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Generative Artificial Intelligence and Expertise Development among Generation Z: A Critical Review of Cognitive Offloading, Critical Thinking, and AI Literacy

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Abstract – Generative AI has opened new possibilities for explanations, summarization, translation, feedback, and content creation. It has been quickly embraced by young people and has opened possibilities for customization and accessibility but has also been associated with cognitive offloading, academic integrity, automation bias and the long-term development of expertise. This narrative review is structured around the interdisciplinary literature to explore the potential impact of generative artificial intelligence (GAI) on knowledge acquisition, memory, critical thinking, independent reasoning, deliberate practice, and professional judgment, specifically focusing on Generation Z, with evidence collected from peer-reviewed research, foundational cognitive and educational literature, official policy reports, and institutional guidance up to June 13, 2026. So far, there is no evidence that can be used deterministically to infer that AI has a negative impact on cognition. Rather, results are highly dependent on the design, instruction, supervision, and utilization of the tools. Structured applications can enhance explanation, feedback, reflection, and higher order thinking. On the other hand, uncritical and substitution use can lead to lesser intellectual engagement, false confidence, and cover up deficiencies in competence. Access to information generated should thus not be considered synonymous with knowledge expertise. Responsible AI-literacy framework is proposed where learners try to do things, test evidence, check outputs, reveal the use of AI and demonstrate their independence periodically. The question is not if it is used, but if young people can maintain human agency, accountability, and opportunities for ongoing learning within institutions.

Keywords: Generative artificial intelligence, Generation Z, Critical thinking, Cognitive offloading, AI literacy, Expertise development, Human–AI collaboration, Digital education.

1. INTRODUCTION

The use of generative AI has accelerated from a novelty to a regular part of teaching and learning, working, studying, and communication and, in daily life, searching for information. Text-generating systems can explain complex concepts, summarize a document, translate text, practice questions, organize ideas, suggest computer code, and create polished drafts, all in seconds. As many as two-thirds of the surveyed US teens said they used AI chatbots by 2025 and over half used them for schoolwork. While these are only one country's figures and not those of Gen Z worldwide, they do represent that AI-assisted learning is no longer a niche phenomenon.

This is where Generation Z comes into the picture, as many of them are either finishing formal schooling or starting work or taking early career courses and are also seeing the integration of generative AI into institutional systems. However, care needs to be taken when using generational labels. Young people vary significantly in terms of their educational readiness, earnings, barriers to participation, language, culture, place, access to resources and access to adult support. Generation Z should not therefore be thought of

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as a monolithic generation and not be assumed to be either technologically savvy or particularly susceptible.

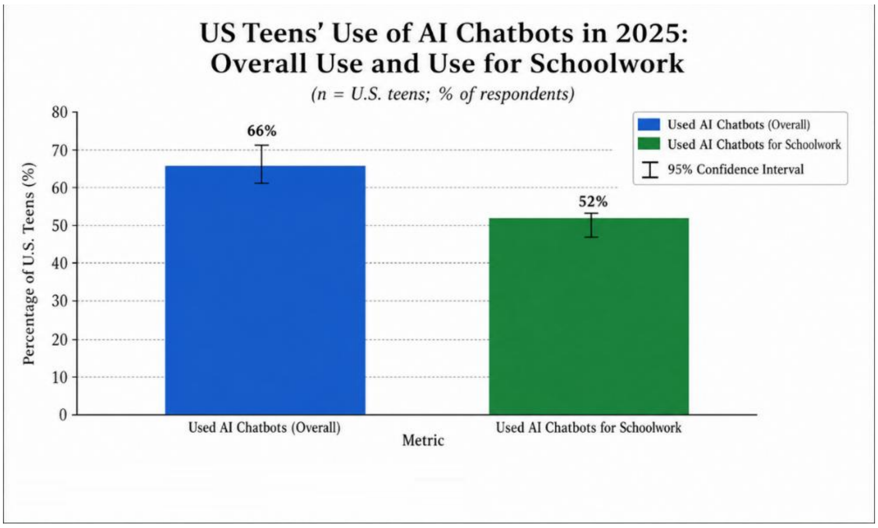

Fig -1: Use of AI Chatbots in 2025

The main conceptual issue is that of the difference between access to information and knowledge. Information is transformed into usable knowledge when an individual can interpret, make connections to previous knowledge, recall information, articulate meaning, and use information in new situations. Pattern recognition, accumulated experience, contextual judgment, ethical responsibility, and the ability to recognize when standard solutions do not apply to a specific case are other dimensions added by expertise. These processes can be supported with a fluent machine-generated response, but it doesn't mean that the user has acquired them.

The current evidence neither screams out a victory for us nor a warning for us. According to systematic and scoping reviews until 2026, the use of AI can be beneficial for critical and creative thinking if integrated into a structured inquiry, verification, reflection, and feedback. Superficial engagement and cognitive offloading are also named in the literature because of the use of systems to simply substitute reading, reasoning, or composition. A recent scoping review concluded that, while there was a bimodal pattern of AI use often as a scaffold, the frictionless and unregulated use of AI could diminish epistemic effort. So, the question isn't about whether AI is good or bad. Whether it is or is not used as a tool for thinking in educational and organizational settings or as a replacement for thinking. This review discusses that distinction and what it means for learning, employment, public knowledge, social equity, business incentives, and the future development of expertise.

2. OBJECTIVES OF THE ARTICLE

The focus is on assessing if there are potential risks to independent thinking and expertise building for Generation Z when relying heavily on generative AI and acknowledging the potential benefits of AI in enhancing learning, access and productivity when applied appropriately.

- Specific Objectives are to differentiate between access to created information, knowledge, understanding, competence, and expertise

- Analyze evidence related to cognitive offloading, memory, metacognition, critical thinking, and independent problem solving
- Describe how the generative language systems generate responses and the distinction between language fluency and factual accuracy
- Examine the personalized explanations, formative feedback, translation, accessibility, and interactive tutoring for educational value
- Recognize potential problems of uncritical dependence, academic outsourcing, fabricated information, loss of privacy and automation bias
- Discuss the importance of deliberate practice, retrieval, error correction, feedback, and productive struggle in development of expertise
- Explain how generative AI is being applied in organizations, such as for knowledge management, workflow automation, decision making, and training employees
- Think about the business models, investments, IP issues and energy consumption related to AI services
- Evaluate potential outcomes for jobs, low-level jobs, skills training, professional training, and economic inequality
- Consider impact on social equity, multilingual access, public knowledge, misinformation, and democratic participation
- Recognise gaps in the available evidence such as lack of longitudinal and cross-cultural studies; and
- Present a framework for AI-literacy that is based on evidence and that maintains human agency, accountability, independent competence, and responsible collaboration.

The article isn't an experiment to see if AI is responsible for cognitive decline, is a fact. Rather, it examines the question of whether there is a correlation between the use of AI and a decline in cognitive involvement and if there is a correlation, whether there is a way to change the pattern of AI use in education.

3. METHODOLOGY

The design of this article is a structured interdisciplinary narrative-review and is not a formal systematic or scoping review. Searches were carried out on the scholarly publisher platforms, academic repositories, government and intergovernmental websites, conference libraries, institutional research pages, and research-discovery systems up to June 13, 2026. Search concepts included terms related to generative AI and critical thinking, terms related to cognitive offloading, memory, deliberate practice, expertise, AI literacy, academic integrity, automation bias, education, professional judgment, employment, productivity, digital inequality, and misinformation.

Peer-reviewed empirical studies, systematic and scoping reviews, well-known conference proceedings, basic cognitive research, official statistics, regulatory documents, and institutional reports were prioritised. Sources were omitted if they mainly relied on promotional statements, anonymous comments, unsubstantiated predictions, or unconfirmed statistics. The use of preprints was limited, and preprints were labelled as preliminary evidence. Manufacturer's claims for commercial products were not considered separately.

Research Design Relevance, Source Authority, Methodological Transparency, Sample Characteristics, Measurement Validity, Publication Status, and Consistency with broader evidence were used to assess quality. Randomized studies and meta-analyses, systematic reviews and official datasets were given more weight than self-reported studies or isolated demonstrations. Conflicting results were kept and interpreted about task design, learner expertise, time, scaffolding, and measurement of outcome.

Literature was then organised thematically under the following categories cognition, technology, learning, integrity, professional practice, organisational adoption, business, economics, equity and governance. There are some limitations of the review. It is not a replicable systematic search, there is a more rapid pace of change with generative AI than with traditional publication cycles, and many existing studies are short-term, geographically limited, and or rely on self-report. The conclusions, therefore, reflect the state of the evidence and not causal effects per se.

