning theory, posits that learning occurs through observable behaviors that are shaped by environmental stimuli, rewards, and punishments, a process famously articulated through operant conditioning [33]. In the context of AI-based education systems, this theory finds renewed relevance. GenAI tools can provide immediate feedback and reinforcement, which are critical components for strengthening desired behaviors and improving learning outcomes [34][35][36]. For example, automated quizzes and practice problems can instantly inform students whether their answers are correct, providing the immediate positive or corrective feedback necessary for operant conditioning to be effective. This ability of AI to deliver instant feedback at scale represents a significant advancement. In accordance of Aad, & Hardey [7], human teachers can provide feedback, their capacity is often limited by class size and time constraints, leading to delays. GenAI's capacity for instant and personalized feedback means that the core principles of operant conditioning can be applied more consistently and broadly than ever before, potentially accelerating skill acquisition, particularly in subjects that benefit from repetitive practice and immediate correction. This makes AI a highly scalable reinforcement mechanism. However, it is crucial to note that simply providing answers can be detrimental; empirical evidence suggests that while AI-based tutoring can improve performance during practice, students who rely on it without proper guidance may underperform when AI access is removed, indicating a reduction in genuine skill acquisition without appropriate guardrails [37][38]. This highlights the need for careful design to ensure deep learning rather than mere performance enhancement.

2.1.2. Constructivism, Experiential Learning, and Cognitive Apprenticeship

Beyond traditional behaviorist and cognitivist frameworks, Generative AI also significantly impacts modern learning theories such as constructivism, experiential learning, and cognitive apprenticeship [39]. Constructivism posits that learners actively construct their own understanding and knowledge through experience and reflection. GenAI facilitates this by enabling the creation of highly interactive and dynamic learning tools, including gamified courses, virtual laboratories, and immersive simulations [40][41]. These environments allow students to engage with complex concepts in a hands-on, exploratory manner. For instance, virtual dissection in a biology class or historical simulations in a history lesson provide immersive and instructive learning opportunities that were previously constrained by physical limitations or safety concerns. This capability to create realistic, interactive simulations bridges the gap between theoretical knowledge and practical application, allowing students to carry out experiments and explore scenarios that were impossible before due to physical or logistical restraints [42][43][44]. This directly addresses a core challenge in experiential learning, which emphasizes learning by doing. The ability to simulate complex real-world scenarios democratizes access to high-fidelity experiential learning, potentially leading to a more practical and applied understanding of concepts across various disciplines without the need for expensive physical infrastructure. This aligns with the broader idea of the "democratization of learning," making quality educational experiences accessible to a wider population [45][46][47][48].

2.2. Emerging Pedagogical Models and Frameworks

The rapid proliferation of Generative AI tools has not only influenced existing learning theories but has also catalyzed the development of entirely new pedagogical models and frameworks [49][50]. These models are designed to provide structured approaches for responsibly integrating AI into educational practices, ensuring that its transformative potential is harnessed effectively while mitigating associated risks [51][52].

2.2.1. The AI-TEACH Model

One such comprehensive framework is the AI-TEACH Model, which proposes a structured approach to AI integration in education built upon five interconnected pillars: Transformative Learning, Ethical AI Practices, Adaptive Learning, Collaborative Environments, and Holistic Development. This model is designed to enhance teaching and learning outcomes by leveraging AI, while simultaneously upholding principles of inclusivity, equity, and innovation. Figure 2 depicts the conceptual diagram of AI-TEACH Model for Holistic AI Integration in Education [53][54][55].

The AI-TEACH framework is grounded in established educational theories such as the SAMR model, TPACK, Universal Design for Learning (UDL), social constructivism, and self-determination theory. It extends these theories by specifically integrating AI-specific applications and ethical considerations, providing a robust and holistic approach to AI integration that addresses both the technical and human aspects of education [56][57].

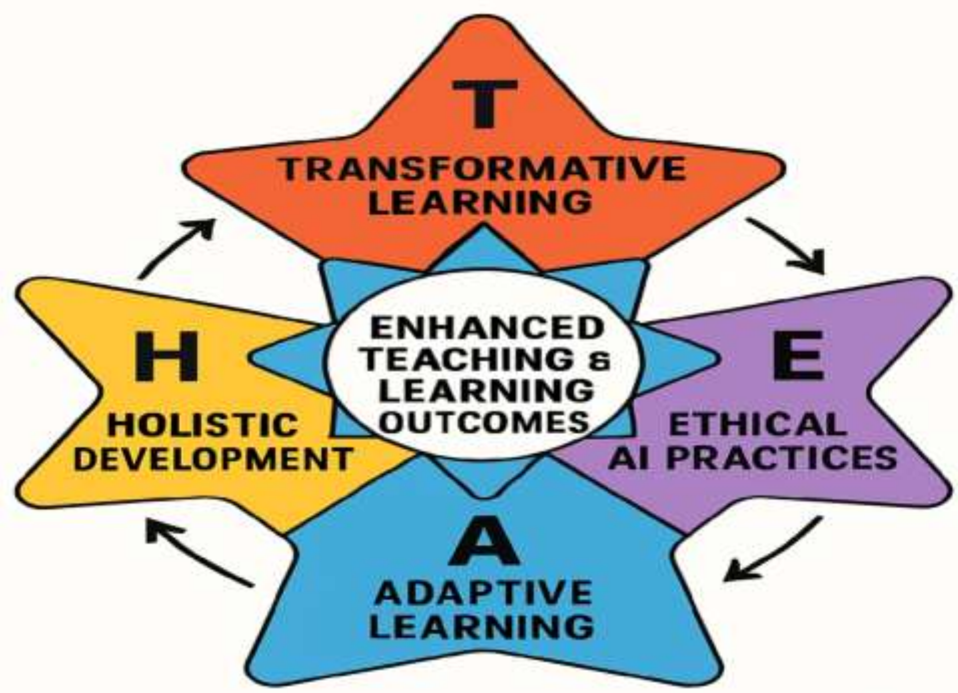

Figure 2: AI-TEACH Model for Holistic AI Integration in Education

2.2.2. Frameworks for AI-Supported Assessment

The integration of Generative AI into educational environments introduces both significant opportunities and complex concerns regarding assessment design, academic integrity, and quality assurance. To navigate these complexities, a structured framework for GenAI-supported assessment in higher education has been proposed, organized around the needs and responsibilities of three key stakeholders: instructors, students, and control authorities. This framework operates across three hierarchical levels of assessment, corresponding to typical academic assessment phases: course-level assessment, midterm testing, and unit tasks. Figure 3 demonstrates the Conceptual Diagram of a Multi-Level Framework for Generative AI-Driven Assessment. It delineates how AI can assist in designing adaptive tasks, providing timely feedback, and ensuring institutional accountability [58][59][60].

At **Level 1: Course Assessment**, which typically involves summative evaluations like final exams, GenAI tools can significantly assist lecturers in designing comprehensive exam formats and generating final exam questions that are precisely aligned with course outcomes. This can also extend to producing consistent, rubric-based grading and feedback at scale, alleviating a substantial administrative burden. For students, intelligent chatbots offer robust support in reviewing course content, simulating exam environments, and addressing last-minute queries with tailored feedback and revision prompts, thereby enhancing their preparedness [61][62]. From the perspective of control authorities (e.g., accreditation bodies, quality assurance units), GenAI enables systematic monitoring of assessment quality, fairness, and alignment with accreditation standards. AI-powered dashboards can summarize grading patterns, highlight anomalies in final results, and ensure transparency and integrity throughout the summative assessment process.

Level 2: Midterm Assessment focuses on formative evaluations that track student progress throughout a course. Here, AI can generate customized midterm questions, assist in balancing question difficulty to ensure fairness, and evaluate structured responses using predefined rubrics [63][64][65]. Chatbots can further clarify exam instructions and help interpret student performance trends for instructors. For students, AI tools provide personalized practice tasks and simulate exam-style questions, offering constructive feedback on their performance to guide future learning and address identified weaknesses. For control authorities, this stage provides an opportunity to monitor continuous assessment integrity, ensuring consistency in exam administration, tracking progress data, and assessing the degree to which midterm evaluations align with curriculum benchmarks [66][67].

