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The Transformational Impact of AI on Employment

ABSTRACT

This article analyzes the transformational impact of artificial intelligence on employment by integrating four source perspectives (history of AI development, scientific research, consulting firm reports, and statements from technology creators) across five dimensions of consequences: economic, organizational, developmental, social, and human. The methods included literature and report reviews as well as systematic analysis of 204 statements from industry leaders, synthesized in a comparative table of issues and exposure assessments, which allowed capturing both convergent points and divergences between source types. The results indicate agreement on productivity growth, selective occupational exposure, and inequality risks without compensatory policies; organizationally, they confirm the need for new operational governance (governance, audit, roles around data and models) and transition toward agent orchestration. In the developmental dimension, the skills-first paradigm and mass reskilling are consolidating, while socially, trust, transparency, and bias minimization become crucial; at the individual level, relief and increased stress coexist along with transition costs. The analysis is embedded in the cyclical history of AI "summers" and "winters," emphasizing that despite unprecedented progress,

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the pace may slow due to lack of AGI breakthrough, hardware limitations, and explainability and regulatory challenges, though agent architectures are already transforming work roles and processes today. Implications include recommendations for public policies, education, and management practices, emphasizing investments in complementary competencies and responsible AI governance.

KEYWORDS: artificial intelligence; employment; labor market; automation; augmentation and complementary competencies; AI governance and explainability

INTRODUCTION

Artificial intelligence (AI) is revolutionizing the contemporary labor market at a pace that exceeds the expectations of even the most optimistic futurologists from a decade ago. This transformation affects every aspect of employment – from the automation of routine tasks to the creation of entirely new job categories whose existence we could not have imagined until recently.

The impact of AI on the labor market manifests in three key dimensions that require separate analysis. First, at the macroeconomic level, we observe fundamental changes in the structure of the entire labor market. Traditional industrial and service sectors are undergoing rapid modernization, while new industries focused on AI technology are emerging. This dynamic leads to market polarization – on one hand eliminating positions requiring medium qualifications, while on the other creating demand for high-level specialists and workers performing tasks requiring typical human competencies.

Second, from the perspective of individual professions, AI operates selectively but with varying intensity. Some professions – such as translators, financial analysts, or radiologists – experience direct competition from algorithms. Others, particularly those requiring creativity, empathy, or complex social reasoning, remain relatively safe, although AI is becoming an increasingly sophisticated supporting tool.

The third dimension concerns the individual experience of workers and the broader social context. At the personal level, AI forces continuous requalification and adaptation to new tools, which for part of a society means opportunities for development, while for others it represents a source of anxiety and uncertainty. Socially, this transformation raises questions about the redistribution of automation benefits, the need for new forms of social security, and the necessity of education preparing for a future dominated by human-machine collaboration.

This article presents a comprehensive analysis of this phenomenon through the lens of four different perspectives: the historical development of AI, current scientific research, consulting firm reports, and opinions of AI technology creators themselves. The confrontation of these sources allows for understanding not only the scale and direction of ongoing changes but also divergences in assessing their consequences – from techno-optimistic visions of a prosperity era to warnings about mass structural unemployment.

History of AI development: From first steps to contemporary times

The history of AI development represents a journey from theoretical concepts of the first half of the 20th century to contemporary systems utilizing deep machine learning. The development of this field was characterized by cyclical periods of enthusiasm and disappointment, referred to as "AI summers" and "AI winters," which shaped the contemporary landscape of AI.

The foundations of AI were laid in 1950 by Alan Turing, who in his groundbreaking work "Computing Machinery and Intelligence" posed the key question: "Can machines think?" and proposed the Turing Test as a method for evaluating machine intelligence (Turing, 1950). The official birth of the discipline occurred in the summer of 1956, when John McCarthy organized a summer workshop at Dartmouth College, during which the term "artificial intelligence" was first used (McCarthy et al., 1955). This conference, known as the Dartmouth Summer Research Project on Artificial Intelligence, is recognized as the founding moment of AI as a scientific discipline.