4. FROM INFORMATION ACCESS TO THE AI KNOWLEDGE GAP

The AI knowledge gap is the difference between accessing AI-generated content and the ability to assess, remember, describe and use it. This is not a traditional digital divide that is primarily based on access to devices or the internet, but is based on prior knowledge, source-evaluation skills, language, instructional support, confidence calibration, and recognizing uncertainty.

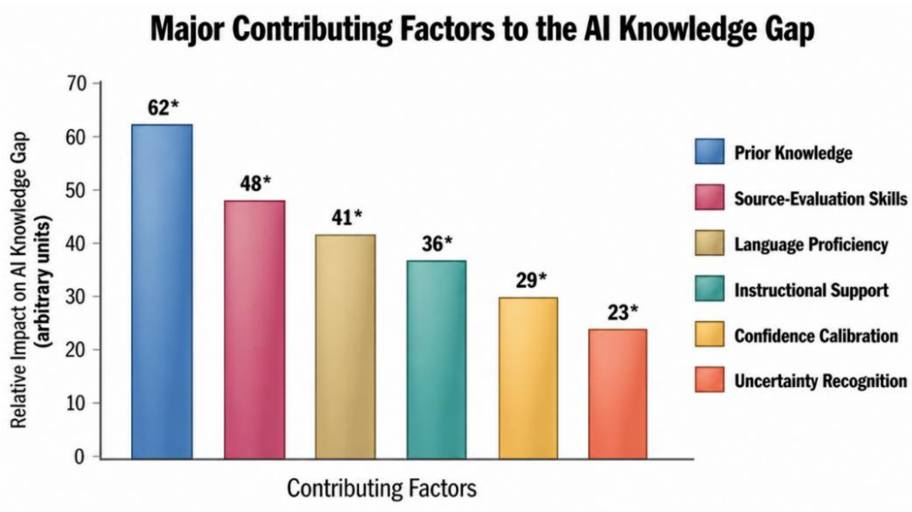

Fig -2: Major Contributing Factors to the AI Knowledge Gap

Equality of access does not equal benefit. An informed user can compare a generated response with known concepts, recognise any assumptions that are missing and find any inconsistencies, as well as re-word the question. A novice may not know enough to realize that there is a plausible answer that is incomplete or incorrect. AI could thus further enhance the importance of prior knowledge while simultaneously making the initial knowledge more accessible. This results in a paradox those who need help the most also are least able to assess it.

Digital inequality is still a reality. In 2024, some 2.6 billion people were still not connected to the internet. Other factors that influence access to high quality assistance include subscription fees, computing resources, language support, disability access, and institutional support. Linguistic inequality is particularly relevant as systems tend to work better in the languages and domains for which they have a lot of training and evaluation data. This can result in unequal access and unequal reliability and cultural representation for communities. An instrumental user is one who uses instruments for purposes other than what they were designed for, while an epistemically responsible user is one who uses them for the purposes for which they were created. In connected populations, there may be an added distinction between the instrumental user and the epistemically responsible user. Instrumental users are interested in getting a completed product. Responsible users analyze the construction of the answer, evidence used, perspectives missing, and if they can explain the issue without the help of the answer. There is no age difference. It is impacted by educational opportunity, disciplinary knowledge, teacher guidance, workplace norms, and system design.

The knowledge gap proposed should not be considered as a personal gap. It has a part of institutionalism. Schools that only evaluate final products can unwittingly be encouraging automation. If an employer is only judging the speed of output and not understanding, this can lead to dependency. Systems that give full answers may limit retrieval, hypothesis formation, and error correction opportunities. Thus, the social challenge extends beyond the provision of access to AI. It means distributing and sharing the conditions for good use of AI basic education, domain knowledge, critical literacy, protected practice time, reliable sources, and accountable human support. In the absence of these conditions, it is possible to have expanded access and unequal understanding.

5. HOW GENERATIVE AI PRODUCES ANSWERS

Generative AI systems are developed using machine learning, where computational models learn statistical patterns in data instead of just manually defined rules. Neural networks are layered mathematical systems that tweak internal parameters as they learn to better predict and are used in many existing language systems.

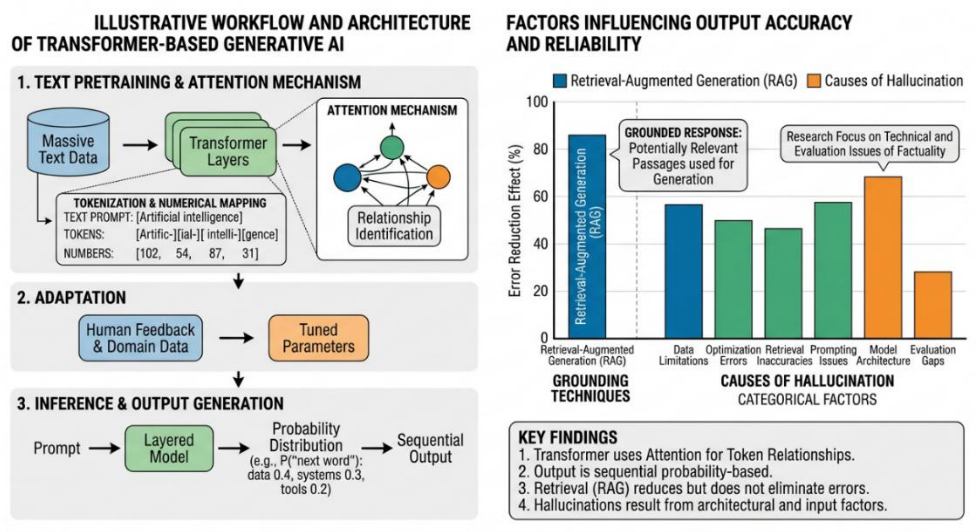

Fig -3: Workflow and Architecture

The transformer architecture, which was first introduced by Vaswani (2017), is the predominant architecture. Transformers are based on an attention mechanism, which is used to determine the relationship between different parts of the input. A sentence is broken down into smaller units known as tokens, which can be words, word parts, punctuation marks, or other symbols. Tokens are mapped to numbers, run through several layers and a probability distribution for the next token is estimated. These probabilities are used to sequentially generate output.

Pretraining is the process of feeding a model with a huge amount of text or other media, to let it learn statistical relationships, linguistic structures, and recurring patterns. For later adaptation, curated examples, human feedback, domain data, or task specific instructions can be used. Inference is the final step of a trained model where it is given a prompt, and it produces a response. Context window is the number of inputs and previous conversation that can be considered in a specific interaction. Prompt wording can impact output as the model is conditioned to predict based on instructions and context it is given. But prompting is not a probabilistic generator to authoritative database. A model can duplicate a pattern that is a citation, policy, formula, or historical fact but not verified with an outside source.

By grounding the generation in a document collection or search system, retrieval-augmented generation, grounding can be improved. While generating the response, the model brings up potentially relevant passages and uses them. Retrieval diminishes the amount of error but does not eradicate it. The system can include irrelevant content, misunderstand a text, mix incompatible texts, or draw conclusions that are not backed up by the retrieved texts. If the output is not supported or fabricated, this phenomenon is termed as hallucination. It does not necessarily mean consciousness or perception, but refers to content that is factually wrong, internally inconsistent, or unfaithful to its source that is generated. These errors are due to data limitations, optimizations, retrieval, prompting, model architecture, and evaluation. These weaknesses may be hidden in fluent language as grammatical coherence and factual accuracy are distinct properties. Research on hallucination has consistently been reviewed with the focus on the technical and evaluation issues of factuality, not as a defect solved. This is a mechanism that can be understood to inform their use. The output of AI should not be considered knowledge from an infallible source, but as a preliminary contribution that needs to be evaluated.

6. COGNITIVE OFFLOADING, MEMORY, AND INDEPENDENT REASONING

Cognitive offloading the cognitive load of a task by using another action or object. Examples include writing a reminder, using a calculator, using a map, and storing information electronically. Offloading is not in and of itself a bad thing. It can free up limited working memory resources for planning, interpreting, and creating. It's what gets offloaded that's the relevant concern. Delegation of routine transcription, yet higher order cognition retained by the learner, may be supported by the tool. When a learner assigns the task of formulating the questions, selecting the evidence, reasoning, composing, and verifying at the same time, there is hardly any cognitive work that can serve as the basis for durable knowledge.

There is a limited amount of information that is held and manipulated in working memory during an activity. Organized knowledge from long-term memory helps to decrease these demands and facilitate comprehension. If a learner extracts and uses knowledge many times, then structures are created that facilitates the reasoning process in the future. In various learning contexts, retrieval practice and self-generation and testing have been linked to greater long-term retention than passive rereading. AI can give answers before learners try retrieval so that some of the activity which helps to form memory might be eliminated.