Level 3: Unit Assessments represents the most granular level, involving low-stakes quizzes and knowledge checks designed to provide real-time insights into students' understanding of specific topics. Lecturers benefit from AI-enabled automation of these assessments and quick feedback mechanisms, allowing them to gain immediate insights into student comprehension. Students can interact with AI chatbots to clarify confusing concepts, test their knowledge, and receive immediate feedback, which supports mastery learning and promotes critical thinking and self-regulated learning strategies. For control authorities, this level yields granular data on assessment engagement and learning progression, enabling AI tools to identify early signs of disengagement or

learning gaps and facilitating timely interventions. This supports evidence-based quality assurance at the micro-curricular level [68][69].
The framework also incorporates a five-step assessment procedure: Assessment Planning, Preparation and Training, Assessment Delivery, Evaluation and Feedback, and Reflection and Improvements. At each step, GenAI provides supportive functions to all stakeholders, from generating example rubrics and suggesting assessment scenarios during planning to offering personalized learning recommendations during reflection. A crucial aspect of this framework is its emphasis that while GenAI tools offer significant benefits, critical decisions regarding instructional design, assessment criteria, and course outcomes remain the fundamental responsibility of the human instructor. The AI tools are designed to complement, not replace, the academic judgment and pedagogical expertise of educators. This model supports key didactic principles such as flexibility, accessibility, consistency, and systematic progression, helping educators identify knowledge gaps, personalize learning trajectories, and reinforce skill development effectively [70][71].

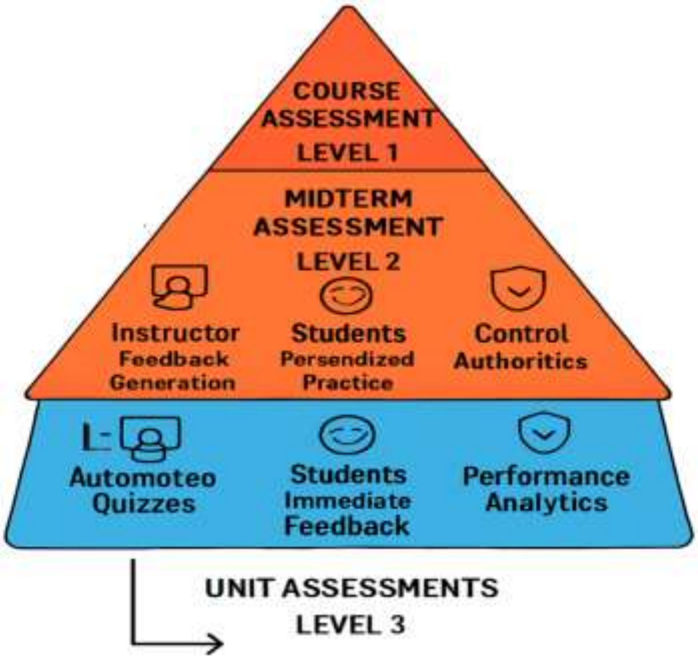

Figure 3: Multi-Level Framework for Generative AI-Driven Assessment

2.3. Ethical and Governance Frameworks for Responsible AI Adoption

The integration of Generative AI into educational systems, while promising, is fraught with significant ethical implications that necessitate the development and implementation of robust governance frameworks. A foundational principle, as articulated by UNESCO's 2023 guidance, is the adoption of a rights-based approach to GenAI in education, emphasizing ethical alignment, inclusion, and long-term sustainability. This human-centered approach ensures that AI serves to augment, rather than replace, the vital role of educators, keeping meaningful interpersonal interactions at the core of the learning environment [72][73][74].
Several key ethical concerns demand immediate attention. First, the proliferation of "deepfakes" and the broader issue of truthfulness and accuracy in AI-generated content pose a substantial risk. GenAI, by its nature, can fabricate information, including non-existent references, and propagate inaccurate details or even convincing conspiracy theories. Research indicates that most generative models are truthful only about 25% of the time according to some benchmarks, highlighting a significant reliability issue. This technical limitation, where the quality and scope of GenAI outputs are directly tied to potentially flawed or biased training data, directly leads to ethical concerns about accuracy and bias. If the underlying data is limited, biased, or inaccurate, the AI's outputs will inevitably reflect these shortcomings, potentially leading to skewed or incorrect information being presented as fact. The "black box nature" of some GenAI systems further complicates this, making it difficult to trace the precise origin of a bias or inaccuracy, thus impeding efforts to correct it [75].
Second, the issue of algorithmic bias is critical. AI models can inadvertently learn and perpetuate existing social biases (e.g., sexist, racist, ableist) from their training data, leading to biased decision-making, reinforcing stereotypes, or unfair practices within educational contexts [76][77]. This can disproportionately disadvantage historically underserved student populations, exacerbating existing educational inequities. Addressing this requires a proactive and multi-faceted approach that extends beyond mere ethical guidelines; it demands technical interventions such as ensuring diverse and representative training datasets, implementing continuous bias monitoring, and clearly documenting mitigation efforts. Furthermore, educators must retain override options, preserving their agency in AI-assisted instruction [78][79].
Third, copyright ambiguities arise concerning who owns the rights to AI-created works and whether copyrighted data can be used for training purposes, especially when AI models mimic existing artistic styles. Fourth, the potential for misuse, such as students using AI to complete homework without genuine engagement, raises

significant academic integrity issues. This also includes the risk of AI generating harmful or inappropriate content [80].

3. PRESENT APPLICATIONS OF GENERATIVE AI IN EDUCATION

Generative AI is rapidly moving from a nascent technology to a ubiquitous tool within the educational sector, offering innovative solutions that address long-standing challenges and enhance various aspects of teaching and learning. Its current applications span from deeply personalized learning experiences to significant administrative efficiencies, fundamentally reshaping how educational institutions operate [81][82].

3.1. Personalized and Adaptive Learning Environments

One of the most transformative applications of Generative AI in education lies in its unparalleled capacity for personalized and adaptive learning. Unlike traditional, static curricula, AI systems can dynamically analyze a wealth of student data, including their aptitude, progress, individual interests, and preferred learning styles, to construct highly customized lesson sequences, assignments, and review materials. This tailored approach ensures that no learner is left behind, as the content and pace of instruction are continuously adjusted to meet their unique needs, thereby significantly enhancing both knowledge acquisition and student engagement and motivation [83].

For example, AI-powered tools possess the ability to generate multiple versions of a single lesson, each meticulously tailored to different learning levels within a diverse classroom. This allows an educator to provide a science activity on plant growth, for instance, that is specifically designed for a 6-year-old with kinesthetic preferences, suggesting outdoor experiments instead of conventional worksheets. This level of customization moves beyond the traditional "one-size-fits-all" model of education. The mechanism enabling this dynamic customization is AI's continuous assessment of student performance and its ability to recalibrate learning pathways in real-time. This is not merely about pre-setting a learning path but about adapting as the student interacts with the material and demonstrates their understanding [84][85].

3.2. Automated Content Creation and Curriculum Development

Generative AI is fundamentally transforming the processes of content creation and curriculum development within education by enabling educators to rapidly produce a diverse array of high-quality educational materials. This capability significantly streamlines tasks that traditionally demand considerable time and effort from teaching staff. Teachers can now leverage AI to create comprehensive instructional resources, including detailed lesson plans, varied assessment tools like tests and quizzes, engaging assignments, and even entire course modules [86].

Beyond basic text generation, AI can generate specific activity sheets, creative story prompts, or innovative hands-on project ideas that are meticulously aligned with specific developmental goals or learning objectives. For instance, an educator can prompt an AI tool to "Design five screen-free math games using leaves, sticks, and stones to teach addition and subtraction to 2nd graders," and the tool will respond with fully fleshed-out, developmentally appropriate ideas, eliminating the need for extensive manual searching or brainstorming. This capability extends to producing interactive and dynamic learning tools, such as gamified courses, virtual laboratories, and immersive simulations, which make abstract or difficult concepts more accessible and engaging for students. These AI-generated tools facilitate hands-on, immersive, and instructive learning opportunities, allowing students to engage with subjects in ways that were previously impossible due to physical or logistical constraints [87].

3.3. Intelligent Tutoring Systems and Real-time Feedback

Intelligent Tutoring Systems (ITS) represent a significant advancement in personalized education, powered extensively by Generative AI. These systems are designed to provide individualized instruction, dynamic feedback, and tailored recommendations, adapting in real-time to a student's unique strengths and weaknesses. Research indicates that ITS can substantially improve student test scores, with reported increases ranging from 16% to 40%. A key advantage of these AI-driven tutors is their availability, offering 24/7 learning support as on-demand digital teachers [88].

