REPORT

Generative AI and critical thinking
Implications of changing employment patterns

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Introduction

This report represents a contribution led by Digital Enlightenment Forum (DEF) to the Horizon project EUDHIT. It is inspired by Digital Humanism lectures and discussions, (caiml.org/dighum/dighum-lectures/). Actually, the trigger and inspiration for writing this report came from a presentation by Alexander Pretschner (2025) on the relationship between Generative AI and software development delivered as part of the Digital Humanism Lectures. In this report we focus mostly on Generative AI (abbreviate as GenAI) but also more generally on Artificial Intelligence (AI).

Critical thinking, broadly defined as the ability to analyse, evaluate, and synthesize information to make reasoned decisions, is a fundamental cognitive skill essential for academic success, professional competence, and informed citizenship (de Bie et al., 2015). It involves several cognitive processes, including discerning truth from falsehood, problem-solving, decision-making, and reflective thinking, which are crucial for navigating complex and dynamic environments. Critical thinking is necessary to analyse, compare, and integrate information (Rusandi et al., 2023) in order to navigate the evolving digital landscape and make value-based choices.

Generative AI (henceforth simply GAI) has a dual-edge nature with respect to cognitive development. It can enhance learning outcomes by providing personalised instruction and immediate feedback, thus supporting skill acquisition and knowledge retention. A recent OECD report on the use of GAI in education confirms this double-edged nature of GAI as some studies indicate improved student output and learning, others report opposite results when tools provide direct solutions rather than supporting true learning processes (OECD, 2026, p. 11). According to the OECD, the drawback of the use of GAI in education is that students depend too heavily on GenAI, metacognitive engagement – the mental processes and effort that turn answers into understanding – drops. Emerging evidence shows that over-reliance on these tools can lead to cognitive offloading (Gerlich, 2025a), which means that individuals delegate cognitive tasks to external aids, reducing their engagement in deep, reflective thinking (Sparrow et al., 2011). While cognitive offloading can free up cognitive resources, it may also lead to a decline in cognitive engagement and skill development. The pervasive availability of GAI tools, which offer quick solutions and ready-made information, can discourage users from engaging in the cognitive processes essential for critical thinking and young people from developing the related skills.

As early as 2019, the saying from 2011 by Marc Andreessen, “Software is eating the world,” was replaced by “AI is eating the software” (van Attekum et al., 2019). If one writes ‘software developers and generative AI’ in google it gets as first entry (from google AI) that “Generative AI is causing a structural shift in software development, reducing demand for entry-level roles by automating basic tasks but increasing demand for senior developers”. And a similar kind of reply comes from ChatGPT. According to a recent editorial by the Economist (The Economist, 2026), software stocks are getting pummelled by the threat of the new coding capabilities of GAI. But GAI seems to “threaten” also other professions such as that of junior lawyers that could be substituted by ChatGPT (McCarthy & Cain, 2025). The phenomenon, however, seems to be even more general and affect almost all entry level jobs, at least judging by media articles appeared in the US. According to the Wall Street Journal AI is wrecking the job market for college graduates (Ellis & Bindley, 2025). The New York Times warns of an upcoming apocalypse for recent graduates (Roose, 2025). As reported by Forbes in May of 2025, Dario Amodei, co-founder and CEO of Anthropic predicted that AI could wipe out roughly 50 percent of all entry-level white-collar jobs within five years. Emerging empirical evidence shows that GAI seems to displace the jobs of juniors (Brynjolfsson et al., 2025a; Hosseini et al., 2025), including of junior software developers (Brynjolfsson & Mitchell, 2017; Eloundou et al., 2024; Westby & Modestino, forthcoming). This trend resounds with the more general treatment of automation in the economics literature that we will analyse later. For those tasks more amenable to automation, in general, increasing labour productivity generally benefits more highly skilled workers, who can leverage technology and innovation to become even more efficient. In contrast, low-skilled workers often experience job displacement or wage stagnation as automation and technology replace routine tasks. For example, as productivity initially rises with the introduction of generative AI, employers may hire fewer lower-skilled software developers whose tasks can now be done using less labour and more technology. This may lead to greater inequality between senior and junior software developers, at least in the short term during the initial transition when adopting this new technology, as more time and effort is required of seniors to validate/verify the AI-produced work.

The evidence on the labour impact of GenAI on juniors is only emerging and it is uncertain whether it will be only a short-term trend or if it is here to stay. Assuming that such trend is confirmed and will be of a more mid-term nature, then the problem emerges how the seniors of the future will develop the needed critical thinking without passing through an earlier junior stage?

In this report we will tackle this question based on an extended and interdisciplinary review of the literature that identified a total of 162 sources. The report is structured as follows. In section 2 we present a brief methodological note on the identification of the sources. In Section 3 we will explore prevalent definitions of critical thinking; in section 4 we will review and analytically summarize the empirical evidence of the impact of GAI on critical thinking; in section 5 we go in some depths on the economics of AI in general and on the emerging evidence concerning the labour impact of GAI; based on the curated facts established in the previous sections in Section 6 we develop four future scenarios using as axes (i) GAI impact on labour and (ii) GAI impact on critical thinking. The aim of this exercise is to produce both a best- and a worst-case scenario. We conclude this Section with policy recommendations to avoid the latter.

Brief methodological note

Reviews can range from unstructured and fairly subjective in the selection of sources and limited in scope (i.e. narrative reviews) to very structured along the lines of the Cochrane protocol (Higgins & Green, 2011); they can be comprehensive with a narrow vertical but longitudinal focus including only empirical items (i.e. systematic review) and sometimes only quantitative empirical items (meta-analysis). Two 'reviews of reviews' have conceptually mapped the field (Grant & Booth, 2009; Paré et al., 2015), from which we extracted the table below.

Parameters	Systematic	Scoping	Critical
Scope of question	Narrow (Longitudinal)	Broad (Cross-sectional)	Broad (Cross-sectional)
Search strategy	Comprehensive	Comprehensive	Selective and/or representative and/or iterative and purposive
Nature of sources	Empirical only	Empirical and conceptual	Empirical and conceptual
Explicit inclusion criteria	Yes	Yes	Not always
Quality assessment	Yes	Not essential	Not essential
Reporting	Statistical method plus narrative analysis	Content/thematic, possibly frequency analysis	Narrative / interpretative

Table 1 Typology of reviews. Source: adapted from (Grant & Booth, 2009; Paré et al., 2015)

In addition, there is also the type of so-called rapid reviews, which are a form of knowledge synthesis in which components of the systematic review process are simplified to produce information in a timely manner (Khangura et al., 2012; Tricco et al., 2015). It is a mix between the snowballing and the systematic reviews approaches. The literature sources used as evidence in this report have been identified using a mix between the scoping and the rapid review methods.

For this report a systematic review approach was not feasible for two main reasons. Systematic reviews usually tackle longitudinally and vertically a well-delimited and focused research question on which a consolidated body of literature exists, using explicit and reproducible criteria for inclusion and quality appraisal of items. First, we had to tap holistically and horizontally very different and multidisciplinary bodies of literature. Second, the phenomena we tackled are just emerging and the corresponding literature are not fully consolidated. Therefore, we adopted a mix of the scoping and rapid reviews, although as in the systematic reviews we screened for the quality of the contributions and we included only scientific articles. We first analysed some reviews of the literatures in the various field tackled (critical thinking in general, impact of AI and GAI on critical thinking, and impact AI and GAI on the labour market) and from there we selected what we considered the more relevant article with snowballing approach. We, thus, identified a total of 162 sources, out of which 135 are used and cited in this report.