Previous studies on internet search showed that individuals can remember the location of information, but not the actual information. The same goes for generative AI, which can synthesize, explain and draft, in addition to storing and retrieving. However, current studies don't prove that normal use of AI leads to any permanent damage to memory or creates a clinical condition known as "cognitive atrophy."

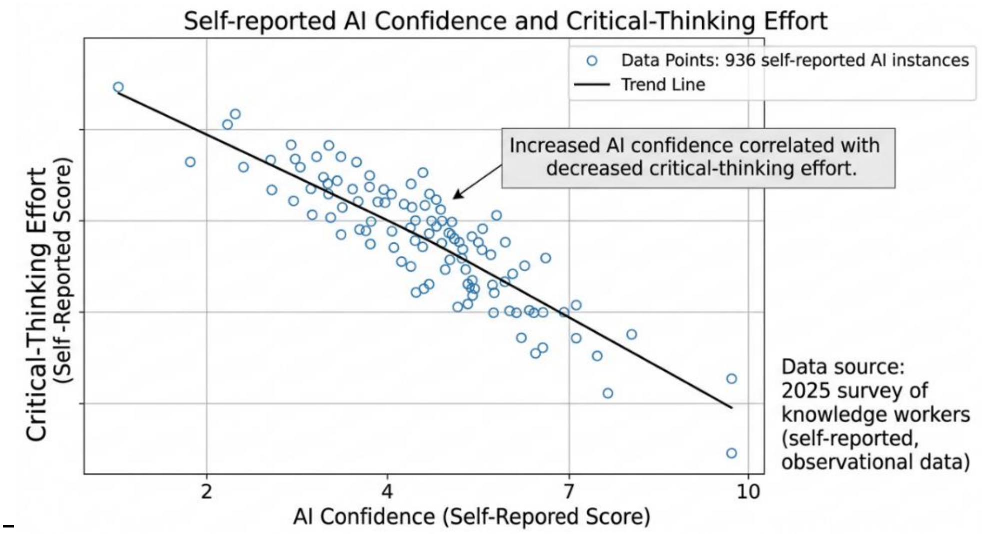

Fig -4: Self-reported AI Confidence and Critical Thinking Effort

To analyze how generative AI is being used in the workplace, 936 self-reported instances of generative AI usage were gathered from a survey of 319 knowledge workers in 2025. Increased AI confidence was correlated with decreased critical-thinking effort, while increased confidence in own task knowledge was correlated with increased critical-thinking effort. The study also indicated that the process of critical thinking moves to the direction of verification, integration, and oversight. The data were self-reported and observational and cannot be used to demonstrate cognitive decline.

A preliminary EEG study of AI-assisted writing of essays found differences between the manner of writing and the neural connections and recall. It is too small and too limited in task and is a preprint, so it's too early to make sweeping statements about cognitive decline. The overall conclusion is that offloading is a balanced act, which can be strategic or substitutive. The educational goal should be to remove the low value load, but not the retrieval, interpretation, decision-making and independent performance.

7. DELIBERATE PRACTICE AND THE DEVELOPMENT OF EXPERTISE

Knowledge does not equal one right answer. A relatively stable ability to achieve performance in a wide range of situations, to recognize significant patterns, to detect and correct errors, to modify principles and to make defensible decisions in the face of uncertainty. The literature on deliberate practice focuses on activity that is focused on improvement, including clear goals, feedback, repeated correction, and activities that are outside of a student's comfort zone. Subsequent research has demonstrated that deliberate practice is a key factor but not the only factor in the differences in performance opportunity, education, motivation, prior ability, health, and social factors are also crucial. Thus, expertise should not only be viewed as an outcome of effort, but also as a developmental achievement, which is built upon practice and context.

Generative AI can enhance deliberate practice by offering timely feedback, generating diverse examples, simulating conversations, or increasing or decreasing the complexity of tasks. A learner may try a problem, explain the work, be given a critique and then try to correct the solution and finally solve a similar problem without help. Here the AI enhances the quantity and frequency of practice without the learner being cognitively responsible.

The other way around is when the system provides the learner with a full product before he creates a plan. This can then result in the confusion of completion and competence. A student might write the correct computer program without knowing how the program is organized, write a statement that he she can't explain verbally, or write a calculation that he she doesn't realize the assumptions don't make sense.

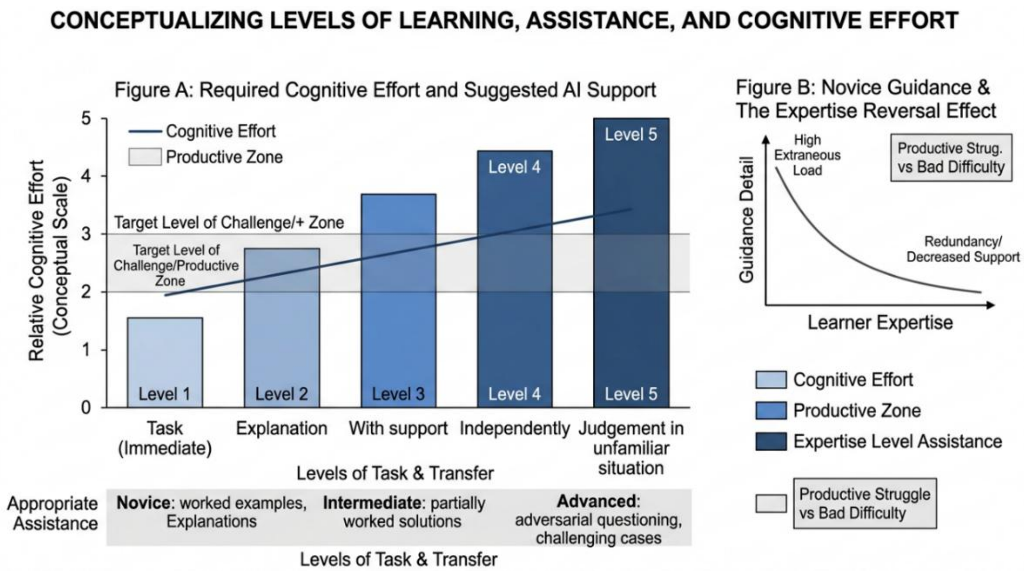

Fig -5: Conceptualizing of Learning, Assistance and Cognitive Effort

As students learn science, it is also found that guidance must be different based on expertise. Worked examples may be useful for novices as it decreases the extraneous cognitive load, but they might become redundant as knowledge increases. This is called expertise-reversal-effect. Thus, the assistance that an AI system can give should not be the same at each stage. Explanations and partially worked solutions may be needed for novices and less support, more challenging cases and adversarial questioning may be more appropriate for the more advanced.

There are five levels to be differentiated Task, Explanation, With support, Independently and Judgement in an unfamiliar situation. Only if activities are intentionally planned for transfer, can AI potentially enhance the first level right away and the others over time. Productive struggle is not to be romanticized bad difficulty can be a turn-off to learning. The aim is to have a challenge that is levelled up to the goal. AI should be used to keep learners in a productive zone of effort, but not to do the learner's thinking for him.

8. CRITICAL THINKING, VERIFICATION, AND AUTOMATION BIAS

Automation bias is the bias towards the automated recommendation and not seeking out contradicting evidence. Previous studies before the advent of generative AI have shown that decision support systems can lead to an improvement in general performance, but also to new errors if the user takes the suggestions without checking. This risk is exacerbated by the fact that the responses are immediate, personal, confident, and linguistically well crafted, typical of generative systems. Fluency can be used as an indicator of competence by users. Confirmation bias can lead to a greater acceptance of the output if

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it reinforces an already held belief, anchoring can lead to an initial generated answer influencing later judgment even in the face of new evidence.

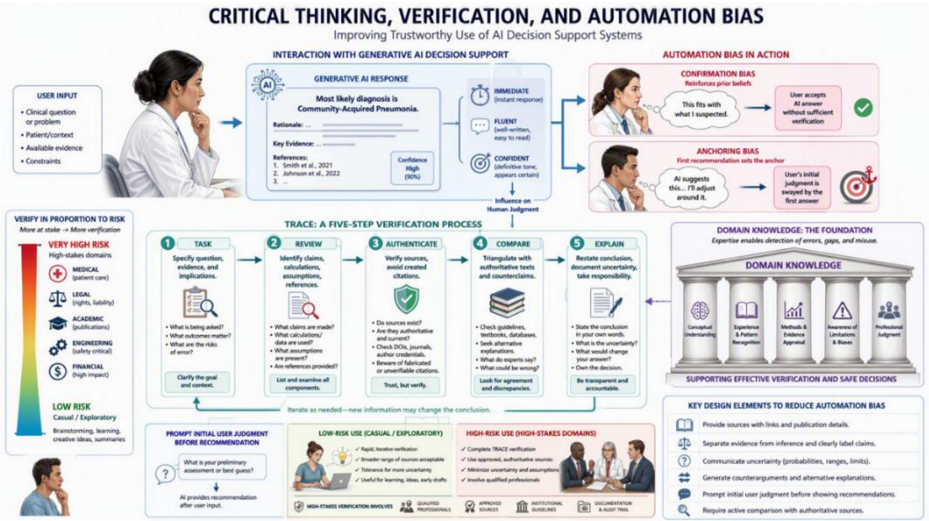

Fig -6: Critical Thinking Verification And Automation BIAS

An experimental study revealed that sometimes participants obeyed AI labelled advice despite the information in the context or their own first evaluation. The results indicate that it is not maximal trust that is required, but calibrated trust.