The effectiveness of ITS stems from their ability to provide immediate feedback on student work and course assignments. These systems analyze student submissions and offer practical insights to identify and close knowledge gaps without the typical time lag of conventional grading systems. For instance, if a student struggles with a concept, the AI can provide hints, explanations, or additional practice as needed, adapting to the student's learning pace. Large Language Models (LLMs), a core component of many ITS, further enhance this capability by being able to refine responses, explain complex concepts in multiple ways, and act as patient, non-judgmental companions. This fosters curiosity and self-directed learning by offering subtle cues or more directive questions that guide a student's thinking in a productive direction, encouraging deeper questioning rather than simply providing direct answers [89][90].

3.4. Streamlining Administrative Tasks and Educator Support

Generative AI tools are proving to be invaluable assets in significantly reducing the administrative burden on educators, thereby freeing up substantial time that can be reallocated to more impactful, student-centered activities. These tools excel at automating repetitive and time-consuming tasks that traditionally consume a considerable portion of a teacher's day. This includes the efficient grading of tests and assignments, drafting comprehensive rubrics, and meticulously tracking student progress. For instance, AI can instantly check multiple-choice or true/false formats and rapidly assess written assignments for grammar, style, content, and concept mastery, even flagging potential plagiarism. This automation not only enhances operational efficiency but also ensures consistent and often unbiased assessments, reducing human error and subjectivity [91].

Beyond assessment, AI assistants offer extensive support in various other administrative functions. They can build bespoke lesson plans tailored to specific learning objectives, create engaging presentations, and generate personalized student reports that provide detailed insights into individual performance. Table 1 shows the Key Applications of Generative AI Across Educational Functions. These intelligent tools can also brainstorm and generate ideas for educational activities and test creation, providing educators with a wealth of customizable content in minutes. This capacity to quickly generate worksheets, flashcards, and multiple-choice questions in a desired tone, format, and length is a significant time-saver for instructional designers and teachers [92][93].

Table 1: Key Applications of Generative AI Across Educational Functions

Educational Function	**Examples of Generative AI Application**	**Associated Benefits**				
Personalized Learning	- Custom lesson sequences, assignments, and reviews based on student data (aptitude, interests, style).	- Tailored study guides, practice questions, and simulations for test prep.	- Adaptive content delivery that adjusts in real-time to student progress and knowledge gaps.	- Increased student engagement and motivation.	- Improved knowledge acquisition and concept retention.	- Reduced learning gaps and individualized support.
Content Creation & Curriculum Development	- Generation of draft lesson plans, rubrics, parent newsletters, and differentiated task cards.	- Creation of interactive and dynamic learning tools: gamified courses, virtual labs, simulations.	- Production of multilingual materials, story prompts, and hands-on project ideas.	- Significant time savings for educators.	- Enhanced creativity and variety in learning materials.	- More accessible and engaging content for diverse learners.
Intelligent Tutoring & Feedback	- Real-time, personalized instruction and feedback on assignments and quizzes.	- Adaptive hints and prompts that guide students towards understanding without giving direct answers.	- 24/7 access to expert-level support and explanations.	- Improved student test scores and mastery of concepts.	- Fosters curiosity and self-directed learning.	- Immediate identification and correction of misconceptions.
Administrative Support	- Automated grading of tests and written assignments.	- Management of routine tasks: attendance, scheduling, document filing, data entry.	- Predictive analytics to flag at-risk students and inform interventions.	- Frees up educator time for direct student interaction and relationship-building.	- Data-driven insights for administrative decisions and resource allocation.	- Enhanced operational efficiency across institutions.
Accessibility & Inclusivity	- Automatic speech recognition, text-to-speech, and real-time captioning.	- Machine translation for multilingual learners and global collaboration.	- Virtual reality simulations removing physical barriers to learning.	- Equal access to instructional tools for students with disabilities.	- Promotion of a more inclusive and equitable learning environment.	- Enhanced communication and engagement for diverse student populations.

3.5. Enhancing Accessibility and Inclusivity in Learning

Generative AI technologies are poised to significantly enhance accessibility and inclusivity within educational settings, addressing barriers that have historically limited equitable learning opportunities for diverse student populations. These advancements are particularly impactful for students with disabilities and multilingual learners, ensuring broader participation and engagement in the learning process [94].

One key application is the provision of advanced accessibility solutions. Features such as automatic speech recognition, text-to-speech functionalities, and real-time captioning tools can profoundly aid visually and hearing-impaired learners, enabling them to access and interact with educational content more effectively. For instance, a student with a hearing impairment can follow a lecture through live-generated captions, while a visually impaired student can have text-based materials converted into audible formats. This proactive approach to accessibility aligns closely with the principles of Universal Design for Learning (UDL), which advocates for designing learning environments and materials that are inherently accessible to all learners from the outset. GenAI's ability to generate content in varied formats (text, audio, visual) and to adapt to individual needs inherently supports UDL, reducing the need for retrofitting accommodations by building flexibility into the core of learning materials and interactions. This fosters equitable access to high-quality education for a broader population [95][96].

4. CHALLENGES AND LIMITATIONS IN GENERATIVE AI INTEGRATION

While the transformative potential of Generative AI in education is undeniable, its widespread integration is accompanied by a complex array of challenges and limitations that demand critical attention and proactive strategies. These concerns span from fundamental issues of academic integrity to intricate questions of data governance and the very nature of human cognitive development [97].

4.1. Academic Integrity, Plagiarism, and Authenticity

One of the most pressing challenges posed by Generative AI in education is the profound impact on academic integrity, raising significant questions about plagiarism, authenticity, and the true authorship of student work. The ease with which GenAI tools can generate human-like text, conduct "research," integrate ideas, and even write complete papers tempts students to use them as shortcuts, bypassing the essential intellectual processes that are core objectives of academic assignments. This shortcutting behavior can short-circuit the crucial process of critical thinking, analysis, synthesis, and original writing, thereby depriving students of genuine learning and intellectual growth [98][99].

The proliferation of AI-generated content makes it increasingly difficult for educators to distinguish between student-produced work and AI-assisted or AI-generated submissions. This introduces a substantial risk of AI-assisted cheating and plagiarism, compromising the authenticity of academic achievements. The current landscape of AI detection tools further complicates this issue. While various tools exist, their accuracy is inconsistent, and none are currently highly effective in reliably identifying AI-generated content. Moreover, the rapid pace of AI development means that generative AI software is likely to continue evolving faster than detection capabilities, perpetuating an "arms race" between AI generation and detection. This dynamic conflict challenges the very notion of "originality" in student work. If AI can produce a seemingly perfect essay, what exactly is being assessed? [100][101]

4.2. Data Privacy, Security, and Algorithmic Bias

The integration of Generative AI models into educational systems introduces significant concerns regarding data privacy, security, and the potential for algorithmic bias. GenAI models, by their very nature, require access to and training on vast amounts of data. When this data includes sensitive student information, ensuring its privacy and security becomes paramount. Educational institutions must adhere strictly to data protection regulations, such as GDPR, and implement robust cybersecurity measures to prevent data breaches and unauthorized access to student records. The inherent need for extensive data for training purposes creates a vulnerability that must be managed with extreme caution [102].

A more insidious challenge is the phenomenon of algorithmic bias. AI models learn from the data they are trained on, and if this training data contains inherent biases—whether conscious or unconscious, historical or systemic—the AI will inadvertently learn and perpetuate these biases. This can lead to biased decision-making, reinforce stereotypes, or result in unfair practices within educational contexts. For example, an AI system trained on unrepresentative or prejudiced data might disproportionately disadvantage historically underserved students, thereby exacerbating existing educational inequalities. Research indicates that larger and more sophisticated generative AI systems are more prone to absorbing underlying social biases (e.g., sexist, racist, ableist) from their training data, with some models showing a significant increase in toxicity levels compared to smaller models. This creates an inherent risk of "algorithmic inequity," where AI systems, despite their perceived objectivity, can perpetuate or even amplify societal biases within the educational environment [103].

4.3. Impact on Critical Thinking and Human Interaction

A significant concern surrounding the integration of Generative AI in education is its potential impact on the development of critical thinking, creativity, and the preservation of essential human interaction. There is a palpable risk that over-reliance on GenAI technologies could detrimentally affect core educational values, leading to a "deskilling" of both students and teachers. If students habitually rely on AI to generate research, synthesize ideas, or solve complex problems, they may bypass the cognitive effort necessary to develop their own analytical, problem-solving, and creative faculties. This can lead to a suppression of original thought and inventiveness, as the immediate availability of AI-generated solutions might disincentivize deeper intellectual engagement [104][105].