Following the Dartmouth conference, the first period of intensive AI research development lasted until 1974, also called the first AI summer and characterized by optimism and significant funding. During this time, the first AI laboratories were established at Carnegie Mellon University and MIT. Key achievements of this period included the development of expert systems, symbolic algorithms, and the first programs solving mathematical problems, such as Logic Theorist by Newell, Simon, and Shaw. However, the excessive promises of the first AI development period led to disappointment in 1974–1980 (the first AI winter) when it became apparent that systems did not meet expectations. A key moment was the Lighthill report from 1973, which criticized the lack of realization of earlier unrealistic AI goals (Lighthill, 1973), leading to drastic cuts in research funding in Great Britain.

The 1980s (1980–1987, second AI summer) brought a renaissance of AI interest thanks to the development of expert systems such as MYCIN for diagnosing bacterial infections or XCON for configuring computer systems. By the end of this decade, however, it became apparent that expert systems had serious limitations, which, combined with the failure of the Japanese Fifth Generation Computer Project and limitations of perceptron-type neural networks demonstrated by Minsky and Papert in 1969 (Minsky & Papert, 1969), led to another period of stagnation in 1987–1993 (second AI winter).

The revival of AI occurred in the 1990s thanks to the development of machine learning, statistical algorithms, and increased computing power. Of key significance were successes such as Deep Blue's victory over Garry Kasparov in 1997 and the development of the internet, which enabled access to larger data sets. The breakthrough moment of the contemporary era was the achievement of AlexNet in the ImageNet competition on September 30, 2012, when a deep convolutional network developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton achieved a top-5 error of 15.3%, surpassing the closest competitor by 10.8 percentage points (Krizhevsky et al., 2017).

Another breakthrough was the publication in 2017 of the work "Attention Is All You Need" by Vaswani and colleagues, which introduced the transformer architecture based solely on the attention mechanism, eliminating the need for recurrent and convolutional layers (Vaswani et al., 2017). This innovation became the foundation for the development of large language models. In 2018, the Google AI team published work on the BERT model (Bidirectional Encoder Representations from Transformers), which utilized bidirectional context processing and established new standards in natural language understanding tasks (Devlin et al., 2018). In parallel, OpenAI developed the GPT series of models, starting with GPT-1 in 2018, through GPT-2 in 2019, to GPT-3 in 2020, which with 175 billion parameters demonstrated emergent capabilities in various language tasks (Radford et al., 2018; Radford et al., 2019; Brown et al., 2020).

The contemporary era is characterized by dynamic development of generative AI, where models such as GPT-4, presented in 2023, and other large language models have radically changed the AI landscape, enabling applications from automatic text generation to complex reasoning and problem-solving (OpenAI, 2023). The current period of AI development is characterized by unprecedented pace of innovation and broad application across various areas of life, from medicine and education to business process automation and artistic creativity.

The most recent frontier in this trajectory is the emergence of agentic AI – systems capable of autonomous, goal-directed action across multi-step workflows, moving beyond the single-prompt interactions that characterized earlier generative AI applications. Where previous milestones, from expert systems to large language models, expanded what machines could know or generate, agentic architectures represent a shift toward what machines can do independently and in coordination. Early industry evidence suggests that AI agents are already being deployed to handle complex, sequential tasks within customer and operational workflows – for instance, conversing with a customer and subsequently executing follow-on actions such as processing payments, verifying transactions, or orchestrating marketing campaigns – with humans retaining responsibility for oversight, governance, and risk management (Mayer et al., 2025). The deployment of multiple coordinated agents capable of managing end-to-end processes thus constitutes the next developmental step in AI's evolution: one that is beginning to reshape not only individual tasks, but the broader organization of work itself.

AI's impact on the labor market in scientific research

The impact of AI on employment is a multifaceted research area that has gained significant attention in recent years. Numerous studies published in scientific journals explore this topic, providing insights into its economic, organizational, developmental, social, and human implications.