The summary of the practical verification process is TRACE:

T -Task: specify the question, the evidence needed and the implications of incorrect answers.

R - Review: Identify claims, calculations, quotations, assumptions, and references in the output.

A - Authenticate: find the source of the information and don't rely on a created citation or summary.

C - Compare: Triangulate key ideas with reliable and authoritative texts and counterclaims.

E - Explain: Restate the conclusion in one's own words, document uncertainty and take responsibility for the final decision.

Level of verification should be commensurate with risk. Brainstorming is not medical, legal, engineering, academic or financial advice, and a casual request for brainstorming does not require the same kind of review as medical, legal, engineering, academic or financial advice. For high stakes areas, checking should be conducted by a qualified professional and approved sources of evidence.

Domain knowledge is also a part of the verification process. Humans can't detect an error unless they have a good sense of what correct reasoning generally should look like. Thus, AI literacy should not be a substitute for education in subjects. It needs to be based on reading, numeracy, scientific thinking, historical knowledge, and professionalism.

Design can help through providing sources, separating evidence from inference, communicating uncertainty, generating counterarguments and asking the user to make an initial judgement before showing a recommendation. Sometimes explanations are not enough, as there could be a plausible

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explanation that can lead to greater trust in the wrong advice. Systems should be active comparison and not passive reassurance.

9. BENEFITS OF AI-ASSISTED LEARNING

It is crucial to acknowledge that, under the right circumstances, generative AI can enhance learning. It can restate a challenging concept at varying levels of complexity, give examples, translate the terminology, create low stakes practice questions, structure notes and give instant formative feedback. These functions may be useful in situations where teachers are hard pressed for time or students do not have access to a personal tutor. Accessibility can also be supported by AI. Text-to-speech, speech-to-text, captioning, simplified explanations, alternative formats, and language assistance can help to lower barriers for learners with disabilities and or learning in an additional language. They are not necessarily equal, but rely on technical quality, affordability, privacy, and cultural and linguistic coverage.

Instructional design is seen to be of importance through experimental evidence. A randomized controlled study in higher education showed that a well-designed AI tutoring system could yield more effective short-term learning outcomes than an AI-lesson study group active learning for the lessons studied. The intervention was based on expert designed prompts, structured interactions, controlled content, and pedagogical principles and therefore the result cannot be extrapolated to unrestricted use of chatbots.

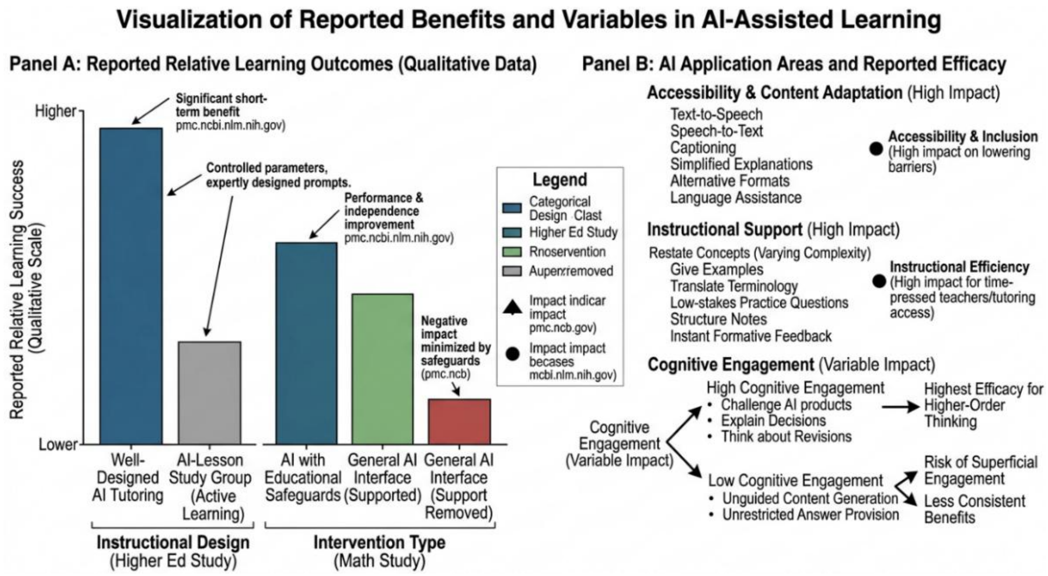

Fig -7: AI Assisted Learning

A large-scale random sample study of high school mathematics revealed a more conservative trend. Students with access to a general AI interface showed greater success with supported practice, with some showing lower success with removal of support. This negative impact was minimized by a tutor that was designed with educational safeguards. The study shows how to make improvement in the performance of the tasks and how to make independent learning. Systematic reviews also indicate that AI is most effective for higher-order thinking when students are asked to challenge the AI-generated products, explain their decisions, interact with AI, and think about their revisions. There is less consistent evidence of benefits, and more risk of superficial engagement, with unguided content generation.

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Unrestricted answer provision is therefore not the most productive form of education. It is a scaffolding approach that is organized. An effective tutor will elicit from the learners to predict, attempt, explain, compare, revise and retrieve. It shows support slowly and ultimately takes it away. Teachers are always key to establishing goals, comprehending students, assessing performance, offering social support and encouragement, and deciding when AI is a supplement or substitute for learning.

10. RISKS TO EDUCATION AND ACADEMIC INTEGRITY

Generative AI makes academic integrity more challenging as it can be used to assist with learning or replace assessed competence. Brainstorming, translation, feedback, editing, and practice may be allowed; the complete creation of an assignment may not be allowed without prior notice as this is considered cheating on the authorship and assessment. The boundary will vary according to the learning outcome(s) being assessed. When the assignment is intended to test independent reasoning, it is possible that a system may generate the argument, even if the content is correct, thus falsifying the assessment. The same issues are present in coding, quantitative work, research reviews, lab reports and take home exams. A neat and tidy piece of work may no longer be enough to show the student's ability.

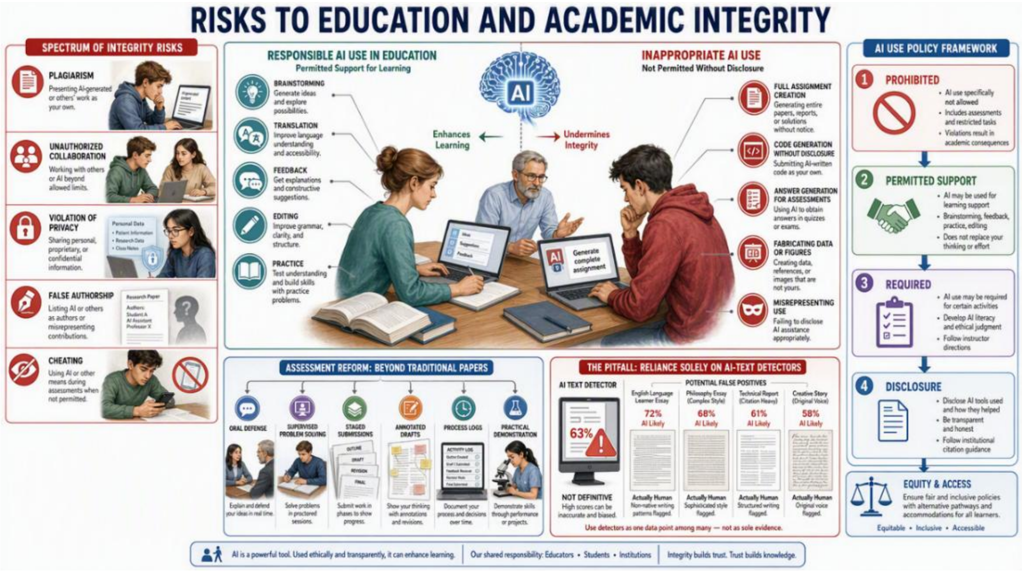

Fig -8: Risks to Education And Academic Integrity

Academic integrity issues involve plagiarism, paraphrasing, false quoting, cheating, unauthorized collaboration, violation of privacy, and falsely claiming authorship. But blanket ban is not likely to be a lasting remedy. Students will come across AI in their work and in the public sphere and it is the duty of educational institutions to educate them about the responsible use of AI. The assessment reform needs to be a mix of secure demonstration of foundational competence and transparent AI-supported work. Oral defence, supervised problem solving, staged submissions, annotated drafts, process logs, reflective commentary, practical demonstration, source audit, local case studies, follow-up questions transfer to new context are all appropriate methods. Assessment should assess the final artefact as well as the selection of evidence, the correction of errors and what the learner can do on his or her own.