On critical thinking

As observed (de Bie et al., 2015, p. 33), there is a large variety of definitions of critical thinking (and corresponding measurement frameworks) often conflicting (Bloom et al., 1956; Dwyer, 2023; Ennis, 1987; Halpern, 1998, 2012; Paul & Elder, 2008), although there have been attempts for connecting and reconciling this multiplicity of frameworks (Dwyer et al., 2014; Mulnix, 2012). Providing a full account of the debate on critical thinking is beyond our scope here, and we will limit ourselves to a selective review. We can notice that some of the empirical studies reviewed in next section adopts different measures of critical thinking. Gerlich(2025a), for instance, use the Halpern Critical Thinking Assessment (Halpern, 2012), whereas Lee et al. (2025) uses the taxonomy developed by Bloom et al. (1956). These are just examples, but other papers still use other measures of critical thinking, and this is a limitation for the comparability of the emerging finding presented in the next section.

The definition of critical thinking developed by Bloom et al. (1956), a hierarchical taxonomy that characterises student learning objectives into six types: knowledge (recall of ideas), comprehension (demonstrating understanding of ideas), application (putting ideas into practice), analysis (contrasting and relating ideas), synthesis (combining ideas), and evaluation (judging ideas through criteria). According to Ennis (1987), critical thinking consists of “reasonable reflective thinking focused on deciding what to believe or do”, which stresses the evaluative nature of critical thinking. According to Paul and Elder (2008), critical thinking is the art of analysing and improving thinking, focusing on intellectual standards such as clarity, accuracy, and logic. Dwyer (2023) defines critical thinking as consisting of a blend of cognitive abilities and critical thinking dispositions, emphasizing skills such as truth-seeking, systematic evaluation, inference, and self-regulation in problem-solving. They include the desire to be informed, the ability to consider multiple perspectives, the identification of relationships, reflective thinking, evidence-seeking, skepticism, respect for others’ views, and tolerance. One of the most influential definitions is the one offered by Halpern: “The term critical thinking refers to the use of those cognitive skills or strategies that increase the probability of a desirable outcome. […] Critical thinking is purposeful, reasoned, and goal-directed. It is the kind of thinking involved in solving problems, formulating inferences, calculating likelihoods, and making decisions. Critical thinkers use these skills appropriately, without prompting, and usually with conscious intent in a variety of settings” (1998, pp. 450–451). This definition is influential as from it the earlier cited Halpern Critical Thinking Assessment (HCTA) measure was developed and is one of the most adopted measurement of critical thinking skills across various domains (Halpern, 2012). HCTA measures critical thinking skills for five skill types: (a) verbal reasoning (e.g., the ability to detect and defend against persuasive or deceptive language usage); (b) argument analysis (e.g., the ability to assess the strength of an argument); (c) thinking as hypothesis testing (e.g., the ability to reason scientifically, to determine whether or not the given information confirms a hypothesis); (d) using likelihood and uncertainty (e.g., using the correct estimate of a probability); and (e) decision making and problem solving (e.g., the ability to define a problem, identify goals and consider both positive and negative results).

Aside from the difference in the various definitions, one can nonetheless identify some basic common elements. For instance, Butler et al. conclude that critical thinking 'involves attempting to achieve a desired outcome by thinking rationally in a goal-oriented fashion' (2012, p. 721). In general, we can summarize that critical thinking is a multidimensional cognitive process presupposing the ability to think clearly and rationally, understand logical connections between ideas, evaluate arguments, and identify inconsistencies in reasoning. This process is crucial for effective problem-solving, informed decision-making, and the acquisition of knowledge. There is a consensus on the importance of critical thinking in the educational system. Students with strong critical thinking skills tend to perform better academically (Fisher, 2011). Critical thinking makes students less susceptible to manipulation, misleading information, and biases (Kuhn, 1999). Critical thinking is a form of metacognition helping students know and regulate their thinking, self-reflection allows students to consider what they have learned (Rivas et al., 2022). These skills are essential for academic achievements and lifelong learning. Critical thinking is necessary to analyse, compare, and integrate information (Rusandi et al., 2023). According to Liang (2023), critical thinking is fundamental in contemporary education to support students drawing conclusions, understanding contributing factors and effects, assessing source credibility, and distinguishing facts from opinions. Critical thinking skills can be developed in sequential stages (Nguyen et al., 2014). Research in education has developed a number of approaches to teaching critical thinking (Wilson & Conyers, 2016), such as structured argumentation exercises (Davies, 2011).

While most of the literature on critical thinking focuses on the educational system, the topic is also increasingly applied in the workplace (Song et al., 2024). The World Economic Forum report The Future of Jobs identifies critical thinking and creativity as two of the main skills that will be in demand in 2022 and beyond (World Economic Forum, 2018). Digital technology and artificial intelligence continue to change the skills needed in the workplace, but some skills go beyond what can be achieved by automated systems and intelligent machines. In particular, critical thinking is considered essential for performance at work and it is highly valued by employers (Dondi et al., 2021; Finley, 2021). Critical thinking in the workplace is considered necessary for problem-solving, evaluating information, and decision-making. Ninety-five percent of the 496 executives and hiring managers at U.S. companies rated critical thinking as either very or somewhat important (Finley, 2021). Despite its importance, numerous studies have revealed that employers are disappointed that new hires (including those with college degrees) do not have sufficient critical thinking skills or are underprepared to apply those skills in the workplace (Song et al., 2024, p. 1). Poor critical thinking skills can lead to low productivity, mistakes, or hasty decisions, thus having negative impacts on the larger goals of a company (Tripathy, 2020). Dondi et al. (2021) defined critical thinking in the workplace as having four key elements: (1) logical reasoning, (2) seeking relevant information, (3) structured problem solving, and (4) understanding biases.

AI and GenAI impact on critical thinking

As summarised by Suriano et al. in the literature there are 'conflicting empirical results on whether ChatGPT enhance or undermine students' critical thinking (2025, p. 2), although in our review the number of articles that stress the risks for critical thinking outweigh the number of those stressing the potential benefits. In paragraph 4.1 we account for the literature focusing on the promises and benefits, whereas in paragraph 4.2 we devote considerably more space to the literature considering the risks. Finally, in paragraph 4.3 we provide a synthetic vertical zoom on the impact of AI and GenAI on software development. It is also important to stress as a limitation that, while the shifts in critical thinking behaviours brought about by GAI extend to a broad set of professions and knowledge workflows (Brachman et al., 2024), the literature is predominantly focused on students and education and much research is need on the relation between GenAI and critical thinking in the workplace.

Promises and potential benefits

AI tools can enhance learning outcomes by providing personalised instruction and immediate feedback, thus supporting skill acquisition and knowledge retention. AI in education helps personalised learning experiences by providing instant feedback and improving efficiency in routine tasks (Onesi-Ozigagun et al., 2024). AI tools like tutoring systems and adaptive tests make learning more personal and enhance the educational experience. For instance, AI-powered data visualisation tools can help users see trends and correlations in large datasets, thereby aiding analytical thinking (Bennett & McWhorter, 2021). They can reduce cognitive load. GAI can boost writing productivity by assisting with tasks such as content generation, idea creation, and stylistic editing, helping both expert and novice writers (Lee et al., 2025).