Many studies have analyzed the economic implications of AI for employment patterns. Liu's research indicates that while AI may strengthen employment in service sectors, especially in developing countries, the overall impact on unemployment levels is complex and differs significantly by industry and region (Liu, 2024). Wang further emphasizes that AI evolution shifts the employment paradigm from quantity to quality, suggesting a substitution effect for low-skilled labor accompanied by a creation effect for high-skilled positions. This dynamic results in moderate short-term impact on total employment but highlights structural contradictions that may lead to increased unemployment in affected sectors (Wang, 2023). Zhou confirms this view, indicating that rapid AI development has triggered significant changes in labor demand, with notable growth in technological roles and decline in traditional manual jobs across various sectors (Zhou, 2023).

Research by Tabbassum et al. reveals organizational challenges posed by AI, especially regarding the need for workers' upskilling and job role redefinition. As AI automates routine tasks, organizations must create new position categories focusing on AI supervision and management. The need for workers with AI-related competencies is crucial for organizations seeking to thrive in technology-driven environments (Tabbassum et al., 2024). Consistent with these findings, Huo et al. describe research based on the Chinese manufacturing industry, where AI implementation positively affected employment quality and structure over time. Their results suggest that while substitution effects may dominate in the short term, long-term benefits include work quality improvement and new role creation (Huo et al., 2024).

From a developmental perspective, research indicates a clear correlation between AI advances and workforce development. Work by Cao et al. on career counseling systems shows how universities adapt curricula to better prepare students for the AI-oriented labor market, emphasizing long-term career development support through AI technologies (Cao et al., 2023). Similarly, Huang's study indicates that with each percentage increase in AI technology, employment indicators may improve significantly, suggesting that educational institutions and training programs adapted to AI advances can effectively increase youth employment prospects (Huang, 2024).

Social implications of AI for employment also include interpersonal relations and community engagement. Sultana et al. indicate that while AI may generate high-skilled jobs in areas such as data analysis and digital security, it also carries the risk of deepening social inequalities and widening the wage gap, especially among low-skilled workers (Sultana et al., 2024). Kamkankaew et al. argue that AI's transformational role in enterprises requires ethical approaches at all levels, emphasizing stakeholder trust and integrity in AI implementation (Kamkankaew et al., 2024). As AI transforms workplace dynamics, the potential for social disruption grows, requiring careful balance between technological progress and social responsibility.

Human implications, especially at the individual level, are equally significant. Research such as Chen and Fu's work explains how industrial robots and AI transform employment opportunities for vulnerable groups, often leaving them disadvantaged in highly competitive labor markets (Chen, 2023; Fu, 2024). Additionally, Yan's research discusses AI's dual impact, where increased work efficiency can simultaneously lead to job displacement, challenging individuals to carefully navigate this complex landscape (Yan, 2024). At the individual level, understanding AI's potential for both creating and displacing jobs is crucial for workers wanting to future-proof their careers.

Beyond aggregate evidence, recent empirical studies provide concrete illustrations of how large language models and conversational agents are transforming specific labor market segments. In customer service, a large-scale field experiment in a U.S. call center showed that access to a generative AI assistant based on a conversational large language model increased agents' productivity by about 14 percent on average, with the strongest gains for less-experienced workers who could effectively "borrow" patterns of expert behavior encoded in the model (Brynjolfsson, Li, & Raymond, 2025). The study also documented improvements in customer satisfaction and a reduction in employee attrition, suggesting that AI augmentation can simultaneously raise performance and improve work experience in routine but cognitively demanding service roles.

In the domain of software engineering, large language models (LLMs) have emerged as pivotal tools for supporting various development tasks, including automated code generation from natural language descriptions, intelligent code completion, and code understanding. According to the systematic literature review by Hou et al. (2024), tools such as GitHub Copilot leverage program context and syntax structures to provide accurate code suggestions, thereby enhancing development efficiency and reducing the risk of manual coding errors. Furthermore, these models assist developers in grasping complex functionalities and generating relevant documentation, which streamlines the overall software development lifecycle (Hou et al., 2024).