The guidance of regulators for the higher education sector to improve assessment is growing and increasingly suggests that surveillance and detection are not sufficient; redesign of assessment is

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needed. Due to the differences in models, text length, language, text revisions, and the population of texts, the results of AI-text detectors should not be used as a final indicator of plagiarism. False accusation can have a negative impact on students and can disproportionately impact multilingual writers (Tertiary Education Quality and Standards Agency, 2023). Institutions should have well-defined categories for use prohibited, permitted support, required, and disclosure. Expectations need to be specific to the assessment and not in general policy. Equitable access or meaningful alternative non-AI should also be provided for students. The goal is not to make sure that older assignments remain the same. It is to ensure that evidence provided by graduates is valid evidence of knowledge and judgment that is claimed by the qualification.

11. PROFESSIONAL KNOWLEDGE, JUDGMENT, AND PUBLIC SAFETY

Professional work involves technical knowledge and contextual judgment, ethical responsibilities, communication, and accountability. Generative AI can be used to summaries records, draft common documents, find relevant information, provide initial analysis, or suggest potential interpretations. But it does not take the responsibility of the professional for legal or ethical issues.

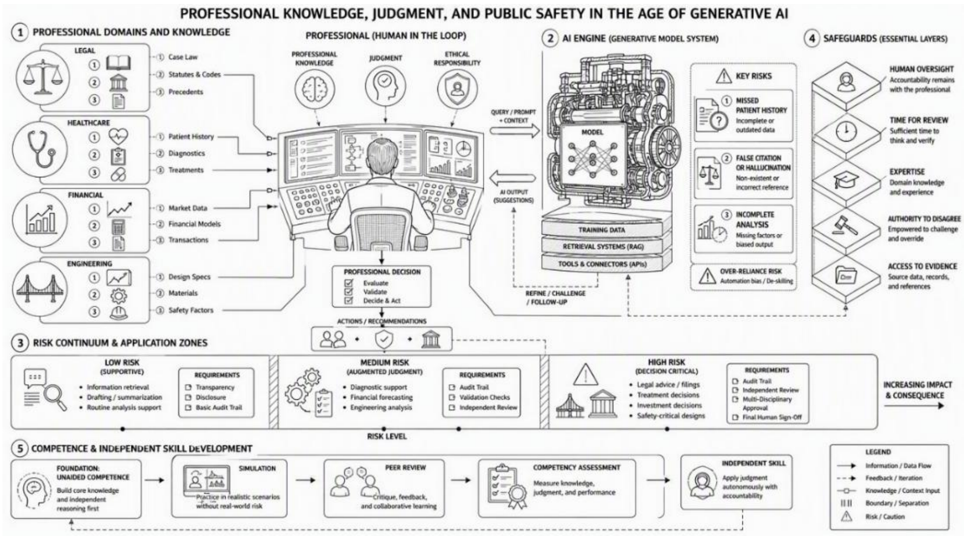

Fig -9: Professional Knowledge Judgement and Public Safety in the Age of Generative AI

In the health care setting, a seemingly logical answer might be missing the patient history, uncertainty, contraindications, atypical presentation, or local clinical guidance. In law, material may be generated that falsely quotes an authority, mixes jurisdictions, or makes up a citation. The general analysis in finance can be done without considering liquidity needs, tax situation, time horizon, or risk tolerance. Physical safety can be impacted by engineering errors, public-administration errors can impact eligibility and rights, and access to services.

Automation bias is especially problematic when the user cannot challenge a system, for whatever reason, such as lack of time, authority, or expertise. A systematic review on the use of generative AI in healthcare in 2026 noted that there are concerns about automation bias, deskilling, and cognitive consequences, but that there are also ways to mitigate these risks, such as human oversight, continuous reskilling, and governance. The evidence base is still in its infancy and should not be taken as evidence of the current universalized clinical deskilling. If the human just approves an output, human in the loop isn't

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enough. Effective oversight should be given access to the evidence, be given enough time to consider the evidence, have the necessary expertise to consider the evidence, have the authority to disagree with the recommendation, and have arrangements in place that do not incentivize an automatic agreement.

Consequences should be used to classify uses. Low risk applications could be formatting or brainstorming. Medium-risk applications may need to be checked for source and sample checked. Qualified approval, documented evidence, testing, audit trials, incident reporting, and appeals corrections should be required for high-risk applications. Unaided competence needs to be maintained in professional education. Automating simple work before it's understood can lead to a thinning out of the path to expertise for junior workers. On the other hand, if all the tasks are done manually, it will be a waste of resources and it will not utilize the available tools. A sensible model is to have a combination of supported work and independent practice, simulation, peer review, and periodic competency assessment. The idea is simple: AI can provide data and suggestions, but it's crucial that the final decisions are made by a knowledgeable individual or a responsible entity. In cases where rights, safety, health and or significant financial interests are at stake, output generated should be interpreted as a decision support and not as final decision.

12. ENTERPRISE TECHNOLOGY AND ORGANIZATIONAL ADOPTION

Generative AI is being used to retrieve knowledge, process documents, provide customer support, assist with research, analyze data, train, develop software, and streamline administrative tasks. Often adoption is driven by speed, consistency, availability of services and less routine work. The 2026 AI Index indicated that the majority of organizations are experimenting with AI, but many of these efforts are not necessarily sustained or safe for deployment, and they may not necessarily provide value (Stanford Institute for Human-Centered Artificial Intelligence, 2026).

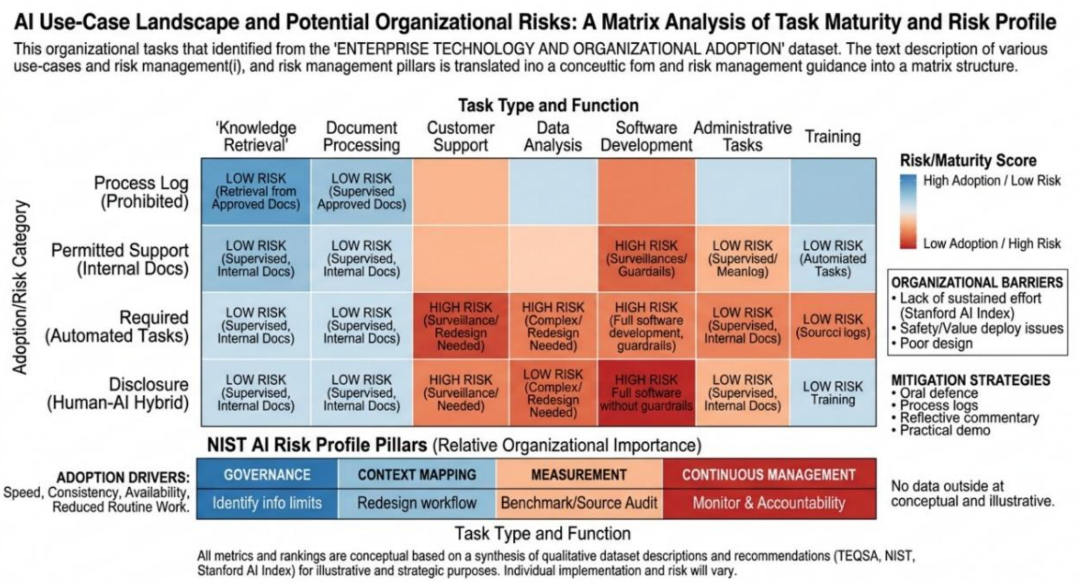

Fig -10: Matrix Analysis of Task Maturity and Risk Profile

A typical enterprise system consists of user interface, language model, access controls, organizational data sources, retrieval components, monitoring and integration with existing software. Retrieval-supported systems can use approved internal documents to help them generate a response. Systems that use tools can do such things as query a database, write letters, or change records. The more capabilities they have, the more they can do and the more dangerous they are.