UNESCO has explicitly cautioned that an "over-reliance on AI-driven solutions in education could lead to a devaluation of human interaction, critical thinking, and the development of essential social-emotional skills". This highlights a paradox: while AI can enhance learning and provide instant answers , its very efficiency might inadvertently lead to a form of cognitive "deskilling." If AI performs the "thinking," students may not develop their own capacities for critical evaluation, complex reasoning, and creative problem-solving. This is not merely a theoretical concern; student surveys indicate that a notable proportion are concerned about becoming overly dependent on GenAI technologies. This situation underscores the imperative for a balanced approach: AI should serve to *augment* human capabilities, not to replace them. Educational strategies must evolve to teach students [106].

4.4. Resource Allocation, Digital Divide, and Equitable Access

The integration of Generative AI into educational systems, while offering numerous benefits, also presents substantial challenges related to resource allocation, the potential exacerbation of the digital divide, and ensuring equitable access for all learners. The development and maintenance of sophisticated GenAI systems are inherently resource-intensive. This includes significant costs associated with acquiring high-quality, diverse training data, securing the necessary computing power for model training and deployment, and recruiting or developing specialized talent to build, manage, and integrate these systems effectively. These substantial financial and human capital requirements create a significant barrier to entry for many educational institutions [107].

This economic disparity directly impacts equitable access. Well-resourced schools and districts are far more likely to possess the financial capacity and technological infrastructure to implement advanced AI-driven tools, such including high-speed internet access, up-to-date devices, and robust IT support. Conversely, underfunded districts often lack these fundamental resources, creating a pronounced "digital divide" that can widen existing educational inequalities. This means that the benefits of AI-enhanced personalized learning, automated feedback, and rich content creation may disproportionately accrue to students in privileged environments, while historically underserved students are left further behind. In this concern, Table 2 reflects *Major Ethical Concerns and Proposed Mitigation Strategies for Generative AI in Education.* This is a common concern among educators, who highlight the high implementation costs as a major issue. The reliance on advanced technology inherently poses challenges in regions with limited access to necessary resources, exacerbating existing disparities [108].

Table 2: Major Ethical Concerns and Proposed Mitigation Strategies for Generative AI in Education

Ethical Concern	**Description of the Challenge**	**Proposed Mitigation Strategies**			
Academic Integrity & Plagiarism	Difficulty in distinguishing AI-generated content from human work; students using AI as a shortcut, leading to cheating and undermining genuine learning.	- Redesign assessments to focus on critical thinking, process, and human-unique skills (e.g., reflection, collaboration, curation of	- Educate students on ethical AI use, plagiarism, and consequences.	- Develop clear institutional policies on AI use in assignments.	- Foster a culture of academic honesty and value for original thought.
Data Privacy & Security	GenAI models require vast amounts of sensitive student data for training, posing risks of breaches and misuse.	- Implement robust data protection regulations (e.g., GDPR compliance) and cybersecurity measures (encryption, anonymization).	- Ensure transparency in data collection and usage policies.	- Conduct regular AI audits to assess data security and effectiveness.	
Algorithmic Bias	AI models can learn and perpetuate biases from training data, leading to unfair decisions, stereotypes, and disproportionate disadvantage for certain student groups.	- Use diverse and representative training datasets to minimize bias.	- Implement continuous bias monitoring with clear documentation of mitigation efforts.	- Ensure educator override options to preserve human agency and judgment.	- Develop recommendati ons for inclusive and culturally relevant AI prompts.

Impact on Critical Thinking & Human Interaction	Over-reliance on AI may suppress original thought, creativity, and the development of essential social-emotional skills, devaluing human interaction.	- Emphasize human-centered use: AI should augment, not replace, educators and human interaction.	- Redesign pedagogy to foster critical evaluation of AI outputs, prompt engineering, and problem formulation.	- Promote active, inquiry-based learning where AI is a tool for exploration, not a source of direct answers (e.g., using "guardrails" in tutoring systems).	
Quality Control, Hallucinations & Reliability	AI outputs can be inaccurate, fabricated, or logically inconsistent ("hallucinations"), and students often lack the skills to evaluate their reliability.	- Develop and promote AI literacy for all stakeholders, focusing on critical evaluation, skepticism, and verification of AI-generated content.	- Educate users on AI's limitations, including its tendency to fabricate information.	- Implement human oversight and review mechanisms for AI-generated content used in critical educational contexts.	
Equitable Access & Digital Divide	High costs of AI implementation and disparities in infrastructure (devices, broadband) can widen existing educational inequalities.	- Advocate for policies and funding to ensure equitable access to AI tools and necessary infrastructure across all schools and communities.	- Promote the development of affordable and accessible AI solutions. - Focus on "AI for all" to prevent widening technological divides.		

4.5. Quality Control, Hallucinations, and Reliability

A significant and pervasive limitation of Generative AI in education pertains to the quality, reliability, and accuracy of its outputs. The performance of GenAI models is intrinsically linked to the quality and nature of their training data; if this data is limited, biased, or contains flaws, the AI's generated content will inevitably reflect these shortcomings. This inherent data dependency means that the output can sometimes be unpredictable, inappropriate, or factually incorrect, necessitating rigorous human quality checks and oversight [109].

A particularly concerning phenomenon is "hallucination," where GenAI models fabricate information, including non-existent references or logically inconsistent details, presenting them as factual. This can lead to the propagation of inaccurate details or even the crafting of convincing conspiracy theories. Empirical data from benchmarks like the TruthfulQA test indicate that, on average, most generative models are truthful only about 25% of the time, highlighting a substantial reliability deficit. This low truthfulness rate poses a critical challenge, especially in educational contexts where factual accuracy is paramount [110].

The problem is further exacerbated by the fact that students often lack the necessary skills to critically evaluate the material produced by GenAI. They may not be equipped to identify inaccuracies, biases, or fabricated information, potentially incorporating false statements and made-up references into their academic work. This creates a critical skill gap: in an information environment increasingly saturated with AI-generated content, the ability to *generate* content becomes less important than the capacity to *curate, critique, and verify* it. Students need to be explicitly taught how to question the validity of AI outputs, identify inconsistencies, and understand the inherent limitations of these tools [111].

5. FUTURE TRAJECTORIES AND TRANSFORMATIVE POTENTIAL

The trajectory of Generative AI in education points towards a future characterized by profound transformation, reshaping the roles of key stakeholders, evolving pedagogical approaches, and fundamentally altering the landscape of lifelong learning. This section explores these anticipated shifts and the strategic considerations necessary to navigate this evolving educational paradigm [112].

5.1. The Evolving Roles of Educators and Students

The advent of Generative AI is not merely changing how educators and students perform their tasks, but rather fundamentally altering their very roles within the learning ecosystem. For educators, GenAI is emerging as an indispensable tool, designed not to supplant human teaching but to significantly alleviate the creative and cognitive load associated with planning, personalizing, and delivering engaging, hands-on education. This profound shift means that teachers' roles will evolve from primarily being information dispensers to becoming more strategic, creative, and deeply focused on human connection, serving as mentors and facilitators. Future AI tools are envisioned to act as intelligent teaching assistants, capable of running simulations, managing classroom engagement dynamics, and even generating tailored follow-up exercises based on real-time student responses. This redefinition allows educators to leverage their unique human talents where they have the greatest impact: fostering critical thinking, building relationships, motivating learners, and cultivating a positive learning environment. The emergence of the "human-AI collaborative educator" signifies a symbiotic relationship where AI handles routine and generative tasks, empowering teachers to focus on higher-order pedagogical functions and individual student needs [113].

For students, the implications are equally transformative. The core academic skills required in an AI-driven world are shifting significantly. The emphasis will move away from merely generating knowledge from scratch to the more sophisticated processes of curating knowledge production, and from simply creating content to refining, critiquing, and enhancing AI-generated outputs. This means students will need to cultivate a new set of competencies, including AI literacy, advanced critical thinking, effective problem formulation, and adaptability to navigate an increasingly AI-driven world. They will be expected to critically evaluate AI-generated content, assess potential biases, and understand the ethical implications of AI use. The concept of the "AI-literate learner" implies that students will not just be passive consumers of AI-generated information but active shapers and critical evaluators of AI outputs, becoming proficient in prompt engineering and understanding the limitations of AI tools. Children, in particular, are expected to become accustomed to conversational interaction models with Large Language Models (LLMs), anticipating personalized responses and continuous context awareness from other interactive systems. This will likely lead to a demand for similar conversational systems across various technological interfaces, fundamentally changing their expectations of technology [114].

5.2. Future Pedagogical Shifts and Curriculum Evolution

The future of education, profoundly influenced by Generative AI, will witness significant pedagogical shifts and a continuous evolution of curriculum design. These changes will move learning experiences towards unprecedented levels of personalization and interactivity, fundamentally altering traditional teaching and learning methodologies.