Building on evidence from software engineering, complementary findings come from experimental research on generative AI in knowledge work. Noy and Zhang (2023) study the productivity effects of providing access to ChatGPT in a preregistered online randomized experiment with 453 college-educated professionals performing occupation-specific, incentivized mid-level writing tasks. They document sizable productivity gains: access to ChatGPT reduced task completion time by about 40% while increasing output quality by about 18%, as assessed by blinded professional evaluators. The authors further report that these gains were broadly distributed and tended to reduce productivity inequality, because participants with lower baseline performance benefited relatively more. Consistent with rapid diffusion dynamics, treated participants were also more likely to report using ChatGPT in their actual jobs in subsequent follow-up surveys (Noy & Zhang, 2023).

Survey evidence from a large technology company suggests that LLM-based chat tools are increasingly being incorporated into everyday knowledge work. Brachman et al. (2025) conducted two surveys among employees of a major technology firm and found that workers already draw on LLMs for a range of tasks, including content creation and editing, information retrieval, and drafting communications such as emails. Participants also reported using LLMs to obtain advice – whether technical, strategic, or procedural – by describing their desired outcome in natural language rather than navigating formal documentation or specialist colleagues. Looking ahead, respondents envisioned a future in which such models would be more deeply embedded into enterprise data and collaborative workflows, effectively extending the reach of LLM assistance across a broader set of organizational tasks. These findings suggest that conversational AI interfaces may function as general-purpose access points to organizational knowledge, potentially lowering skill and information barriers for workers across a wide range of roles (Brachman et al., 2025).

Research shows that AI's impact on employment is differentiated: it promotes growth and productivity while simultaneously deepening skill inequalities, unemployment pressure, and changes in workplace social relations. The interaction of these variables requires comprehensive approaches from policymakers, educational institutions, and organizations to leverage AI's positive implications while mitigating its negative effects.

Changes in the labor market caused by AI according to consulting firms and international organizations

AI has become a general-purpose technology that in a short time is changing productivity patterns, employment structure, and daily work organization. Conclusions from current reports by the largest consulting firms and international organizations form a coherent narrative: AI simultaneously unleashes significant economic value, forces enterprise reorganization and redefines competencies, while generating social and psychological tensions that cannot be ignored. Key dimensions of AI's impact on economy and humans are:

– economic: productivity growth, occupational exposure and inequality risks (Chui et al., 2023; Georgieva, 2024; Georgieff, 2024);
– organizational: rebuilding operational models, gap between adoption and monetization, and AI governance (Beauchene et al., 2025; PwC, 2025);

– developmental: acceleration of competency life cycles and transition to skills-first (World Economic Forum, 2025; Cisco, 2024);
– social (relations): communication mechanization, trust and polarization (World Economic Forum, 2025; Manning, 2024);
– human (individual): anxiety about job obsolescence, psychological burdens and importance of support (Lerner, 2024; Beauchene et al., 2025).

From the global economy perspective, AI is a powerful engine of productivity and growth. McKinsey estimates that generative AI alone can contribute $2.6–4.4 trillion annually in additional value when tools are widely implemented in knowledge-intensive processes, especially in financial services, sales and supply chain (Chui et al., 202). Simultaneously, the IMF indicates that about 40% of jobs worldwide are already "within reach" of AI impact, and in advanced economies exposure reaches about 60%, meaning both complementary potential (augmentation) and substitutive (automation) for mental work (Georgieva, 2024). The OECD adds that without adequate policies, AI diffusion may increase wage inequalities, as premiums for AI-complementary skills accumulate among higher-skilled specialists, while workers performing routine office tasks are more exposed to substitution (Georgieff, 2024). Consequently, the net direction depends on the pace and quality of technology absorption and the scale of investment in complementary competencies (Hatzius et al., 2023).