Data governance is of the essence. It is important for organisations to identify which information can be submitted, where it is processed, how long it is stored, who has access to it and whether confidential information can affect the outputs of the future. There are different levels of controls needed for sensitive personal, legal, medical, security, research and commercial information than for public information.

Quality assurance should comprise of benchmark testing, adversarial testing, source-grounding checks, security review, bias analysis, human evaluation and monitoring after deployment. Performance should be evaluated on the actual tasks and populations of the organization and not merely by general demonstrations. Version changes need to be recorded as the behaviour of systems can vary with time.

The National Institute of Standards and Technology suggests that there be four pillars to AI risk management: governance, context mapping, measurement, and continuous management. It has a generative AI risk profile that includes risks of fabricated information, privacy, information security, harmful bias, intellectual property, human overreliance, and more.

Successfully adopting an organization is not just a matter of software installation. It requires redesigning the workflow, consulting with employees, training, accountability and determining what tasks can't be automated. Poorly designed adoption can lead to more work on reviews, errors can be spread, autonomy can be undermined and or shadow use of systems outside of the approved system. Implementation should complement workers in tasks where human judgment is important and automate tasks where the task, evidence, failure modes and correction procedures are well understood. Staff should be taught to challenge and question as well as to encourage.

13. BUSINESS MODELS AND COMMERCIAL INCENTIVES

There are various business models in support of Generative AI. Consumer services can be offered free to promote usage and paid for features. Other models are subscription, usage based fees, enterprise licensing, infrastructure rent, custom integration, technical support and data or distribution partnerships. These models generate authentic motivation to enhance ability, trust and ease of use. They can also be a driver for hasty deployment without a proper understanding of social impacts. Embedded systems, such as those in search, communication, education, and office work, can create switching costs: when users make their routines around a system, it will be difficult to switch to an alternative.

Fixed and operating costs are significant, affecting the economics. Training and deployment of large models involves special computing hardware, data centres, electricity, cooling, networking, engineering, safety evaluation, and maintenance. The cost of capital could be one of the factors leading to concentration of the market, as only a few organisations can build frontier scale systems. Many smaller companies may be involved via application, specialized models, integration, or infrastructure acquired from larger companies. Incentives can influence knowledge behavior in a commercial context. A service can gain from having users come back often, delegating more work, having users store more content or adding the system to more processes. It doesn't mean that all providers are trying to make people dependent, but it does give a justification for policymakers and institutions to look at engagement design, default settings, data practices, and interoperability.

Intellectual-property issues also have an impact on the business climate. Material used for model development can be copyright protected and outputs from the models may involve issues of copyright, licensing, attribution and market substitution. The United States Copyright Office has determined that AI-generated works, in which there is a sufficient expression of human authorship, may be eligible for copyright protection but works that are completely AI-determined, even if a human provided prompts, are not protected by copyright. Issues related to training data are still controversial and dependent on the context.

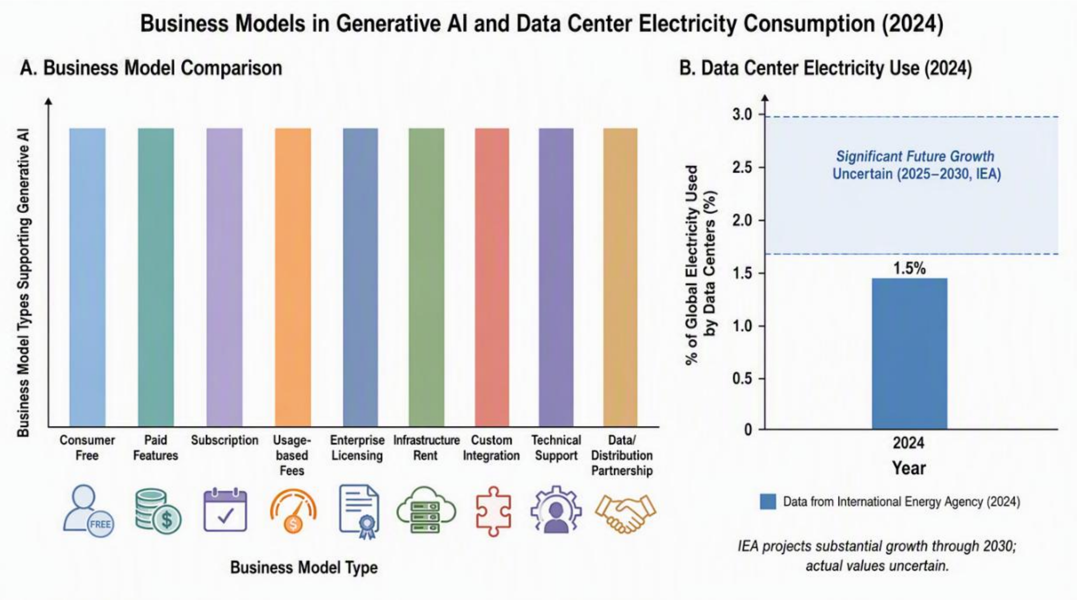

Fig -11: Business Models in Generative AI and Data Center Electricity Consumption 2024

Another economic factor of production is energy. The International Energy Agency estimated that data centres in 2024 used approximately 1.5% of global electricity, and predicted significant growth up to 2030, noting that there is a significant amount of uncertainty. Efficiency per task can increase even as the total use increases, as adoption and task complexity grows International Energy Agency, 2025. So, when selecting a subscription, productivity and price should not be the only factors to consider, but the infrastructure, environmental impact, labour, data rights, competition, and long-term user capability should also be considered.

14. ECONOMIC CONSEQUENCES AND THE FUTURE OF WORK

Generative AI does not impact all tasks across all occupations the same. Majority of jobs are a mix of activities that have varying automation potential. A profession can keep its name but have significant alterations in the way the profession is divided into tasks, the skills needed, how one enters the profession, and the expectations for performance. Experiment and field evidence have reported increases in productivity in writing, customer support, programming, and other structured tasks with varying effects depending on the task and the experience of the worker. In several studies less experienced workers benefited from the technology as the technology enabled them to access patterns that were akin to higher performing practice. Gains in productivity, however, do not necessarily set up lasting learning or better judgment.

In 2025, the International Labour Organization (ILO) published an occupational-exposure index that found

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that around a quarter of the world's jobs could be affected by generative AI, but that task transformation was more likely than job replacement. There was still a high exposure to clerical occupations, and an increase in exposure to technical and professional occupations. Exposure measures are measures of potential technology and are not necessarily measures of job loss.

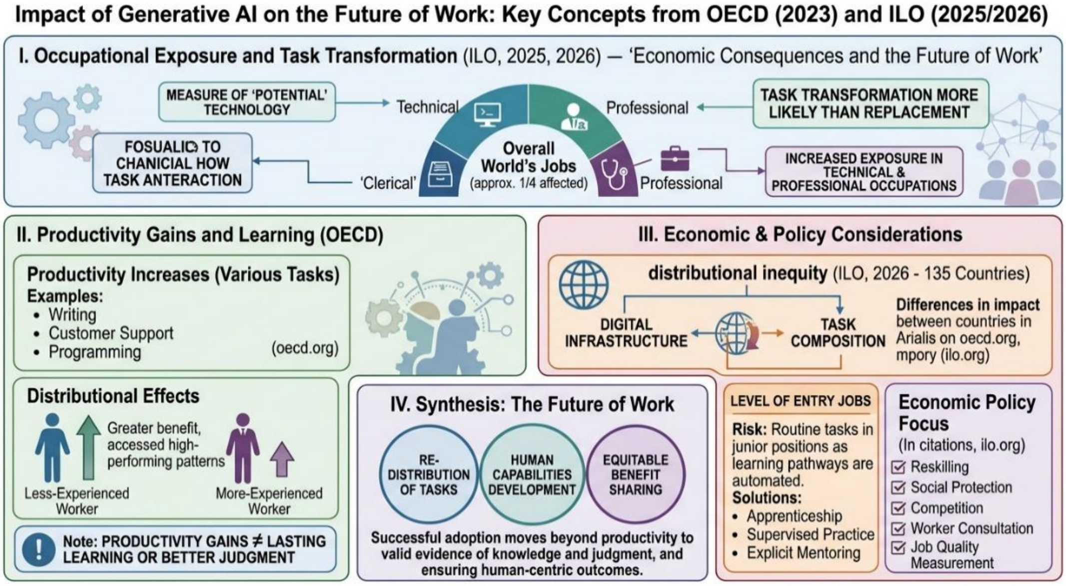

Fig -12: Impact of Generative AI on the Future of Work

The distributional impact can vary. AI can help workers with expertise in their field to scale and enhance the quality of their work. Others might feel more monitored, less independent, and/or that they must work more without review or less stable working hours. Digital disruption may have an impact on countries with less digital infrastructure, but not necessarily in the form of increased productivity. A 2026 joint analysis of 135 countries highlighted the role infrastructure and task composition play in these inequities. The level of entry jobs should be given special consideration. Routine tasks within junior positions can be a way for workers to learn and gain tacit knowledge about professional standards. Without the development of alternative learning pathways, organizations could gain in the short term but undermining future skills. Apprenticeship, supervised practice, simulation, rotation, and explicit mentoring might then be more critical.