Based on a review of the literature and on direct experimentation of ChatGPT Rudolph et al. conclude that this tool could enhance critical thinking skills in students, as it allows for the examination of the same topic from multiple perspectives (Rudolph et al., 2023). According to these authors, this process of diversified analysis can broaden people's views, enabling them to consider the subject from different angles and enriching their thinking processes. According to a study by Lawasi et al. (2024), the use of artificial intelligence (AI) in education has the potential to significantly enhance students' critical thinking skills. The authors studied how AI tools enhanced critical thinking among students majoring in English Education, using a mixed method approach that combined quantitative surveys and qualitative interviews to assess the frequency and contexts of AI usage and its impact on critical thinking. The results of the survey indicated that 64% of respondents use AI tools several times a week, predominantly in educational settings. A smaller percentage of respondents use AI daily (14%), while another 14% use AI rarely, and 7% use it several times a month. Interviews with frequent AI users indicate that AI assists in expanding ideas and providing deeper insights, but its effectiveness depends on the users' ability to ask precise questions and critically interpret AI-generated content. A few other empirical studies using limited evidence seem to support the idea that that ChatGPT can enhance users' critical thinking (Essel et al., 2024; Guo & Lee, 2023; Nguyen Minh, 2024). In some other articles focused on GAI and critical thinking both opportunities and risks are discussed (Chan et al., 2023; Michel-Villarreal et al., 2023; van den Berg & du Plessis, 2023).

Integrating generative dialogue systems in research and education has drawn considerable interest in recent years. This is because these technologies promise to revolutionize research and education by streamlining repetitive tasks, aiding in data interpretation, and pioneering new learning and assessment methods (George & Wooden, 2023; Zhai & Wibowo, 2023). Rathika et al. (2024), proposes the development of an AI-powered interactive virtual tutor designed to support students throughout their educational journey. By analysing students' learning patterns, emotional states, and progress, the AI tutor offers personalized recommendations and interventions, enhancing both cognitive and emotional aspects of learning. They conclude that AI-driven virtual tutors could revolutionize personalized education.

As anticipated in the introduction the recent review by the OECD on the use of GenAI in education considers both the promises and the risks (OECD, 2026). Among the promises the OECD states that GAI can scale personalised learning support, enhance feedback quality, and automate parts of assessment, adding that effectively integrating GenAI into teaching and learning may require that teachers encourage student agency and emphasize process, such as how students think and learn, rather than student output. A similar view, although more optimistic, is that held by Rusandi et al. (2023), according to whom it is possible to building bridges between ChatGPT use and critical thinking in students.

According to these authors AI can complement learning and research processes when used ethically and responsibly, by integrating specific teaching methods in education and research can help develop better critical thinking skills and a deeper understanding of the contexts in which AI is used.

AI and GenAI risks for critical thinking

Several studies have highlighted how the use of technology in general (so not with a special focus on AI or GAI) can impact cognitive processes, including attention, memory, executive functions, and reasoning (Amez & Baert, 2020; Meltzer et al., 2023; Nakagawa et al., 2022). In particular, it has been demonstrated that technology use can affect a crucial cognitive ability in education, namely the ability to engage in complex critical thinking (Cheng et al., 2022; Hartanto et al., 2023; Ku et al., 2019). In this paragraph before reporting the findings of various studies, we illustrate two mechanisms through which AI and especially GenAI can negatively impact critical thinking.

The first mechanism, explored empirically by Gerlich (2025a), which we further discuss later, is the so-called 'cognitive offloading', which occurs when individuals delegate cognitive tasks to external aid, thus reducing their engagement in deep, reflective thinking. The first to highlight this phenomenon, calling it the 'Google Effect', was Sparrow et al. (2011). This phenomenon is particularly concerning in the context of critical thinking, which requires active cognitive engagement to analyse and evaluate information effectively. Cognitive offloading, as described by Risko and Gilbert (Risko & Gilbert, 2016), involves using external tools to reduce the cognitive load on an individual's working memory. While this can free up cognitive resources, it may also lead to a decline in cognitive engagement and skill development. The pervasive availability of AI tools, which offer quick solutions and ready-made information, can discourage users from engaging in the cognitive processes essential for critical thinking. For example, Sparrow et al. (2011) demonstrated that the availability of information through search engines can affect memory retention and the inclination to process information deeply. Furthermore, it has been highlighted how increased trust in AI tools can result in greater cognitive offloading, which in turn reduces engagement in critical thinking (Gerlich, 2025b). Recent research emphasizes that the relationship between AI and cognitive offloading is multifaceted, with trust playing a key role (Gerlich, 2024). For instance, AI-powered data visualisation tools can help users see trends and correlations in large datasets, thereby aiding analytical thinking (Bennett & McWhorter, 2021). However, there is a risk that over-reliance on AI for analysis may undermine the development of human analytical skills. Zhai et al. (2024) found that students who heavily relied on AI dialogue systems exhibited diminished decision-making and critical analysis abilities, as these systems allowed them to offload essential cognitive tasks. Also, Walter (2024) reported that over-reliance on AI tools for academic tasks led to reduced problem-solving skills, with students demonstrating lower engagement in independent cognitive processing.

A second mechanism proposed by Suriano et al. (Suriano et al., 2025) relates to dual process theories (Stanovich & West, 2000; Tversky & Kahneman, 1974) and the distinction between System 1 and System 2. System 1 is heuristic based, automatic, and instinctive forming quick judgement and decisions based on previous experience or emotions (Rumana, 2023). System 2 is reflective and applies controlled processes engaging into rational thinking but has scarce resources, is so to speak lazily and cannot be always activated. System 2 is the source of critical thinking (Sowden et al., 2019). It is argued that steady interaction with ChatGPT can lead to the passive use of such a tool with System 1 overruling System 2, thus reducing the ability to reason critically. Only when heuristic responses are blocked and replaced by critical thinking can we accurately choose the information we use to form opinions or make decisions (Fabio & Suriano, 2023).

We start with one of the only two studies that are not focused only on students (Gerlich, 2025a; Lee et al., 2025). Gerlich (2025a), starting from the perspective of cognitive offloading, used a quantitative survey and in-depth interviews with 666 respondents covering different age groups and educational backgrounds. The quantitative data were analysed statistically using ANOVA and correlation analysis, whereas thematic analysis was conducted on the interview transcripts. They report a negative correlation between frequent AI tool usage and critical thinking abilities, mediated by increased cognitive offloading. Younger participants exhibited higher dependence on AI tools and lower critical thinking scores compared to older participants. Students who rely heavily on these tools may struggle to think independently and develop skills like metacognition, which is the ability to reflect on one’s thinking. Gerlich confirms what previous studies have highlighted (Ahmad et al., 2023; Çela et al., 2024). Çela et al. (2024), through a quantitative survey of students in Albania report a statistically significant negative correlation between reliance on AI tools for assignments and students' problem-solving skills, suggesting that excessive dependence on AI can hinder the development of independent problem-solving abilities. Ahmad et al. (2023), though a study of 285 students in Pakistan and

China report the risk that overrelation on AI tools can cause metacognitive laziness and decreased capacity of decision-making.

Lee et al. (2025) surveyed 319 knowledge workers to investigate 1) when and how they perceive the enaction of critical thinking when using GAI, and 2) when and why GAI affects their effort to do so. Participants shared 936 first-hand examples of using GAI in work tasks. They find that quantitatively, when considering both task- and user-specific factors, a user's task-specific self-confidence and confidence in GenAI are predictive of whether critical thinking is enacted and the effort of doing so in GenAI-assisted tasks. Specifically, higher confidence in GAI is associated with less critical thinking, while higher self-confidence is associated with more critical thinking. Qualitatively, GenAI shifts the nature of critical thinking toward information verification, response integration, and task stewardship.