Future AI systems are expected to offer even more tailored learning experiences, dynamically adapting to individual student needs with increased automation and enhanced interactive elements. This includes the development of highly sophisticated, human-like AI teachers capable of providing 24/7 explanations and guidance, serving as tireless learning companions. These AI tutors will not merely deliver information but will adjust individual learning programs based on a student's goals, knowledge, and learning preferences, emphasizing areas requiring the most attention and providing instant feedback on their work. This represents a shift from traditional content delivery to "adaptive scaffolding," where AI offers hints and prompts tailored to a student's misconceptions, guiding them towards understanding rather than simply providing direct answers [115].

Curriculum design will need to evolve to integrate AI tools not merely as supplementary aids but as integral components for core academic tasks. This includes rethinking approaches to essay writing, research, and problem-solving, by incorporating the tremendous advances and enhancements that GenAI brings to these tasks. The focus will increasingly shift away from rote memorization and towards developing skills that complement AI capabilities, such as critical thinking, creativity, and ethical reasoning. The core academic skills needed will be less about generating knowledge from scratch and more about curating knowledge production, refining, critiquing, and improving AI-generated artifacts. This means that the teacher's role will evolve into one of designing learning experiences where students actively *curate* and *critique* AI-generated knowledge, rather than passively receiving it.

5.3. Generative AI's Role in Lifelong Learning and Skill Acquisition

Generative AI is poised to play a pivotal role in shaping the future of lifelong learning and continuous skill acquisition, which are becoming increasingly critical in a rapidly evolving global workforce. Experts emphasize that lifelong learning is no longer optional but a necessity to keep pace with the implications of GenAI, as certain skills may be automated or replaced, necessitating the continuous acquisition of new competencies. This means that the ability to learn *with* and *from* AI will become a paramount skill for individuals seeking to remain relevant in their careers.

The transformative potential of GenAI in this domain is significant. Future careers are projected to rely more heavily on AI-assisted skill acquisition. AI can provide highly personalized learning recommendations and adaptive support for continuous professional development, helping individuals identify knowledge gaps and acquire new skills throughout their careers. This includes tailored content, interactive experiences, and real-time feedback mechanisms that facilitate skill mastery and address specific learning needs. For instance, AI-powered platforms can offer customized training modules for new job roles, simulate real-world work scenarios for practice, and provide immediate feedback on performance, accelerating the learning curve for complex skills.

This capability to provide personalized, adaptive learning at scale effectively democratizes access to high-quality training and reskilling opportunities. These opportunities were once limited by factors such as cost, geographical location, or access to specialized human experts. As the World Economic Forum's Future of Jobs Report 2023 indicates, nearly 23% of jobs are expected to change over five years, with 69 million new roles created and 44%

of workers' core skills projected to change by 2028. In such a dynamic labor market, GenAI can serve as a crucial enabler for continuous reskilling and upskilling, ensuring that individuals

5.4. Policy Development and Governance in an AI-Driven Educational Landscape

As Generative AI becomes increasingly embedded within the educational ecosystem, the development of robust policy and governance frameworks is not merely advisable but essential to ensure its responsible, ethical, and equitable integration. The rapid pace of AI development often outstrips the speed of policy formulation, creating a critical need for proactive and adaptive regulatory approaches [116].

Evidence of this emerging policy landscape is already apparent. By April 2025, at least 28 states had published guidance on AI in K-12 settings, with various legislative bills proposing oversight, regulation, and the establishment of "sandbox" programs for AI in education. These initiatives highlight a growing recognition among policymakers of the need to manage AI's impact. Key policy priorities consistently emerging from these discussions include the creation of comprehensive curricular frameworks for AI literacy, significant investment in educator professional development to equip teachers with the skills to effectively leverage AI, ensuring equitable access to these technologies across all demographics, robust protection of student data privacy, and providing ongoing support for the implementation of AI tools within educational institutions.

International bodies are also emphasizing a human-centered approach to AI governance in education. UNESCO's frameworks for students and teachers, for instance, are designed to guide countries in understanding both the immense potential and inherent risks of AI, promoting safe, ethical, and responsible engagement with these technologies. These frameworks explicitly state that policies must ensure AI complements human decision-making and intellectual development, rather than undermining or replacing it. They also stress the importance of respecting human rights and cultural diversity in the design and use of AI technologies. The California Community Colleges' Vision 2030, which strategically includes Generative AI as a core direction, exemplifies a proactive approach to integrating AI into the future of teaching and learning. This forward-looking stance recognizes that simply reacting to AI's advancements is insufficient; instead, institutions must actively shape how AI is used to reimaging learning.

5.5. A Vision for Education and Learning in 2030 and Beyond

Looking towards 2030 and beyond, the vision for education and learning is one where Generative AI is deeply and seamlessly integrated into the educational fabric, fundamentally transforming its accessibility, quality, and efficacy. This future anticipates a global landscape where high-quality learning experiences become more affordable and universally accessible, transcending geographical and socioeconomic barriers. Education will be characterized by continuous adaptation of instruction, dynamically responding to each student's unique strengths, weaknesses, and learning preferences, providing 24/7 access to expert-level support through AI-powered systems.

The pedagogical focus will shift significantly. Instead of prioritizing rote memorization, the emphasis will be on fostering and enhancing critical thinking, creativity, and metacognition, with AI serving as a powerful tool to augment these essential human skills. The UNESCO Education 2030 Agenda explicitly champions harnessing AI's potential while rigorously ensuring inclusion and equity, striving for a future where "AI for all" is a reality, and everyone can genuinely benefit from the ongoing technological revolution. This commitment aims to prevent AI from widening existing technological divides, ensuring that its innovations and knowledge are accessible to all.

In this future, the very purpose of education will be reimagined. The traditional model of knowledge generation will be massively enhanced and accelerated by GenAI, leading to an evolution of thinking where the focus shifts towards the refinement, critiquing, and improvement of AI-generated products, rather than creating content from scratch. This means students will be prepared to "curate knowledge production," becoming adept at evaluating, synthesizing, and building upon AI-provided information. The curriculum will increasingly emphasize skills such as problem formulation, ethical reasoning, and the ability to discern valid information from AI-generated outputs, transforming learners into sophisticated navigators of an information-rich world.

The evolving roles of educators will see them as architects of learning experiences, designing environments where students interact with AI to achieve deeper understanding and develop higher-order skills. AI will provide diagnostic insights, allowing teachers to intervene early and guide students more effectively. For students, the expectation will be that technology is conversational, context-aware, versatile, and transparent, fostering a new paradigm of human-computer interaction. Figure 4 and Figure 5 shows the student perception regarding Generative AI in education and trend of Generative AI adoption in education respectively. This vision of education in 2030 and beyond is one of dynamic adaptation, where AI serves as a catalyst for more personalized, engaging, and equitable learning, preparing individuals not just for existing jobs but for future careers that will rely heavily on AI-assisted skill acquisition and continuous lifelong learning.

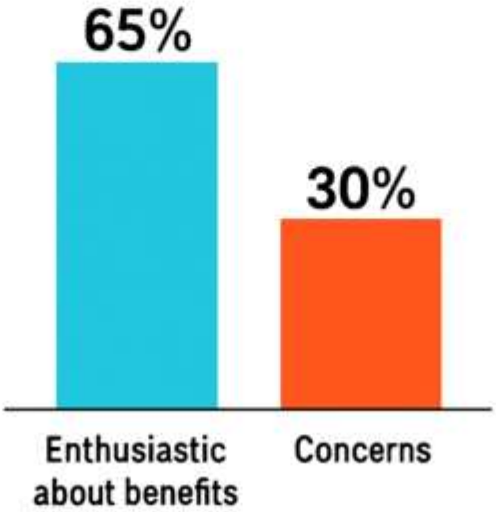

Figure 4: Student Perceptions: Enthusiasm vs. Concerns Regarding Generative AI in Education