Economic policy needs to be geared towards reskilling, worker consultation, portable training, competition, social protection, and job quality measurement, not just towards job numbers. Businesses should determine if there are any negative consequences of productivity gains, such as higher error rates, less learning, or less employee autonomy. The future more than likely won't be universal replacement or the same work. It's a re-distribution of tasks. The question of whether this will generate common prosperity will depend on who has control of the technology, who is trained, how benefits are shared and whether the development of human capabilities is an objective of the organization.

15. SOCIAL EQUITY, DEMOCRACY, AND PUBLIC KNOWLEDGE

Generative AI can help expand the reach of explanations, translation, administration, and educational material to the public. This may be of social value for those who have language, disability, geographic and/or financial barriers. However, benefits are contingent on a reliable connection, appropriate

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technology, data security, language support and trusted human institutions.

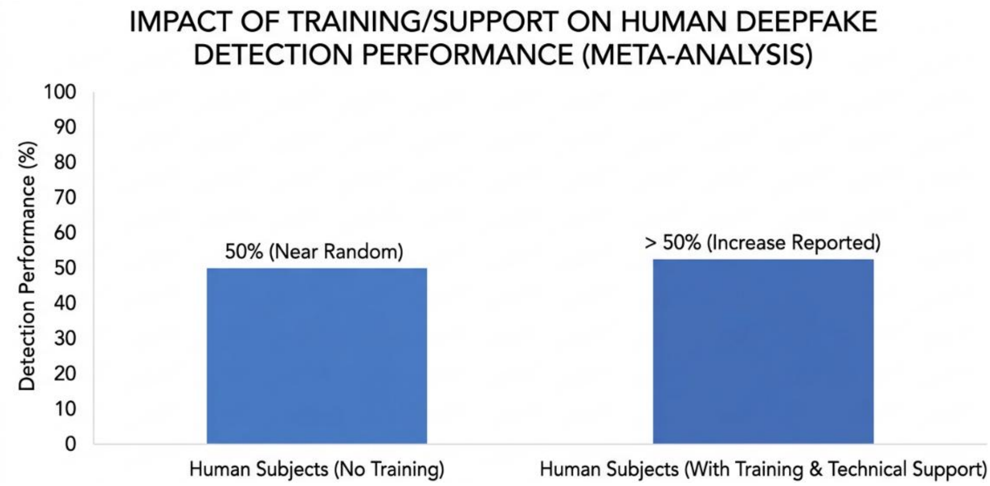

Fig -13: Impact of Training Support on Human Deepfake

There can be several levels of AI divide access none, access limited, access lower quality, not enough literacy, ability to challenge errors. There are many more benefits than just availability, such as paid tiers, advanced hardware, institutional subscription, and specialist integration. Those with good education also may benefit as they are better able to ask good questions and assess answers. Synthetic content is an additional threat to public knowledge. Generative systems save time and money to generate realistic text, audio, images and video. Not all synthetic artefacts are deceptive; there are many legitimate uses, such as accessibility, education, satire and creative work. However, these technologies can also create impersonation, false evidence, and massive amounts of false content.

In a study of 56 papers, a meta-analysis revealed that there was generally a level of performance that was near random for human subjects in detecting high-quality deepfakes, but training and technical support increased this. This implies that a mere look carefully is not enough. The danger of democracy is not just that of convincing people of one falsehood. If there is a persistent doubt as to whether any content is authentic, then a generalized distrust or a skepticism or verification burden can develop. Generative AI can generate disinformation, but it also has the potential to help with detection, translation, fact-checking and public communication, research reviews say.

Societal responses should include protection for freedom of expression, rapid correction, media literacy, public-interest research access, platform accountability, and provenance standards, and independent journalism. Labels can only be of help if they are correct, comprehensible, and difficult to remove. Detection systems should be used to supplement, not supplant, human verification. Democracy requires citizens to be able to make comparisons, see the differences and to be able to tell apart what has been confirmed from what has not. Thus, AI literacy should not be limited to civic education, scientific literacy, historical reasoning, and institutional transparency but rather be taught as technical prompt writing.

16. MEASURING LEARNING, DEPENDENCY, AND EXPERTISE IN AI-ASSISTED ENVIRONMENTS

The potential of generative AI to enhance or diminish human knowledge is greatly influenced by the definitions of learning, critical thinking, dependency, and expertise. Don't assume that doing a task immediately means that learning is permanent. A student can write a well-crafted essay using AI but not have much of the content. On the other hand, a learner could have AI feedback to help them to know their misconceptions and then be able to show better independent work. Research needs to differentiate the quality of the output produced because of the assistance from the knowledge the user has gained because of the assistance.

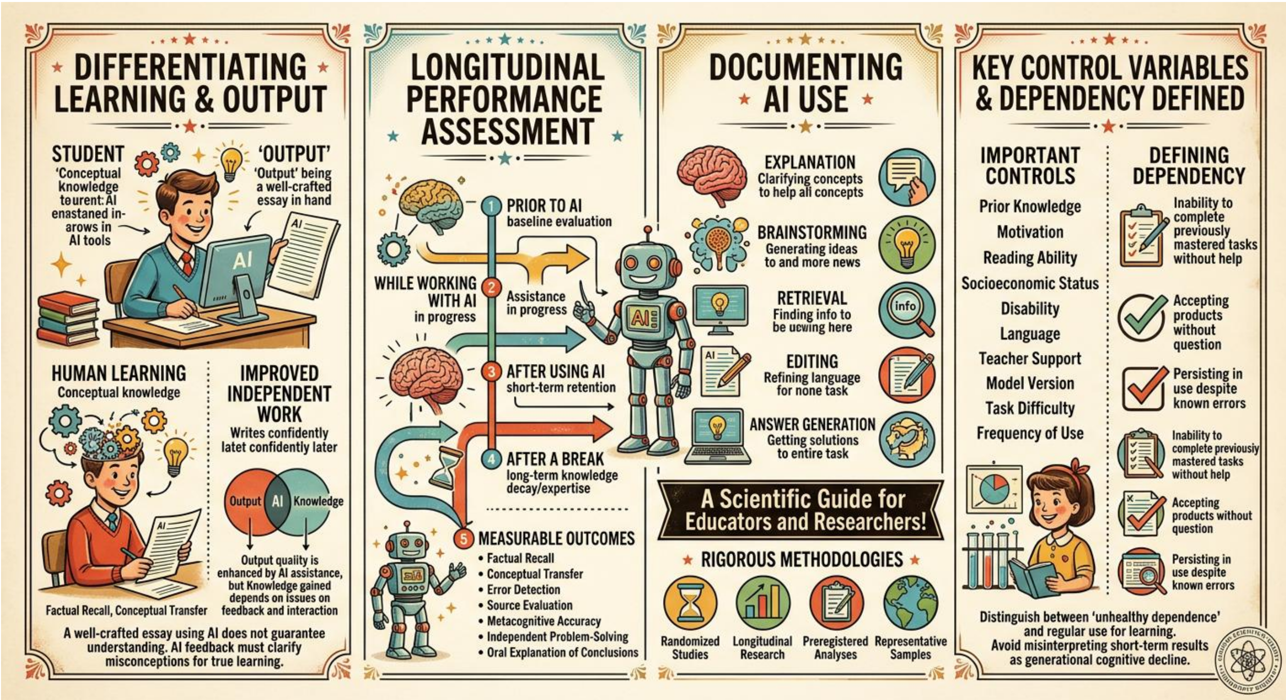

Fig -14: A scientific figures infographic assessing the impacts of AI on human learning

Future research should assess performance at multiple points in time: prior to using AI, while working with AI, after using AI and after a break from using AI. Outcomes consist of factual recall, conceptual transfer, error detection, source evaluation, metacognitive accuracy, independent problem-solving, and oral explanation of conclusions. It is also important for researchers to document the nature of the AI use, such as explanation, brainstorming, retrieval, editing, answer generating or completely replacing. Cross sectional surveys are not as strong as designs to make causal conclusions. Randomized studies, longitudinal research, preregistered analyses, representative samples and replication across countries and educational systems are needed. Prior knowledge, motivation, reading ability, socioeconomic status, disability, language, teacher support, model version, task difficulty and frequency of use should be taken into consideration in studies. The absence of these controls could mean that differences that are observed are due to the influence of AI and not due to existing educational inequalities.