A review of the literature and of AI application in education, after illustrating the potential benefits for teaching, concludes that there is serious concern as to how widespread dependency will impact or hamper their critical thinking skills (Lampou, 2023). Over-reliance on AI dialogue systems potentially impair critical cognitive skills such as critical thinking (Dergaa et al., 2023), decision-making, and analytical thinking (Grassini, 2023). Through a review of the literature Dergaa et al. found that while ChatGPT have the potential to enhance academic writing and research efficiency, their use also raises concerns about the impact on the authenticity and credibility of academic work and the capacity for critical thinking. The authors conclude calling for comprehensive policy discussions on the potential, threats, and limitations of these tools that emphasise the importance of ethical and academic principles.

Grassini (2023) speculative essay delves into the discussions ongoing on the use of such tools in education, exploring the potential and problems associated with applying advanced AI models in education and emphasising the potential negative impacts on analytical thinking. ChatGPT can offer immediate access to a vast amount of information presented in a personalized manner, but it also raises questions about the potential influence of these interactions on students' ability to critically evaluate such information (Kasneci et al., 2023). According to Kasneci et al. a clear strategy within educational systems and a clear pedagogical approach with a strong focus on critical thinking and strategies for fact checking are required to integrate and take full advantage of large language models in learning settings and teaching curricula. Various other studies argue and show that over-reliance on AI tools could lead to a range of issues, including diminished critical thinking (Iskender, 2023), analytical thinking, and decision-making abilities (Pokkakillath & Suleri, 2023) susceptibility to AI-generated errors or AI hallucinations. AI hallucinations (Gao et al., 2023), algorithmic biases (Mbalaka, 2023), plagiarism (De Angelis et al., 2023), AI hallucinations in AI dialogue systems are characterized by the generation of inaccurate or misleading information. There are also concerns about the potential negative impact of ChatGPT widespread use on cognitive abilities, particularly in academic writing (Liu et al., 2023). An experimental study concludes that, since AI can provide solutions quickly, students may not engage as much in actively solving things or thinking hard about what they learn (Liang et al., 2024).

A passive use of ChatGPT could supplant thinking processes by generating a kind of cognitive dependence. Individuals using ChatGPT might be inclined not to actively engage in cognitive processing since they can easily rely on this system that incorporates a wide range of functionalities (Cotton et al., 2024). Krupp et al. (2024) show that many students accept inaccurate answers and use copy-and-paste without critically evaluating information, highlighting the importance of educating students on the responsible use of AI. These authors working in higher physics education examined problem solving strategies, through a study where students with a background in physics were assigned to solve physics exercises, with one group having access to an internet search engine (N=12) and the other group being allowed to use ChatGPT (N=27). Their results showed that nearly half of the solutions provided with the support of ChatGPT were mistakenly assumed to be correct by the students, indicating that they overly trusted ChatGPT even in their field of expertise.

Finally, some work has focused on studying the effects of GenAI use on memory (Abbas et al., 2024; Robert et al., 2024). Robert et al. (2024) tested the hypothesis that the use of GenAI can produce 'digital amnesia'. They did so through two studies, the first with 616 college students and the second with 383 college students. Their results show that GenAI can harm the ability to learn and remember and cause "digital amnesia". Abbas et al. (2024) analysed the consequences of using ChatGPT for memory using two studies. Study 1 developed and validated an eight-item scale to measure ChatGPT usage by conducting a survey among university students (N = 165). Study 2 used a three-wave time-lagged design to collect data from university students (N = 494) to further validate the scale and test the study's hypotheses. Their findings are that the use of ChatGPT was likely to develop tendencies for procrastination and memory loss and dampen the students' academic performance.

Will AI and GenAI change software development?

In this final paragraph we briefly and selectively zoom on the impact AI and GenAI on software development. Academic contributions focusing on the economic rationale for using AI and GenAI and on the current adoption rate tend to assume a revolution in software development (especially for junior programmers) is occurring and to paint optimistic economic scenarios. Such views are heralded and inflated in industry reports and media that we do not need to repeat below. There are, however, also a few contrarian views that we will consider below.

Large language models (LLMs) like ChatGPT work by predicting the next item in a sequence. So, they can write code by predicting the next item in a pattern based on prior patterns observed in large amounts of data. The reason why LLMs can have a great immediate impact on software development is that their tasks have a greater degree of overlap with tasks performed by LLMs such as ChatGPT compared to other occupations (Eloundou et al., 2024). Software developers in particular use GenAI to produce routine code, giving general guidance on solving their particular problem, learning new concepts, and brainstorming solutions during each stage of software development, including the planning, implementation, and testing phases (Khojah et al., 2024). A randomised control trial conducted involving software developers working at Microsoft, Accenture, and an anonymous Fortune 100 company. When data are combined across three experiments and 4,867 developers, the analysis reveals a 26.08% increase in completed tasks among developers using the AI tool (Cui et al., 2025). Notably, less experienced developers had higher adoption rates and greater productivity gains. Other experimental evaluations and industry reports frequently tout productivity gains ranging from 20% to 55% (Bakal et al., 2025; Paradis et al., 2025; Peng et al., 2023). Daniotti et al. (2025) trained a neural classifier to identify GenAI generated Python functions in 80 million GitHub commits (2018–2024) by 200,000 developers and track how fast—and where—these tools take hold. They find that by December 2024, GAI wrote an estimated 30.1% of Python functions from U.S. contributors, 24.3% in Germany, 23.2% in France, 21.6% in India, 15.4% in Russia and 11.7% in China. They also find that juniors use such tools more than seniors. They then use results from earlier cited experiment about increased productivity, together with wage and other data for the US, to conclude that the annual value of AI-assisted coding in the United States at $9.6– $14.4 billion, rising to $64–$96 billion using the higher estimates of productivity effects reported by randomized control trials (55% see above). They concede, however, that GenAI adoption is widely uneven, which could widen skill and income gaps. Another interesting study exploring the impact of GenAI on software development, involving a survey with software developers in the IT sector conducted in workplace settings, was developed by Bonin et al. (2025). Their findings are a) 97% of the surveyed IT workers used ChatGPT; and b) participants report significant personal productivity gain and perceive organizational efficiency improvements that correlate positively with AI adoption by their organizations. On the other hand, many respondents show concern about job security given GenAI adoption and also report problems such as inaccurate outputs (64.2%), regulatory compliance issues (58.2%) and ethical concerns (52.2%). Also, according to Sauvola et al. (2024), GenAI will revolutionise the future of software development. These authors observe that GenAI is increasing productivity and with its rapidly expanding capabilities is a major step forward in this field. On the other hand, they also conclude that the software development industry needs new tools to understand the potential, limitations, and risks of generative AI, as well as guidelines for using it.

We now move to three contrarian views. According to Anderson et al. (2025), who contrast the views on increased productivity because of hidden costs of GAI in software development, excessive reliance on GenAI can unintentionally accelerate the accumulation of technical debt, leading to escalating maintenance costs and eventual revenue erosion. Technical debt refers to the difficulty in revising, reusing, scaling, or maintaining code that results from poor programming practices during software development (Ramasubbu & Kemerer, 2016). Anderson et al. (2025) study is based on interviews with software engineers and insights from the literature, on the basis of which they developed and computer simulation. According to their model productivity benefits follow an inverted-U pattern: GenAI assistance improves overall performance, but after a threshold, compounded technical debt undermines system maintainability and profitability. They conclude that 'Engineers are still going to be necessary, at least today, for owning that curation, judgment, guidance and direction'. A very interesting lab study on junior software programmers was conducted by Prather et al. (2024) and is worth summarising both in its premises and in its findings. According to these authors junior programmers at the start of their career tend to struggle with problem solving because of lack of metacognitive (read critical thinking) awareness and strategies. They cite previous research that show how junior programmers have difficulty as forming incorrect conceptual models of the problem or having a false sense of progress after testing their solution. Their hypothesis that the use of GAI can compound these problems. They organised 21 lab sessions, where junior programmers coded using GAI tool. The lab sessions involved participant observation, interviews, and eye-tracking (as a measure of the efforts). They observed a sharp difference between programmers that did and did not struggle.