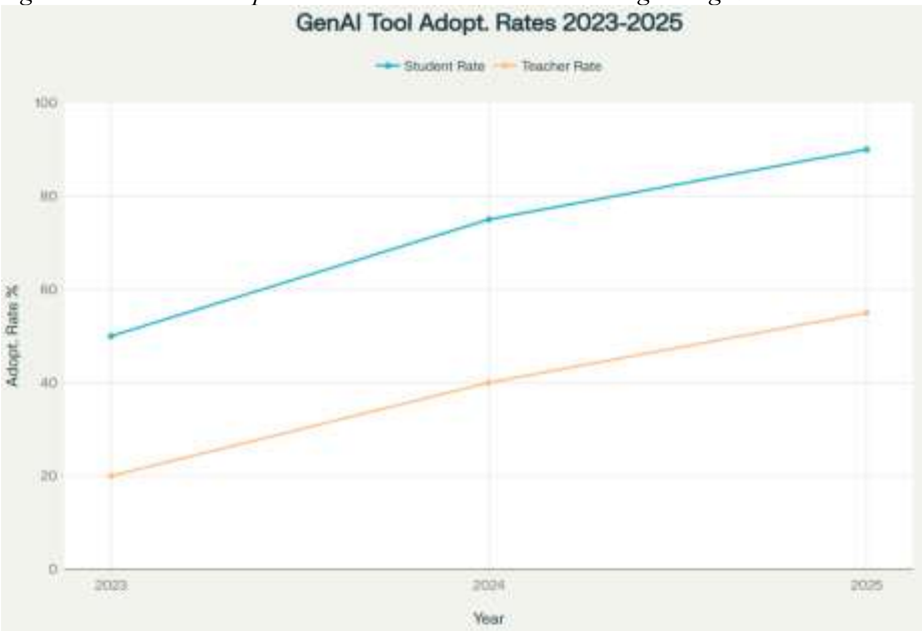

Figure 5: Generative AI Adoption Trends: Teacher vs. Student Usage (2023-2025)

6. CONCLUSION

Generative AI represents a profound transformation in education, fundamentally reshaping pedagogical practices, knowledge acquisition, and skill development. This research demonstrates that GenAI aligns with established learning theories while introducing innovative frameworks such as the AI-TEACH Model, enabling personalized learning, automated content generation, and intelligent tutoring that augment rather than replace human capabilities.

However, successful integration demands addressing critical challenges. Academic integrity concerns require innovative assessments prioritizing higher-order thinking over output generation. Data privacy, algorithmic bias, and inequitable access necessitate robust governance frameworks and transparent practices to prevent educational disparities. Maintaining the balance between AI-enhanced efficiency and preserving critical thinking skills remains essential to avoid cognitive deskilling.

The future educational landscape will feature evolved roles for stakeholders. Educators will become "human-AI collaborative facilitators," leveraging GenAI for administrative tasks while focusing on mentorship, emotional development, and uniquely human competencies. Students will emerge as "AI-literate knowledge curators," skilled in critically evaluating AI outputs and engaging in sophisticated prompt engineering. This transformation necessitates pedagogical shifts toward adaptive scaffolding and curriculum evolution prioritizing AI-complementary skills including complex problem-solving and collaborative innovation.

GenAI's democratizing potential extends to fostering lifelong learning ecosystems, making expert knowledge accessible across geographical and socioeconomic boundaries. By automating routine tasks and providing continuous intelligent support, GenAI enables educators to dedicate greater attention to high-value pedagogical activities. The technology enhances inclusivity through assistive functions, multilingual translation, and adaptive content delivery.

REFERENCES

[1] Baskara, F. R. (2024). Generative AI as an enabler of sustainable education: theoretical perspectives and future directions. *British Journal of Teacher Education and Pedagogy*, *3*(3), 122-134.

[2] Ali, M. M., Wafik, H. A., Mahbub, S., & Das, J. (2024). Gen Z and generative AI: Shaping the future of learning and creativity. *Cognizance Journal of Multidisciplinary Studies*, *4*(10), 1-18.

[3] Batista, J., Mesquita, A., & Carnaz, G. (2024). Generative AI and higher education: Trends, challenges, and future directions from a systematic literature review. *Information*, *15*(11), 676.

[4] Monib, W. K., Qazi, A., Apong, R. A., Azizan, M. T., De Silva, L., & Yassin, H. (2024). Generative AI and future education: a review, theoretical validation, and authors' perspective on challenges and solutions. *PeerJ Computer Science*, *10*, e2105.

[5] Liang, E. S., & Bai, S. (2025). Generative AI and the future of connectivist learning in higher education. *Journal of Asian Public Policy*, *18*(2), 329-351.

[6] Bozkurt, A., Xiao, J., Farrow, R., Bai, J. Y., Nerantzi, C., Moore, S., ... & Asino, T. I. (Eds.). (2024). The manifesto for teaching and learning in a time of generative AI: A critical collective stance to better navigate the future. *Open Praxis*, *16*(4), 487-513.

[7] Aad, S., & Hardey, M. (2025). Generative AI: hopes, controversies and the future of faculty roles in education. *Quality Assurance in Education*, *33*(2), 267-282.

[8] Khan, A. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *J. Electrical Systems*, *20*(6s), 1051-1058.

[9] Sharma, K. K., Verma, P. K., & Garg, P. (2024). IoT-Enabled Energy Management Systems For Sustainable Energy Storage: Design, Optimization, And Future Directions. *Frontiers in Health Informatics*, *13*(8).

[10] Gupta, S., Yadav, N., Singh, K., & Garg, P. (2025). APPLICATIONS OF SIMULATIONS AND QUEUING THEORY IN SUPERMARKET. *Reliability: Theory & Applications*, *20*(1 (82)), 135-140.

[11] Beniwal, S., Garg, P., Rajpal, R., Sharma, N., & Mittal, H. K. (2025). Fusion of Opportunistic Networks with Machine Learning: Present and Future. *Metallurgical and Materials Engineering*, *31*(1), 311-324.

[12] Garg, P. (2025). Explainable AI & Model Interpretability in Healthcare: Challenges & Future Directions. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 104-133.

[13] Rani, P. (2025). From Data to Diagnosis: Unleashing AI and 6G in Modern Medicine. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 69-103.

[14] Dixit, A., Garg, P., Sethi, P., & Singh, Y. (2020, April). TVCCCS: Television Viewer's Channel Cost Calculation System On Per Second Usage. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012046). IOP Publishing.

[15] Sethi, P., Garg, P., Dixit, A., & Singh, Y. (2020, April). Smart number cruncher–a voice based calculator. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012041). IOP Publishing.

[16] S. Rai, V. Choubey, Suryansh and P. Garg, "A Systematic Review of Encryption and Keylogging for Computer System Security," *2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT)*, 2022, pp. 157-163, doi: 10.1109/CCiCT56684.2022.00039.

[17] L. Saraswat, L. Mohanty, P. Garg and S. Lamba, "Plant Disease Identification Using Plant Images," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 79-82, doi: 10.1109/CCiCT56684.2022.00026.

[18] L. Mohanty, L. Saraswat, P. Garg and S. Lamba, "Recommender Systems in E-Commerce," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 114-119, doi: 10.1109/CCiCT56684.2022.00032.

[19] C. Maggo and P. Garg, "From linguistic features to their extractions: Understanding the semantics of a concept," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 427-431, doi: 10.1109/CCiCT56684.2022.00082.

[20] N. Puri, P. Saggar, A. Kaur and P. Garg, "Application of ensemble Machine Learning models for phishing detection on web networks," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 296-303, doi: 10.1109/CCiCT56684.2022.00062.

[21] R. Sharma, S. Gupta and P. Garg, "Model for Predicting Cardiac Health using Deep Learning Classifier," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 25-30, doi: 10.1109/CCiCT56684.2022.00017.

[22] Varshney, S. Lamba and P. Garg, "A Comprehensive Survey on Event Analysis Using Deep Learning," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 146-150, doi: 10.1109/CCiCT56684.2022.00037.

[23] Garg, P., Dixit, A., & Sethi, P. (2022). Ml-fresh: novel routing protocol in opportunistic networks using machine learning. *Computer Systems Science & Engineering, Forthcoming*. Tech Science Press.