In companies, AI forces rebuilding of operational models and work architecture. BCG draws attention to the "value gap" between rapid solution implementation and slower business benefit realization, rooted in immature processes, lack of quality data, absence of "production" roles around AI (e.g., AI product owners, model custodians, data stewards) and insufficient security and compliance practices (Beauchene et al., 2025). PwC shows that organizations combining technological investments with talent development programs and clear governance over model lifecycles achieve advantage, from data acquisition to monitoring drift and side effects (PwC, 2025). In practice, the transition to hybrid human-AI teams means hierarchy flattening in analytical tasks, redefinition of management roles around algorithmically supported decisions, and inclusion of risk and compliance functions at the design stage of solutions (Beauchene et al., 2025).

However, the competency landscape changes most dramatically. The WEF report indicates that demand for analytical skills, critical thinking, problem-solving, as well as social and creative competencies grows in professions exposed to AI, while simultaneously decreasing demand for routine and repetitive tasks (World Economic Forum, 2025). The skills-first paradigm is consolidating: employers increasingly abandon hard formal requirements in favor of micro-certifications and portfolios, while the skill update cycle accelerates, requiring continuous on-the-job learning (World Economic Forum, 2025). Industry data confirms that over 90% of technological roles are being reprofiled, forcing massive reskilling response from companies and educational systems – from short bootcamps to dual programs (Cisco, 2024). Appropriate emphases are primarily complementary skills: understanding business context, data work, designing human-AI interaction, and algorithmic ethics (Georgieff, 2024).

Social relations and trust capital do not remain indifferent to communication automation. An increasing portion of correspondence and customer contact is supported by language models, which raises efficiency but can be emotionally "flattened," causing interactions to lose spontaneity and warmth (World Economic Forum, 2025). At the macro level, concern grows that the scale of AI benefits will accumulate in the highest productivity sectors and in large technological centers, strengthening economic and social polarization if not accompanied by inclusive development programs and tool access for SMEs (Manning, 2024). For this reason, model transparency standards, generated content labeling, and explainability mechanisms become not only regulatory requirements but also conditions for maintaining trust in labor markets and public services (Georgieff, 2024; World Economic Forum, 2025).

From the individual's perspective, AI is a source of ambivalence: it liberates from tedious tasks and enables development of more creative roles, while simultaneously generating anxiety about competency obsolescence. The APA notes increased worker anxiety related to task uncertainty, pace of change, and "algorithmic monitoring," especially when implementations occur without adequate preparation and dialogue (Lerner, 2024). Conversely, advisory research shows that well-designed implementation programs – combining on-the-job training, mentoring, and clear evaluation criteria – raise the sense of agency and satisfaction because workers see real "relief" and faster feedback thanks to AI tools (Beauchene et al., 2025). In practice, two things matter: tangible development path (what to master and in what order) and sense of psychological safety around experimenting with new tools (Lerner, 2024).

The common denominator of these perspectives is clear. From an economic standpoint, AI represents an opportunity to raise productivity and innovation, but with real risk of benefit concentration without equalizing policies and investment in human capital (Chui et al., 2023; Georgieff, 2024). From an organizational perspective, it is primarily a management project – redefining processes, roles, and responsibility principles, only secondarily a matter of tool selection (Beauchene et al., 2025; PwC, 2025). From a developmental perspective, the most valuable prove to be skills that make humans good AI collaborators: context recognition, critical thinking, empathy, and ethical reasoning (World Economic Forum, 2025). Socially, this requires care for relationship quality and AI use transparency, so trust does not become an adoption bottleneck (Manning, 2024). For humans, the key is that transformation is not "on them" but "with them": when accompanied by meaningful learning paths and support, AI can become a development catalyst rather than a source of chronic stress (Lerner, 2024). In this sense, future advantage will be gained by economies, companies, and people who combine technological ambition with social maturity – and consistently invest in the ability for human cooperation with intelligent systems (Georgieva, 2024; World Economic Forum, 2025).