Their conclusion is that for programmers who struggled, previously known metacognitive difficulties persist, and that GAI can compound them and even introduce new metacognitive difficulties. Finally, we consider the content of the lecture delivered by Alexander Pretschner (2025) and cited in the introduction as the trigger for writing this report. We can start by anticipating the conclusion of this lecture. According to Pretschner (2025, p. 3), GenAI will assist but not replace software engineers, since they "make explicit and conscious choices of what we intend. Not understanding our intentions and off-loading these choices to an AI likely leads to incorrect or inadequate results" (ibid.). The next picture taken from Pretschner's lecture presents software as 'intensive systems' and help illustrates what software engineers can do. Depending on the context software engineers and other professionals:

- Can elicit needs.
- Turn vague needs into requirements.
- Cleanse and prepare data.
- Train and validate Machine Learning (ML) models.
- Build world models, create data models and design architectures – that come as explicit artifacts or as code.
- Write code and tests.
- But they can also do all of the above

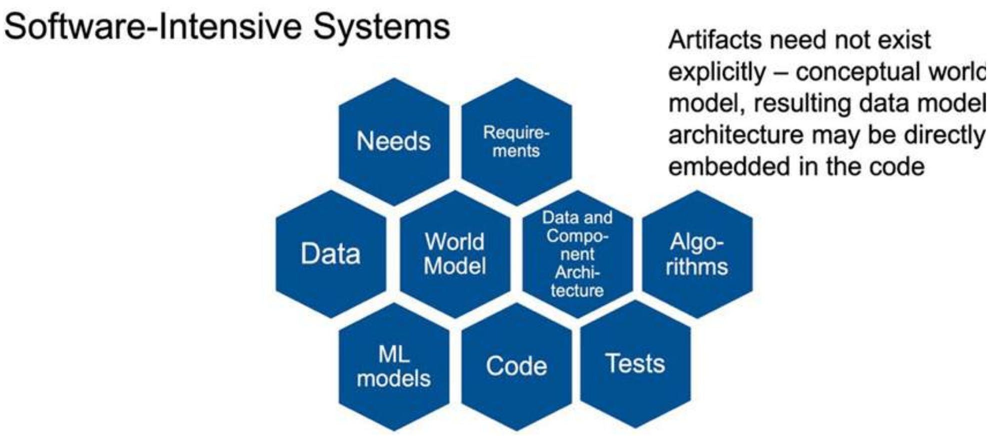

Figure 1 Software systems and what software engineer can do. Source: Pretschner (2025, p. 5)

Pretschner argues and shows that senior software engineers will be assisted but not replaced, although he recognises that this will occur at different levels of seniority (2025, p. 13). The key conclusion of his argument comes in our view on page 35, where he asserts that GenAI assisted coding can describe functionality and structural preferences as a prompt, add further context to prompt – for both technology and business domains, in terms of functionality, extra-functional properties, trade-offs, then either generate code or intermediate format. More context usually improves AI-generated code. But GenAI: “cannot know what we want. It can only pick a statistically likely (== most standard) solution. Junior or non-professional SW engineers do the same. In contrast, senior and professional SW engineers understand what is non-standard in their specific context!” (Pretschner, 2025, p. 25). So, from Pretschner’s lecture one would conclude that GenAI will not fully revolutionise software development, although implicitly one can also derive that a risk of displacement for junior engineers exists.

AI and GenAI impact on employment

In this section we enter a different strand of literature, mostly following in what is called labour economics, that has long studied the impact of technology on the labour market. First, we will review the key contributions providing the pillars of such literature (paragraph 5.1). Next, we report on five recent articles allegedly showing that the adoption of GenAI is substituting entry level jobs in general and also specifically in software (paragraph 5.2). In paragraph 5.3 we present some brief conclusive remarks.

The literature of reference

Much before the advent of GAI, the literature analysed the effect of digitalization and automation, and later of AI, on the job market (Acemoglu, 2025; Acemoglu & Autor, 2011; Acemoglu et al., 2022; Acemoglu & Restrepo, 2022; Autor, 2015; Autor & Dorn, 2013; Autor et al., 2003). This literature contains two main model/hypotheses: the Skill Biased Technological Change (SBTC) and Routine Biased Technological Change (RBTC) hypothesis. The first hypothesis holds that computerisation will substitute low skills jobs, meaning that the risk of jobs being automated will mainly regard low-skilled and low-income individuals. According to the second hypotheses, what matters is not skills but whether the task one performs in his/her job is a routine activity and this determines the possibility that it is automated and substituted by machine (being computer or robot). So, technological progress, especially computerization, has historically reduced demand for routine tasks while complementing complex work, reshaping employment patterns and income inequality. On the other hand, there is not only displacement, but also complementarity between technology and jobs. One of the main proponents of the RBTC hypothesis, David Autor, has recently presented a more realistic approach to the problem of automation asking the question why there are still so many jobs (Autor, 2015).

According to Autor, one of the effects of automation on labour market is also that of increasing the value of the tasks that workers uniquely supply. So, there is both substitution and complementarity between labour and machines and the current polarisation of the labour market may not continue in the future. Along the same line of reasoning, the model proposed by Acemoglu and Restrepo envisage both substitution and complementarity (Acemoglu & Restrepo, 2018). According to these authors, technological innovation can either directly displace workers from tasks that are fully automated (displacement effect) or indirectly increasing labour demand industry or jobs arising as a result of technological progress (productivity effect). Only if the long-run rental rate of capital relative to the wage is sufficiently low, then the equilibrium involves automation of all tasks. Otherwise, the two types of innovations will go hand-in-hand. Yet, they also recognise that in the transitional period polarisation and inequality may increase driven by faster automation and introduction of new tasks. A second strand of literature examines the implications of firm-level AI adoption in the U.S., focusing primarily on the early waves of AI before 2023 (Acemoglu et al., 2022; Autor, 2024; Babina et al., 2024; Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2018; Felten et al., 2021; Frey & Osborne, 2017). This literature generally finds that, prior to 2023, AI adoption was associated with internal reallocation rather than aggregate job loss.

Moving from hypotheses and models to econometric estimations and forecast, the evidence is not conclusive and consensual. Frey and Osborne, in a much debated and criticized paper (2017), using an occupation-based approach estimated that 47% of total US employment is at risk because of computerisation and robotisation. On the other hand, using a task-based approach, a paper by the OECD estimates that in its member countries the loss of job may reach maximum on average 9% of employment (Arntz et al., 2016). Acemoglu & Restrepo, in other contributions using the data in the post-1990 era, found that one additional robot per thousand workers reduces the US employment-to-population ratio by 0.37 percent and wages by 0.25-0.5 percent on average (Acemoglu & Restrepo, 2019). Graetz and Michaels (2017), using data on a panel of industries in 17 countries from 1993-2007, find that industrial robots increased labour productivity, total factor productivity, value added and wages. In relation to employment, robots had no significant effect on total hours worked, but according to the authors there is some evidence that they reduced the hours of both low-skilled and middle-skilled workers. Goos et al show a decrease in the demand of mid-paid jobs in comparison to high and low paid occupations, that are explained both by the RBTC and by task offshoring (2014). Dauth et al (2017) using data for Germany did not find negative significant impact of robots on employment. While industrial robots have a negative impact on employment in the German manufacturing sector, there is a positive and significant spillover effect as employment in the non-manufacturing sectors increases and, overall, counterbalances the negative effect.