[24] Yadav, P. S., Khan, S., Singh, Y. V., Garg, P., & Singh, R. S. (2022). A Lightweight Deep Learning-Based Approach for Jazz Music Generation in MIDI Format. *Computational Intelligence and Neuroscience*, *2022*.
[25] Soni, E., Nagpal, A., Garg, P., & Pinheiro, P. R. (2022). Assessment of Compressed and Decompressed ECG Databases for Telecardiology Applying a Convolution Neural Network. *Electronics*, *11*(17), 2708.
[26] Pustokhina, I. V., Pustokhin, D. A., Lydia, E. L., Garg, P., Kadian, A., & Shankar, K. (2021). Hyperparameter search based convolution neural network with Bi-LSTM model for intrusion detection system in multimedia big data environment. *Multimedia Tools and Applications*, 1-18.
[27] Khanna, A., Rani, P., Garg, P., Singh, P. K., & Khamparia, A. (2021). An Enhanced Crow Search Inspired Feature Selection Technique for Intrusion Detection Based Wireless Network System. *Wireless Personal Communications*, 1-18.
[28] Garg, P., Dixit, A., Sethi, P., & Pinheiro, P. R. (2020). Impact of node density on the qos parameters of routing protocols in opportunistic networks for smart spaces. *Mobile Information Systems*, *2020*.
[29] Upadhyay, D., Garg, P., Aldossary, S. M., Shafi, J., & Kumar, S. (2023). A Linear Quadratic Regression-Based Synchronised Health Monitoring System (SHMS) for IoT Applications. Electronics, 12(2), 309.
[30] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). CNN-BI-LSTM-CYP: A deep learning approach for sugarcane yield prediction. *Sustainable Energy Technologies and Assessments*, *57*, 103263.
[31] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). Evaluation of Remote Sensing and Meteorological parameters for Yield Prediction of Sugarcane (Saccharumofficinarum L.) Crop. Brazilian Archives of Biology and Technology, 66, e23220781.
[32] Beniwal, S., Saini, U., Garg, P., & Joon, R. K. (2021). Improving performance during camera surveillance by integration of edge detection in IoT system. *International Journal of E-Health and Medical Communications (IJEHMC)*, *12*(5), 84-96.
[33] Garg, P., Dixit, A., & Sethi, P. (2019). Wireless sensor networks: an insight review. *International Journal of Advanced Science and Technology*, *28*(15), 612-627.
[34] Sharma, N., & Garg, P. (2022). Ant colony based optimization model for QoS-Based task scheduling in cloud computing environment. *Measurement: Sensors*, 100531.
[35] Kumar, P., Kumar, R., & Garg, P. (2020). Hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks.
[36] Raj, G., Verma, A., Dalal, P., Shukla, A. K., & Garg, P. (2023). Performance Comparison of Several LPWAN Technologies for Energy Constrained IOT Network. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(1s), 150-158.
[37] Garg, P., Sharma, N., & Shukla, B. (2023). Predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(2s), 165-173.
[38] Patil, S. C., Mane, D. A., Singh, M., Garg, P., Desai, A. B., & Rawat, D. (2024). Parkinson's Disease Progression Prediction Using Longitudinal Imaging Data and Grey Wolf Optimizer-Based Feature Selection. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 441-451.
[39] Gudur, A., Pati, P., Garg, P., & Sharma, N. (2024). Radiomics Feature Selection for Lung Cancer Subtyping and Prognosis Prediction: A Comparative Study of Ant Colony Optimization and Simulated Annealing. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 553-565.
[40] Dixit, A., Sethi, P., Garg, P., & Pruthi, J. (2022, December). Speech Difficulties and Clarification: A Systematic Review. In *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)* (pp. 52-56). IEEE.
[41] Garg, P., Dixit, A., Sethi, P., & Pruthi, J. (2023, December). Strengthening Smart City with Opportunistic Networks: An Insight. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 700-707). IEEE.
[42] Rana, S., Chaudhary, R., Gupta, M., & Garg, P. (2023, December). Exploring Different Techniques for Emotion Detection Through Face Recognition. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 779-786). IEEE.
[43] Mittal, K., Srivastava, K., Gupta, M., & Garg, P. (2023, December). Exploration of Different Techniques on Heart Disease Prediction. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 758-764). IEEE.
[44] Gautam, V. K., Gupta, S., & Garg, P. (2024, March). Automatic Irrigation System using IoT. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 100-103). IEEE.
[45] Ramasamy, L. K., Khan, F., Joghee, S., Dempere, J., & Garg, P. (2024, March). Forecast of Students' Mental Health Combining an Artificial Intelligence Technique and Fuzzy Inference System. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 85-90). IEEE.
[46] Rajput, R., Sukumar, V., Patnaik, P., Garg, P., & Ranjan, M. (2024, March). The Cognitive Analysis for an Approach to Neuroscience. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 524-528). IEEE.
[47] Dixit, A., Sethi, P., Garg, P., Pruthi, J., & Chauhan, R. (2024, July). CNN based lip-reading system for visual input: A review. In *AIP Conference Proceedings* (Vol. 3121, No. 1). AIP Publishing.

[48] Bose, D., Arora, B., Srivastava, A. K., & Garg, P. (2024, May). A Computer Vision Based Framework for Posture Analysis and Performance Prediction in Athletes. In *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)* (pp. 942-947). IEEE.
[49] Singh, M., Garg, P., Srivastava, S., & Saggu, A. K. (2024, April). Revolutionizing Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 516-522). IEEE.
[50] Kumar, R., Das, R., Garg, P., & Pandita, N. (2024, April). Duplicate Node Detection Method for Wireless Sensors. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 512-515). IEEE.
[51] Bhardwaj, H., Das, R., Garg, P., & Kumar, R. (2024, April). Handwritten Text Recognition Using Deep Learning. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 506-511). IEEE.
[52] Gill, A., Jain, D., Sharma, J., Kumar, A., & Garg, P. (2024, May). Deep learning approach for facial identification for online transactions. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 715-722). IEEE.
[53] Mittal, H. K., Dalal, P., Garg, P., & Joon, R. (2024, May). Forecasting Pollution Trends: Comparing Linear, Logistic Regression, and Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 411-419). IEEE.
[54] Malik, T., Nandal, V., & Garg, P. (2024, May). Deep Learning-Based Classification of Diabetic Retinopathy: Leveraging the Power of VGG-19. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 645-651). IEEE.
[55] Srivastava, A. K., Verma, I., & Garg, P. (2024, May). Improvements in Recommendation Systems Using Graph Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 668-672). IEEE.
[56] Aggarwal, A., Jain, D., Gupta, A., & Garg, P. (2024, May). Analysis and Prediction of Churn and Retention Rate of Customers in Telecom Industry Using Logistic Regression. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 723-727). IEEE.
[57] Mittal, H. K., Arsalan, M., & Garg, P. (2024, May). A Novel Deep Learning Model for Effective Story Point Estimation in Agile Software Development. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 404-410). IEEE.
[58] Shukla, S. M., Magoo, C., & Garg, P. (2024, November). Comparing Fine Tuned-LMs for Detecting LLM-Generated Text. In *2024 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON)* (pp. 1-8). IEEE.
[59] Kumar, B., IQBAL, M., Parmer, R., Garg, P., Rani, S., & Agrawal, A. (2025, March). The Role of AI in Optimizing Healthcare Appointment Scheduling. In *2025 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 881-887). IEEE.
[60] Kumar, B., Garg, V., Ahmed, K., Garg, P., Choudhary, S., & Baniya, P. (2025, March). Enhancing Healthcare with Blockchain: Innovations in Data Privacy, Security, and Interoperability. In *2025 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 932-938). IEEE.
[61] Raj, V., Prakash, B. K., Kumar, A., & Garg, P. (2024, December). Optimize the Time a Mercedes-Benz Spends on the Test Bench Using Stacking Ensemble Learning. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 445-450). IEEE.
[62] Kaushik, N., Kumar, H., Raj, V., & Garg, P. (2024, December). Proactive Fault Prediction in Microservices Applications Using Trace Logs and Monitoring Metrics. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 410-415). IEEE.
[63] Kumar, A. A., Sri, C. V., Bohara, K. S. K., Setia, S., & Garg, P. (2024, December). Capnivesh: Financing Platform for Startups. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 261-265). IEEE.
[64] Bhandari, P., Setia, S., Kumar, K., & Garg, P. (2024, December). Optimizing Cross-Platform Development with CI/CD and Containerization: A Review. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 175-180). IEEE.
[65] Chaudhary, A., & Garg, P. (2014). Detecting and diagnosing a disease by patient monitoring system. *International Journal of Mechanical Engineering And Information Technology*, *2*(6), 493-499.
[66] Malik, K., Raheja, N., & Garg, P. (2011). Enhanced FP-growth algorithm. *International Journal of Computational Engineering and Management*, *12*, 54-56.
[67] Garg, P., Dixit, A., & Sethi, P. (2021, May). Link Prediction Techniques for Opportunistic Networks using Machine Learning. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.
[68] Garg, P., Dixit, A., & Sethi, P. (2021, April). Opportunistic networks: Protocols, applications & simulation trends. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.