The term dependency also needs to be well defined. But the more often it is used, it is not necessarily unhealthy dependence and the less it is used, the less it is learned. Dependency can be more easily detected by the inability to complete formerly mastered activities without help, by accepting the product without question or by persisting in the use of the product despite known errors. A set of common outcome measures would enable more reliable comparisons of results and would prevent short-term results being used as a measure of generational cognitive decline.

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17. RESEARCH GAP AND UNANSWERED QUESTIONS

Evidence base is growing rapidly and is still underdeveloped. There are many studies that focus on one course, institution, country, task, or model and that have a short time horizon. Users may be more productive or have higher quiz scores in the short term, but whether they retain knowledge, transfer skills or become more independent months or years later is not measurable from short term gains in quiz scores or productivity. The greatest need is longitudinal studies. Research should be conducted to assess the impact of repeated applications of AI on memory, development of writing skills, evaluation of sources, self-efficacy, creativity, and professional judgment. Researchers need to determine whether the decrease in mental effort is temporary or permanent. A decrease in cognitive effort may mean that the learner is receiving effective support or that the learning is not taking place.

Definitions are inconsistent. Critical thinking can be defined as argument quality, performance on standardized tests, self-reported effort, error detection, source verification, or reflective judgment. Dependency can mean how often they are used, if they can't be used without someone else, if they are preferred, if they are integrated into the workflow, or if there is an emotional dependency. Studies can seem contradictory if they are measuring different phenomena because of an absence of consistent definitions.

Generation Z is also an under-researched, global and diverse group. There are university students in well-connected environments, but evidence from these students cannot stand for young people who are outside of formal education, speak other languages, live in less connected environments, or work in nonprofessional occupations. Further studies are needed in countries with low and middle income and with people with disabilities. Another problem is the rapid change of system. A study can test a version of a model which is superseded prior to publication. The versions of the models, settings, prompts, date, interfaces, and access conditions should be documented by the researchers. Independent replication is required, as commercial systems may change, but with limited disclosure.

Comparisons between different usage patterns are proposed Answer generation, Socratic tutoring, Feedback, Retrieval support, Adversarial critique, Collaborative planning, Independent-first workflows. Outcomes should not only be in terms of final product quality, but also delayed retention, transfer, error detection, metacognition, and unaided performance. The consistent findings of systematic reviews up to 2026 are that there is a need for validated measures, stronger causal designs, transparent reporting, and longitudinal evidence. The literature available is inconclusive, but suggests that guided use can aid learning, whereas unstructured substitution can lead to less engagement. It's not yet time to talk of the end of expertise.

18. A RESPONSIBLE AI-LITERACY FRAMEWORK FOR FUTURE GENERATIONS

AI literacy should be a mix of technical knowledge, critical thinking, moral reasoning, hands-on experience, and an understanding of the social implications. It must not be seen as a call to action in the construction sector. Recently, international frameworks have established AI literacy as having the capacity to comprehend systems, assess their outputs, employ them responsibly, and maintain human agency.

The PREPARE framework is a seven-stage process that is linked together:

P -Prompting after the Purpose

Before using AI, the user sets the goal, target audience, evidence needed, what they can use it for, and what the repercussions are if they get it wrong.

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R-Read, understand and infer initially
When learning is the goal, the user tries to recall, explains a method or gives a first approximation without help. This allows diagnostic data to be retained on what the learner really knows.

E - Scaffolding with AI
AI is used to explain, provide feedback, give examples, give counter arguments, translate, or to guide practice, but not automatically to replace. The level of assistance should be gradually decreased as competence increases.

Probe the output (P): Test the output using a probe.

The user poses questions about the assumptions made, evidence that is missing, alternative interpretations and under what conditions the answer might not hold true.

A- Authenticate evidence
Citations, quotations, data, calculations, legal authorities, and technical claims are verified from primary or authoritative sources. Triangulation of important claims is done independently.

R -Reflect and rehearse independently
After using AI for work, learner explains concept without AI, completes a related problem, or applies knowledge in a new situation. This is a measure of whether or not support led to learning.

E - Exercise accountability
The user takes responsibility for the confidentiality of the information, reveals information, if necessary, documents important decisions, asks for qualified review on important matters and is responsible for the product.

Age-appropriate AI education, source-verification exercises, mixed assessments, and independent practice are all ways for schools to utilize the framework. Disclosure, process of evidence, oral defense and discipline specific standards may be required by universities. Families can promote discussion instead of sneaky monitoring. Employers may establish approved systems, rules for confidential data, competency checks and learning time protected. Governments can help to build infrastructure, train teachers, protect consumers, give access to research, and establish rights-based governance. The framework is designed to make the use of AI more brainworm than convenient for convenience's sake. The key is that help should be given to enhance the human capacity to act without help when it is not available, inappropriate, or incorrect.

19. PRACTICAL RECOMMENDATIONS

Students should try to do important learning tasks before asking for full answers, ask AI to give feedback other explanations, check all important implications, and test themselves periodically without help. They should abide by the institutional disclosure rules and not enter in confidential information.

Teachers and educational institutions should establish what is permissible for each assessment, reimagine tasks to focus on reasoning and transfer, and integrate AI-supported tasks with supervised or oral demonstrations. Teachers need time and support to learn how to use the technology and to be assured of the lack of unrealistic expectations that they are expected to be able to monitor all undetected use.

Parents caregivers should explain to their students how AI functions, the process of verifying AI-generated work, and emphasize learning behaviors instead of deeming all AI use as cheating. Appropriateness of boundaries should include privacy, emotional dependence, inappropriate content, and commercial persuasion, all at an age appropriate level.

Applications should be categorized according to the level of risk, maintain independence of competency and have human review with real authority. There is the need for structured learning opportunities for junior staff to learn the tasks that are to be automated.

The following are some of the guidelines that technology designers should adhere to Communicate uncertainty, allow for citation tracing, make it easy to correct, include privacy controls, and design an interface that promotes initial judgment and comparison. Don't sacrifice user autonomy or informed choice for engagement.

There is a need to encourage equitable connectivity, multilingual resources, accessibility, consumer protection, competition, data governance, and independent evaluation. Notice, explanation, review, and appeal should be provided for high stakes automated decision making.

Researchers should preregister studies as appropriate, specify model versions and prompts, and include diverse populations, and use delayed and unaided outcome measures. Statements of reduction in cognitive function should be commensurate with the design and evidence.

For general users, the amount of verification should correspond to potential damage. While AI can be helpful for brainstorming and orientation, authoritative evidence and qualified human judgment is needed for medical, legal, financial, scientific, and safety-related decisions.

20. CONCLUSION

While there are worries about the impact of generative AI on the intelligence of Generation Z, the current evidence does not support this conclusion, nor does it suggest an “end of expertise. This kind of framing is too deterministic and puts the responsibility on young people for an environment of technologies and institutions of which they are not the creators. The evidence rather suggests that the impact is conditional and depends on aspects of instructional design, prior knowledge, type of task, reliability of the system, incentives, and usage habits.

The availability of explanation and support has been significantly increased by generative AI. It can help to reduce language barriers, facilitate accessibility, offer formative feedback, create practice opportunities, and boost productivity. Structured tutoring and inquiry designs, which involve prediction, attempt, explanation, verification, and revision can help to reinforce learning. The dangers are also great. Systems that regularly replace reading, retrieval, reasoning, composition, and error correction may result in acceptable work but not in the knowledge necessary to evaluate the work. Unsupported output can be fluent and lead to automation bias and false confidence. In the educational context, this can be a disassociation of grades and competence. At work, it can differentiate between documentation and good judgment. In society, it can lead to a rise in information access and information overload as to what's trustworthy.

Knowledge is thus not the same as access to information and information is not the same as expertise. Expertise is based on organized memory, repeated practice, feedback, experience in context, ethical responsibility, and performing under new conditions. While AI can amplify the impact of these abilities, it doesn't render their acquisition automatic. It's not just the gap between AI owners and non-owners that will matter in the future. It can be between people and institutions leveraging AI to augment human thought and those that enable short-term convenience to be a substitute for capability building. Don't divide that requires more than personal discipline. It needs assessment systems to be changed, an understanding of AI, equal access, ethical design, proper professional management, and economic rewards to reward long-term skills. We don't want future generations to be faced with the options of either ignoring or handing over judgment to AI. The positive goal is to work together in a disciplined manner to think before prompting, to ask questions before accepting, to check before acting, to practice without help, and to be accountable for choices. In such a context, AI can serve to disseminate knowledge and enhance the human capabilities that underpin expertise.

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