Emerging evidence on GenAI impact on entry level job

After ChatGPT took off in 2022 a new and only emerging body of empirical literature has started to analyse the labour market effects of GenAI (Autor, 2024; Brynjolfsson et al., 2025a; Brynjolfsson et al., 2025b; Chandar, 2025; Cui et al., 2025; Dell'Acqua et al., 2025; Dell'Acqua et al., 2023; Dominski & Lee, 2025; Eckhardt & Goldschlag, 2025; Eloundou et al., 2024; Klein Teeselink, 2025; Noy & Zhang, 2023; Simon, 2025; Westby & Modestino, forthcoming). Below we focus particularly on five studies (Brynjolfsson et al., 2025a; Eloundou et al., 2024; Hosseini et al., 2025; Klein Teeselink, 2025; Westby & Modestino, forthcoming).

Brynjolfsson et al. (2025a) to perform their analysis used the largest administrative dataset of payroll data in the US for millions of workers across tens of thousands of firms through September 2025. The panel allows to track employment dynamics with a high degree of granularity, providing a near real-time view of labour market adjustments. This panel is then linked to established measures of occupational AI exposure. By doing so, they can quantify the realized employment changes since the widespread adoption of generative AI. The main stylised findings of their study are the following. First, substantial declines in employment for early-career workers (ages 22-25) in occupations most exposed to AI, such as software developers and customer service representatives. employment trends for more experienced workers in the same occupations, and workers of all ages in less-exposed occupations such as nursing aides, have remained stable or continued to grow. Second, while employment in general continues to grow, growth for young workers has been stagnant since late 2022. Workers aged 22 to 25 have experienced a 6% decline in employment from late 2022 to September 2025 in the most AI-exposed occupations. Third, not all uses of AI are associated with declines in employment. In particular, entry-level employment has declined in applications of AI that automate work, but not those that most augment it. While they find employment declines for young workers in occupations where AI primarily automates work, they find employment growth in occupations in which AI use is most augmentative.

Hosseini et al., (2025) study uses a dataset that combines LinkedIn resumes and job-posting data from Revelio Labs. The dataset covers nearly 285,000 U.S. firms, more than 150 million employment spells from roughly 62 million unique workers between 2015 and 2025, and almost 200 million job postings. A key advantage of these data is the standardized seniority classification assigned to each position by

Revelio's algorithm, which enables them to track junior and senior employment within firms over time. To measure GenAI adoption use job postings that explicitly recruit "GenAI integrator" roles, following the approach adopted by Hampole et al. (2025). They first identify postings with GenAI-related keywords, next they use a large language model to determine whether the posting reflects a genuine integrator position—one dedicated to implementing or operating GenAI technology in the firm's workflow. By proceeding in this way their sample consists of 10,599 firms that adopted GenAI by March 2025. They compare adopting and non-adopting firms using a difference-in-differences (DiD) design, tracking junior and senior employment quarterly. The main findings are the following. First, adoption of GenAI was minimal and relatively stable prior to 2023, but accelerated sharply thereafter, with a surge of new firms posting integrator roles following the release of advanced GenAI tools in late November 2022. From 2015 to 2022, adopters and non-adopters followed parallel trends in junior employment. However, beginning in 2023 Q1—coinciding with the sharp increase in GenAI adoption—junior employment in adopting firms decreased steeply relative to controls, declining by about 9 percent after six quarters. Senior employment, by contrast, increased more quickly in adopting firms since 2015 and showed no sign of a break in trend after 2022. The post-2022 decline in junior employment among adopting firms therefore reflects adjustments in roles most vulnerable to GenAI, rather than a broad contraction in junior employment across these firms. Beginning in mid-2022, however, a clear divergence emerges: senior employment continues to expand steadily, while junior employment plateaus and then, by mid-2023, begins to fall. This finding is consistent by those of Brynjolfsson et al. (2025a) reported above.

A study analysing the impact of Large Language Models (LLMs) in the UK labour market, using data and analytical approaches similar to the previous two, obtain similar results (Klein Teeselink, 2025). They use a difference-in-differences design that compares outcomes across firms and occupations from 2021 to 2025 based on their differential exposure to LLM capabilities. The results show that highly exposed firms reduce employment, particularly in junior positions. These firms sharply curtail new hiring, with technical roles (software engineers, data analysts) experiencing the steepest declines. At the occupation level, roles more exposed to LLMs also show substantial reductions in job listings, as well as in posted salaries.

Westby & Modestino (forthcoming), using a very large dataset online job vacancies collected by Lightcast and a difference-in-difference design, document three key stylised facts for the US. First, soon after the release of ChatGPT in November 2022 a substantial reduction in the relative share of job vacancies for junior-level software developers (requiring less than 4 years of experience) compared senior-level software developers (requiring 4 or more years of experience). Using differences-in-differences estimates in the 12 months after November 2022 software developer job postings requiring less than four years of experience fell by 16.3 percent relative to that of more senior level positions. The result holds even when controlling for month and location fixed effects, for firm size, industry composition and population, and considering the broader labour market trends affecting all computer and mathematical workers during this time period. Second, adopting a shift-share analysis, it is confirmed that the aggregate fall in demand for junior software developers did not result from the shifting composition of employers who were posting positions but rather from a shift in the experience requirements that employers were looking for. Third, the decline in labour demand for junior- versus senior-level software developers appears to have occurred among larger firms and bigger cities while industries with moderate exposure to the software industry were more insulated from the introduction of Chat-GPT.

Finally, there are the worrying forecasts on the exposure to, and potential job displacement by, ChatGPT and other LLMs model presented by Eloundou et al. (2024) and published in such a prestigious journal as Science. The authors following the reference literature reviewed earlier use exposure to LLMs as a proxy indicator of for potential economic impact, without making the distinction between augmenting and displacement effects. Exposure is defined as the capacity of an LLM to reduce the time required for a human to complete a task by at least 50% while preserving or improving quality. They use the O*NET 27.2 database, covering 1016 occupations and tasks. Employment and wage data from the 2020–2022 were sourced by the US Bureau of Labor Statistics (BLS). The results are that approximately 14% of tasks per occupation on average are exposed to LLMs. They estimate that roughly 1.8% of jobs could have over half their tasks affected by LLMs with simple interfaces and general training. When accounting for current and likely future software developments that complement LLM capabilities, this share jumps to just over 46% of jobs. Most importantly from our perspective the two job groups (clusters) that are most exposed to LLMs are "Scientists and Researchers," then "Technologists," such as software engineers and data scientists.

Concluding remarks

As we have underlined in paragraph 5.1 on the general literature and models of reference, there is both the possibility of complementarity (augmenting) and displacement between technology in general and jobs. And the same applies to AI and GenAI. We also showed that previous empirical estimates were contradictory and non-conclusive. The evidence presented in 5.2 is just emerging and will have to be corroborated by future studies. Having clarified this, the emerging evidence points to the risk for junior level jobs in general and for junior software developers in particular. Below we briefly try to account for this emerging evidence referring to some of the authors from the general literature.