[69] Garg, P., Dixit, A., & Sethi, P. (2021). Performance comparison of fresh and spray & wait protocol through one simulator. *IT in Industry*, *9*(2).
[70] Malik, M., Singh, Y., Garg, P., & Gupta, S. (2020). Deep Learning in Healthcare system. *International Journal of Grid and Distributed Computing*, *13*(2), 469-468.
[71] Gupta, M., Garg, P., Gupta, S., & Joon, R. (2020). A Novel Approach for Malicious Node Detection in Cluster-Head Gateway Switching Routing in Mobile Ad Hoc Networks. *International Journal of Future Generation Communication and Networking*, *13*(4), 99-111.
[72] Gupta, A., Garg, P., & Sonal, Y. S. (2020). Edge Detection Based 3D Biometric System for Security of Web-Based Payment and Task Management Application. *International Journal of Grid and Distributed Computing*, *13*(1), 2064-2076.
[73] Kumar, P., Kumar, R., & Garg, P. (2020). Hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks.
[74] Garg, P., & Raman, P. K. Broadcasting Protocol & Routing Characteristics With Wireless ad-hoc networks.
[75] Garg, P., Arora, N., & Malik, T. Capacity Improvement of WI-MAX In presence of Different Codes WI-MAX: Speed & Scope of future.
[76] Garg, P., Saroha, K., & Lochab, R. (2011). Review of wireless sensor networks-architecture and applications. IJCSMS International Journal of Computer Science & Management Studies, 11(01), 2231-5268.
[77] Yadav, S., &Garg, P. Development of a New Secure Algorithm for Encryption and Decryption of Images.
[78] Dixit, A., Sethi, P., & Garg, P. (2022). Rakshak: A Child Identification Software for Recognizing Missing Children Using Machine Learning-Based Speech Clarification. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-15.
[79] Shukla, N., Garg, P., & Singh, M. (2022). MANET Proactive and Reactive Routing Protocols: A Comparison Study. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-14.
[80] Arya, A., Garg, P., Vellanki, S., Latha, M., Khan, M. A., & Chhbra, G. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *Journal of Electrical Systems*, *20*(6s), 1051-1058.
[81] Garg, P. (2025). Cloud security posture management: Tools and techniques. Technix International Journal for Engineering Research, 12(3).
[82] Tyagi, P., Sharma, S., Srivastava, A., Rajput, N. K., Garg, P., & Kumari, M. (2025). AI in Healthcare:Transforming Medicine with Intelligence. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p4
[83] Bhatt, M., Parmar, R., Arsalan, M., & Garg, P. (2025). Generative AI: Evolution, Applications, Challenges And Future Prospects. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p6
[84] Saraswat, P., Garg, P., & Siddiqui, Z. (2025). AI & the Indian Stock Market: A Review of Applications in Investment Decision. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p10
[85] Sharma, S., Mittal, S., Tevatia, R., Tyagi, V. K., Garg, P., & Kapoor, S. (2025). Unlocking Workforce Potential: AI-Powered Predictive Models for Employee Performance Evaluation. Ind Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p21
[86] Shrivas, N., Kalia, A., Roy, R., Sharma, S., Garg, P., & Agarwal, G. (2025). OSINT: A Double-edged Sword. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p22
[87] Aditi, Garg, P., & Roy, B. (2025). A System of Computer Network: Based On Artificial Intelligence. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p24
[88] Parmar, R., Kapoor, S., Saifi, S., & Garg, P. (2025). Case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p28
[89] Singh, R., Sharma, R., Kumar, R., Nafis, A., Siddiqui, M. A. M., & Garg, P. (2025). Detection of Unauthorize Construction using Machine Learning: A Review. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p30
[90] Kapoor, S., Singh, V., Sharma, S., Garg, P., & Ankita (2025). A Bridge between Blockchain and Decentralized Applications Web3 and Non-Web3 Crypto Wallets. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p35
[91] Verma, M., Sharma, S., Garg, P., & Singh, A. (2025). The Hidden Dangers of Prototype Pollution: A Comprehensive Detection Framework. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p36
[92] Sharma, A., Sharma, S., Garg, P., & Bhardwaj, P. (2025). LockTalk: A Basic Secure Chat Application. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India.

[93] Arora, K., Bawane, R., Gupta, C., Ahmed, K., & Garg, P. (2025). Detection and Prevention of Cyber Attack and Threat using AI. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p38

[94] Dhruv, Rahman, A. A., Rai, A., Siddiqui, M. A. M., Garg, P., & Yadav, D. (2025). Easeviewer: An Esports Production Tool. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p46

[95] Lakshita, Mehwish, Nazia, Ahmed, K., & Garg, P. (2025). Emerging Trend in Computational Technology: Innovations, Applications, and Challenges. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p51

[96] Chauhan, S., Singh, M., & Garg, P. (2021). Rapid Forecasting of Pandemic Outbreak Using Machine Learning. *Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies*, 59-73.

[97] Gupta, S., & Garg, P. (2021). An insight review on multimedia forensics technology. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 27.

[98] Shrivastava, P., Agarwal, P., Sharma, K., & Garg, P. (2021). Data leakage detection in Wi-Fi networks. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 215.

[99] Meenakshi, P. G., & Shrivastava, P. (2021). Machine learning for mobile malware analysis. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 151.

[100] Garg, P., Pranav, S., & Prerna, A. (2021). Green Internet of Things (G-IoT): A Solution for Sustainable Technological Development. In *Green Internet of Things for Smart Cities* (pp. 23-46). CRC Press.

[101] Nanwal, J., Garg, P., Sethi, P., & Dixit, A. (2021). Green IoT and Big Data: Succeeding towards Building Smart Cities. In *Green Internet of Things for Smart Cities* (pp. 83-98). CRC Press.

[102] Gupta, M., Garg, P., & Agarwal, P. (2021). Ant Colony Optimization Technique in Soft Computational Data Research for NP-Hard Problems. In *Artificial Intelligence for a Sustainable Industry 4.0* (pp. 197-211). Springer, Cham.

[103] Magoo, C., & Garg, P. (2021). Machine Learning Adversarial Attacks: A Survey Beyond. *Machine Learning Techniques and Analytics for Cloud Security*, 271-291.

[104] Garg, P., Srivastava, A. K., Anas, A., Gupta, B., & Mishra, C. (2023). Pneumonia Detection Through X-Ray Images Using Convolution Neural Network. In *Advancements in Bio-Medical Image Processing and Authentication in Telemedicine* (pp. 201-218). IGI Global.

[105] Gupta, S., & Garg, P. (2023). 14 Code-based post-quantum cryptographic technique: digital signature. *Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity*, 193.

[106] Prakash, A., Avasthi, S., Kumari, P., & Rawat, M. (2023). PuneetGarg 18 Modern healthcare system: unveiling the possibility of quantum computing in medical and biomedical zones. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 249.

[107] Gupta, S., & Garg, P. (2024). Mobile Edge Computing for Decentralized Systems. *Decentralized Systems and Distributed Computing*, 75-88.

[108] Gupta, M., Garg, P., & Malik, C. (2024). Ensemble learning-based analysis of perinatal disorders in women. In Artificial Intelligence and Machine Learning for Women's Health Issues (pp. 91-105). Academic Press.

[109] Malik, M., Garg, P., & Malik, C. (2024). Artificial intelligence-based prediction of health risks among women during menopause. *Artificial Intelligence and Machine Learning for Women's Health Issues*, 137-150.

[110] Garg, P. (2024). Prediction of female pregnancy complication using artificial intelligence. In *Artificial Intelligence and Machine Learning for Women's Health Issues* (pp. 17-35). Academic Press.

[111] Pokhrel, L., Arsalan, M., Rani, P., Garg, P., & Pinheiro, P. R. (2026). AI-Powered Healthcare Solutions: Bridging the Medical Gap in Underserved Communities Worldwide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 57-86). IGI Global Scientific Publishing.

[112] Kapoor, S., Parmar, R., Sharma, N., Garg, P., & Singh, N. J. (2026). AI and Computational Intelligence in Healthcare: An Introductory Guide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 1-26). IGI Global Scientific Publishing.

[113] Pokhrel, L., Kumar, A., Garg, P., Anand, N., & Singh, N. (2026). AI and IoT in Global Health: Ethical Lessons From Pandemic Response. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 367-394). IGI Global Scientific Publishing.

[114] Parmar, R., Singh, A., Garg, P., Sharma, T., & Pinheiro, P. R. (2026). Blockchain for Ethical Supply Chains: Transparency in Medical IoT Manufacturing. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 337-366). IGI Global Scientific Publishing.

[115] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2024). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 1). Bentham Science Publishers. https://doi.org/10.2174/97898153130311240301

[116] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2025). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2). Bentham Science Publishers. https://doi.org/10.2174/97898153222241250301