Changes in the labor market through the eyes of AI technology creators

AI technology in its contemporary form has been developing for quite some time, as shown in the first part of the article, but its greatest achievements and significance occurred in recent years. Since this area develops extremely dynamically, scientific research and reports may contain delayed information, not including the latest technology changes that are naturally known to AI creators and influential people in this area. To include this information, the views of these people on employment changes resulting from increasingly widespread use of AI technology were studied. The method adopted in this work for studying statements by the most famous AI technology creators in the world and the most influential people associated with it included: identifying key people in the most important companies developing AI in the world, searching for interviews, statements, conference presentations, and articles by previously identified people, and analyzing key statements on labor market changes caused by AI. All steps of this research procedure were also supported by AI.

The search for companies and key people was based on broad searching by Perplexity based on internet, scientific, and social sources. Thirteen companies were identified, including both companies developing large language models and technology companies related to the AI area. From this list of companies, main companies building large language models were selected, namely OpenAI, Google DeepMind, Microsoft AI, Anthropic, Meta AI (FAIR), Baidu AI, xAI, and DeepSeek AI. The selection criteria focused on organizations developing general-purpose large language models with broad applicability across various domains and industries. Companies specializing in domain-specific applications (e.g., Tesla AI for autonomous vehicles) or hardware infrastructure (e.g., NVIDIA for GPUs) were excluded, as the focus was on general-purpose LLM developers whose perspectives address broad labor market transformation. A total of 37 key people were identified in these companies – defined as individuals in senior management or leading development roles (e.g., CEOs, CTOs, Chief Scientists, Research Directors) who publicly discuss LLM development and its business and employment implications – and 256 sources with statements by these people were found, of which 204 sources were used in the study. Rejected sources were mainly sources behind paywalls or requiring login (e.g., newspapers, magazines, LinkedIn, Facebook, platform X). A quantitative summary of analysis sources is in Table 1.

Table 1. Number of sources used in the study

Company	**Number of key people**	**Number of found sources**	**Number of omitted sources**	**Number of sources used**
OpenAI	7	28	8	20
Google DeepMind	4	32	8	24
Microsoft AI	5	33	4	29
Anthropic	6	49	7	42
Meta AI (FAIR)	4	37	10	27
Baidu AI	3	12	4	8
xAI	3	30	4	26
DeepSeek AI	5	35	7	28
Total	**37**	**256**	**52**	**204**

Note. Own elaboration based on data collected.

Sources accepted for the study consisted of textual, audio, and video recordings (actually transcriptions of the latter two) and publications by distinguished people. They include presentations at technology conferences (CES, WWDC, Google I/O, NVIDIA GTC), media interviews (CNBC, Bloomberg, TechCrunch), activity on social platforms (Twitter/X, LinkedIn, which were later rejected due to lack of automatic access to these texts), scientific publications and industry articles, YouTube appearances and technology podcasts, keynotes at industry events. All 204 sources were uploaded to NotebookLM, with audio and video content automatically transcribed using the platform's native transcription functionality. These sources were examined in NotebookLM by posing each of the five research questions as separate queries with explicit instructions to identify and cite statements by key individuals:

1. What do people from interviews think about the current and future impact of AI on the economy?
2. What will be AI's impact on human work, labor market, and occupations?
3. What benefits and threats for humans are associated with AI development?
4. What social consequences will result from AI use?
5. What technical, economic, and social problems are significant in the current phase of AI development?

Each question was formulated to directly reference the key people from the identified companies and request that their names be mentioned in responses. The statements generated by NotebookLM were cross-referenced with original sources through the platform's automatic citation feature, which links each statement to its corresponding source document and specific text passage. Each cited claim was manually cross-checked in the original source to ensure accuracy and appropriate context. Simultaneously, statements by other people participating in discussions appeared if such was the nature of the given source. However, only statements by people originally found in the selection procedure and former employees of these companies founding their own startups were accepted for the study. The verified responses were then systematically categorized according to the five-dimensional analytical framework (economic, organizational, developmental, social, and human consequences) that emerged from the scientific literature and consulting reports, allowing identification of convergent themes and divergent perspectives across sources.