One story that the reviewed evidence tells us is that workers who gained experience often move up the career ladder to more senior roles that involve more complex problem-solving or managerial responsibilities (Garicano, 2000; Ide & Talamàs, 2025). If GenAI disproportionately favours the senior workers and substitutes for entry-level tasks, the lower rungs of these career ladders may be eroding (Garicano & Rayo, 2025). Findings speak to the ongoing discussion on the effects of automation and augmentation on workers (Acemoglu & Restrepo, 2018; Autor, 2015). Inexperienced software developers may experience large productivity gains in routine coding tasks from GenAI (Cui et al., 2025) that makes them more vulnerable to displacement compared to their senior colleagues. AI may raise the leverage of experienced staff, increasing their effective span of control. Reduced hiring may also be the lowest-friction adjustment margin, compounded by inefficient incentives to train entry-level workers who may move firms (Garicano and Rayo, 2025). Consequently, firms may primarily shrink junior inflows rather than displace incumbents.

Why might AI adversely affect exposed entry-level workers more than other age groups? One possibility is that AI disproportionately substitutes for workers using codified knowledge, including both the "book-learning" that forms the core of formal education and the insights in digital company data that can be codified by AI. AI may be less capable of replacing tacit knowledge, the idiosyncratic tips and tricks that accumulate with experience but which are never digitized. In other words, AI may be automating the codifiable, checkable tasks that historically justified entry-level headcount, while complementing the judgment-, client-, and process-intensive tasks performed by experienced workers which require critical thinking skills.

Scenarios and recommendations

Considering the contents of sections 4 and section 5 we have two clear dimensions of uncertainty, since both the literature on the impact of GenAI on critical thinking and that on its impact on entry level jobs cannot be considered conclusive and present contrasting findings and possibilities. Therefore, one dimension of uncertainty is whether the impact of GenAI on critical thinking of juniors will be positive or negative. The second dimension of uncertainty is whether the impact of GenAI in displacing entry level jobs will be low or high. Based on these two dimensions we have developed the four scenarios depicted in the figure below.

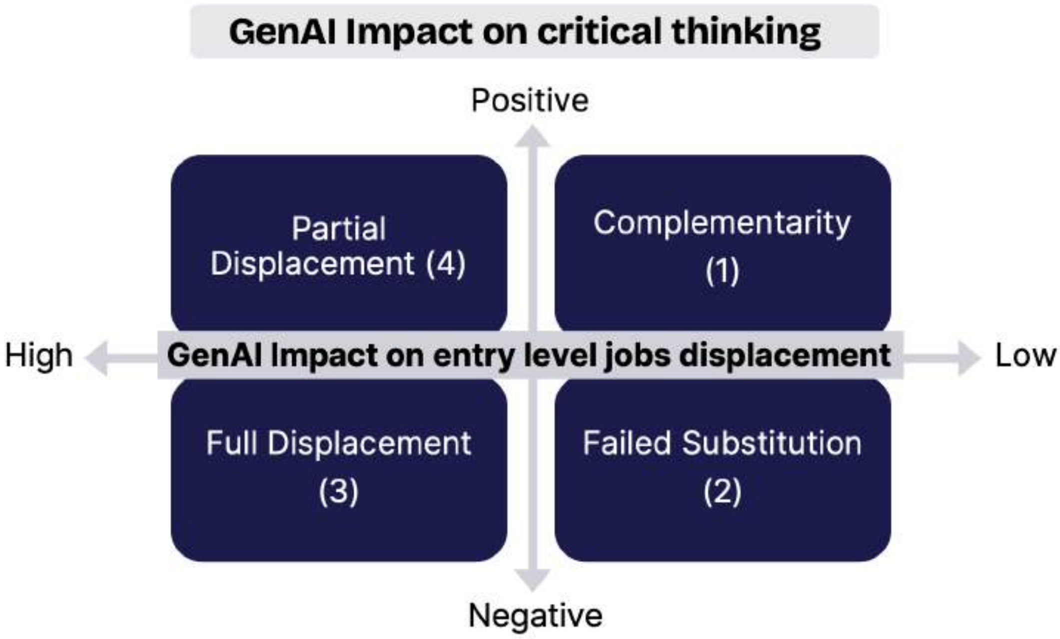

Figure 2 Four Scenarios, Source: Author's elaboration

While all those scenarios are described below, it is evident that from the perspective of their implications the best (scenario 1) and worst (scenario 3) are those that stand out, whereas the other two are intermediate and mixed with less clear-cut implications.

Scenario 1. Complementarity: humans with critical thinking skills assisted by GenAI

In this scenario, GenAI is used in ways that enhance critical thinking while having minimal impact on junior-level job opportunities. This is clearly the best and most desirable scenario. GenAI is used in the educational system and at the workplace as a tool that fosters deeper engagement with content, offering diverse perspectives and promoting critical analysis. For example, students or workers can use GenAI to explore multiple viewpoints, evaluate arguments, and develop their reasoning skills. It serves as an assistant that encourages reflective thinking and enhances cognitive engagement. Despite the rise of GenAI, entry-level positions remain relatively unaffected. As the adoption of GenAI at work advances these entry level positions evolve and are augmented rather than displaced since they become more focused on tasks requiring human interaction, judgment, and emotional intelligence—areas that GenAI can support but not replace. As a result, junior workers continue to perform essential tasks, with their roles augmented by GenAI tools to increase productivity but not to be displaced. Junior workers remain employed, benefiting from tools that improve their performance without losing their jobs. The workforce becomes more critical-thinking oriented, and workers are empowered with new cognitive tools. Obviously, this scenario is at the opposite end if compared with the emerging evidence presented by economists (see paragraph 5.2), and especially if compared by the forecasts by Eloundou et al. (2024). It is also important to stress that to achieve a positive impact of GenAI on critical thinking policy makers can use the levers of reforming the educational system, whereas the actual impact of GenAI on entry level jobs depends on entrepreneurial decisions and market pressures that are more difficult to impact with policy and regulation. And to a large extent the future development of GenAI, its adoption, and impact on jobs, as things stand now, is currently left exclusively in the hands of Big Tech.

Scenario 2. Failed Substitution: inadequate GenAI tools and loss of critical thinking skills

In this scenario, GenAI negatively affects critical thinking while having minimal impact on junior-level job opportunities. GenAI, instead of enhancing critical thinking, diminishes it by providing ready-made answers and reducing the need for deep reflection. Users may rely too heavily on AI for solutions, leading to cognitive offloading and a decline in engagement with complex problem-solving. Over time, this may result in a loss of critical thinking skills as GenAI handles more tasks that would have otherwise engaged users' analytical minds. Despite the negative impact on cognitive engagement, junior-level jobs remain stable. GenAI tools are used to increase efficiency in these roles rather than replace them. Junior workers continue to perform basic tasks, but they become more reliant on AI for execution, without a drastic reduction in job opportunities. Junior workers maintain their positions, but the quality of their work and their cognitive development may stagnate due to over-reliance on AI tools. While job stability is preserved, the workforce may experience a decline in creativity and independent thinking over time. Additionally, over time, there will be senior level workers without the same level of critical thinking skills as the current cohort.

Scenario 3. Full Displacement: loss of jobs and critical thinking skills

In this scenario, GenAI negatively affects critical thinking and causes significant disruption to junior-level jobs. This is clearly the worst-case scenario. GenAI negatively impacts critical thinking by making users more passive in their problem-solving approaches. Over-reliance on GenAI leads to cognitive offloading, where users delegate their intellectual tasks to AI, reducing engagement with the material and impairing the development of critical thinking. As a result, individuals might struggle with problem-solving and decision-making in situations where GenAI tools are unavailable. GenAI dramatically disrupts junior-level positions. As AI takes over routine tasks, many entry-level roles are either automated or significantly reduced in demand. This includes jobs such as customer service representatives, data analysts, and junior software developers, who find their positions replaced by AI systems that can perform the work more efficiently and cost-effectively. Junior workers face significant job displacement, with many roles becoming obsolete due to GenAI automation. At the same time, the decline in critical thinking among workers leads to a less capable workforce, struggling to adapt to new challenges or responsibilities that require deeper cognitive engagement. One major and very dire implication of this scenario is about the substitution of the cohort of senior professionals possessing critical thinking and having their work augmented by GenAI when they retire. If graduates exit the educational system with decreased level of critical thinking and if very few juniors are hired and have the opportunity to grow critical skills at work, who will replace adequately the current incumbent senior level professionals?

Scenario 4. Partial Displacement: hyper scaling destroys jobs despite maintenance of critical thinking skills

In this scenario, GenAI enhances critical thinking while causing significant disruption to junior-level job opportunities. GenAI tools significantly boost critical thinking by offering personalised guidance, improving decision-making skills, and encouraging users to engage in higher-order thinking processes. This can include providing feedback, helping users analyse complex data, and prompting individuals to question assumptions and explore different perspectives. However, GenAI significantly disrupts junior-level jobs by automating routine and repetitive tasks. Many roles that once required entry-level workers—such as data entry, basic customer service, and even junior software development—are now automated by GenAI systems, leading to the displacement of workers in these positions. This shift reduces the demand for junior employees, especially those who perform tasks that can be easily replicated by AI tools. While GenAI improves cognitive skills, it leads to unemployment or a need for retraining among junior workers, especially in industries where tasks can be automated. The future workforce may require greater expertise and higher-level cognitive skills, pushing younger workers to develop new competencies.

Based on the scenario 1 (best case) and scenario 3 (worst case), we can derive two set of recommendations to guide the integration of GAI into educational and labour markets. These recommendations will aim to mitigate potential risks while enhancing the benefits of GAI. They apply, although with different degree of importance both to the best- and worst-case scenarios.

(1) Education and workforce development and adaptation. There is a need for continued focus on developing cognitive skills, such as critical thinking, alongside technical skills, ensuring that GAI tools are used to supplement learning and decision-making processes without replacing the need for independent thinking. The challenge will be ensuring that workers are not overly reliant on these tools, maintaining the need for cognitive engagement.

a. Promote both GAI literacy and critical thinking in the educational system. Integrate GAI into education systems in a way that encourages reflection and active engagement with information. Training should emphasize the value of questioning, analysing, and synthesizing information from multiple perspectives.

b. Support Hybrid Work Environments. Through incentives and social partners dialogue (i.e. industry, trade union, and government) encourage the use of GAI to assist junior workers in decision-making and productivity without replacing their need to think critically. For example, GAI could be used to generate options or analyse data, but the final decision should involve human judgment.

c. Foster Collaboration Between Humans and AI. Policy and regulation should link access to R&D funding to a vision of Digital Humanism promoting collaborative models where GAI complements human decision-making and cognitive abilities. This can ensure that workers retain a sense of agency and avoid cognitive offloading.

(2) Mitigation of GAI automation effects. If GAI leads to substantial job displacement for junior workers, particularly those in roles that involve routine, codifiable tasks, this increases unemployment and may deepen income inequality. The over-reliance on GAI tools also diminishes cognitive engagement, potentially leading to a workforce that is less capable of independent thought and problem-solving, especially when the current cohort of senior level professionals will retire.

a. Automation-Friendly Policies. Ensure that GAI adoption is accompanied by policies to support workers who may be displaced. This could include tax incentives for companies that invest in worker retraining or transition programs, as well as social safety nets to support displaced workers.

b. Strengthen Job Quality Standards. For industries where GAI is more likely to disrupt junior roles, set standards for job redesign that emphasize the need for higher-level cognitive engagement, such as adding complexity to junior roles through new learning opportunities, problem-solving tasks, and leadership training.

c. Establish Ethical Standards for AI Deployment. Ensure that GAI is deployed in a way that complements rather than replaces human workers. Introduce regulations that require companies to assess the impact of GAI on job displacement before its implementation and to invest in human resources alongside technology. In particular, companies should create new training and interns' programmes to ensure recent graduate and junior level professional and practice and learn the needed critical thinking skills from senior professionals.

As we anticipated at the end of the description of the best-case scenario it is probably easier for policy makers to influence and change the practice of the educational system to preserve critical thinking, than impacting the automation decisions of companies. In this respect, a few of the articles reviewed in section 4 already present ideas of how to bridge between the educational system and the adoption of GAI. According to Rusandi et al. (2023) education focusing on developing critical thinking skills and media literacy can help society more effectively recognise and counteract hoaxes and misinformation produced by GAI tools. Another study suggest that critical thinking teaching should be enhanced for teachers' education and it also underscores the need for further research to explore best practices for integrating ChatGPT in lesson planning (van den Berg & du Plessis, 2023). The recent review by the OECD (2026), among others, recommends requiring that teachers encourage student agency and emphasise process, such as how students think and learn, rather than student output. According to Kasneci et al. (2023) a clear strategy within educational systems and a clear pedagogical approach with a strong focus on critical thinking and strategies for fact checking are required to integrate and take full advantage of large language models in learning settings and teaching curricula. Large language models in education require teachers and learners to develop sets of competencies and literacies necessary to both understand the technology as well as their limitations and unexpected brittleness of such systems. We also present the point of view of teachers about the impact of GAI in education by reporting a survey and qualitative interviews conducted with 318 teachers from a diverse range of teaching levels, experience levels, discipline areas, and regions (Bower et al., 2024). The majority of teachers (58%) think that GAI would have a major or profound impact on teaching and assessment. In terms of curriculum, the most frequent response from participants about the changes to what to teach was teaching students how to use AI (n=53) as an integrated part of learning activities in the classroom. Many teachers felt that it was important to teach specifically about how AI tools work (n = 40) including "what they are, as well as the capabilities and limitations" and their "usefulness". Similarly, the importance of teaching students critical thinking, especially relating to evaluating AI responses, was strongly emphasized by teachers. Many detailed how it was imperative to move students beyond being passive recipients of AI, for example, by being "alert and critique what is offered as knowledge. Teachers acknowledged the importance of teaching about ethical and responsible use of AI commenting both generally (for example, "how to ethically use them") and specifically.

To conclude we want to reiterate that policy makers have different levers to impact the two dimensions of the scenarios to make the best-case more likely and avoid the worst-case. Policy makers can initiate the long overdue reforming of the educational system so as to promote concrete, measurable, critical thinking skills taking into consideration the potential opportunities and risks that increased adoption of GenAI tools by students implies. Impacting the current direction of GenAI development, which is geared towards junior level jobs displacement, is another more complicated matter.

The challenge is that this development at the moment is fully in the hands of Big Tech. One possibility is to somehow convince or force Big Tech to change tack, which seems unlikely. Alternatively, policy makers could develop and fund a new line of AI R&D that is not completely in the hands of Big Tech. Although also proposed by the UN (CERN for AI), also this possibility is deemed unlikely. The only real chances to impact this dimension are two. First, policy-makers should consider the AI Act still only work in progress and consider eliminating the loopholes still present for GenAI and adding the obligation of an ethical code of conduct for deployment of GenAI in the workplace. Second, policy makers should step up competition policy to undermine Big Tech monopolistic power.

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Colophon

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Generative AI and critical thinking: implications of changing employment patterns

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About EUDHIT

The European Digital Humanism Initiative (EUDHIT) supports strengthening societies through Digital Humanism, shaping technology for democracy and inclusion and believes in human values at the core of digital futures.

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