From the statements, it appears that we stand at the threshold of technological transformation accelerated by AI, work is transitioning from the era of digital tools to the era of agents, collaborating with humans and among themselves. This movement is not just another iteration of automation – it is a shift in the logic of costs, organization, and competencies, with equally great opportunities and tensions. To capture the dynamics of this transformation, the obtained statements were grouped in a structure that appeared earlier in both scientific studies and consulting firm reports indicating consequences of changes caused in the labor market by AI implementation in practice:

– economic consequences of AI include productivity growth, "intelligence" deflation, value redistribution, concentration risk, and price wars (Sam Altman, OpenAI; Mustafa Suleyman, Microsoft AI; Satya Nadella, Microsoft; Dario Amodei, Anthropic; Demis Hassabis, Google DeepMind; Robin Li, Baidu);
– organizational consequences include task automation, transition to AI agents, role changes (e.g., coding, product management), fluid teams, and new power centers (Mark Zuckerberg, Meta; Satya Nadella, Microsoft; Greg Brockman, OpenAI; Haifeng Wang, Baidu; Mustafa Suleyman, Microsoft AI; Brad Lightcap, OpenAI; Jakub Pachocki, OpenAI);
– developmental consequences indicate growing importance of meta-skills, learning how to learn, and AI tool proficiency, as well as possibilities for accelerating research and discoveries (Demis Hassabis, Google DeepMind; Sam Altman, OpenAI; Jakub Pachocki, OpenAI; Szymon Sidor, OpenAI; Shundong,

Baidu; Dario Amodei, Anthropic; Pushmeet Kohli, Google DeepMind);
- Social consequences include high pace of change, rules negotiated together, attachment to AI, and risks of polarization and bias (Demis Hassabis, Google DeepMind; Sam Altman, OpenAI; Jerome Pesenti, Sizzle AI; Charlie Bell, Microsoft);
- Human consequences include work meaning and agency, occupational displacement, mental health, knowledge democratization and counseling (Satya Nadella, Microsoft; Sam Altman, OpenAI; Mustafa Suleyman, Microsoft AI; Brad Lightcap, OpenAI; Kevin Scott, Microsoft; Mike Krieger, Anthropic; Dario Amodei, Anthropic).

Economically, AI acts as a productivity engine that lowers the cost of "intelligent work" and increases human work value where it combines with tool use competency. The vision of "multiplying technology" encompasses all areas of the economy, moving the boundary of what is profitable (Koray Kavukcuoglu, Google DeepMind). If models can perform tasks that previously cost hundreds or thousands of dollars, completing them at a fraction of a dollar in computing cost, the supply curve of intellectual services shifts sharply right, and prices fall (Sam Altman, OpenAI). This is precisely the "strongly deflationary" nature of computational intelligence, whose target cost may approach zero (Sam Altman, OpenAI; Mustafa Suleyman, Microsoft AI). The macro effect can be tangible: widespread generative AI implementation can add hundreds of billions of euros to GDP in a fifteen-year horizon, as seen in estimates for Italy (Satya Nadella, Microsoft). Simultaneously, workers who incorporate AI into daily processes – e.g., using low-code platforms and automation – more often gain in wages because their role shifts toward IT and system integration (Satya Nadella, Microsoft). In such a world, "radical abundance" is not just a slogan but a description of an economy where shortages give way to abundance, and limitations increasingly have regulatory and energy rather than technological character (Demis

Hassabis, Google DeepMind). However, with abundance comes distributional tension: rapid progress pace may result in "very unequal outcomes" between companies, industries, and regions if new value distribution rules are not renegotiated (Sarah Friar, OpenAI). Not coincidentally, this is accompanied by thinking about new redistribution models: instead of classical UBI, the proposal is "participation in global AI computing power," i.e., access to GPU as new "opportunity currency" (Sam Altman, OpenAI). Simultaneously, cost dynamics and model standardization push the market toward price war – faster than many expected (Robin Li, Baidu). At the end of this economic vector, concern about power and capital concentration in a narrow group of companies controlling models, data, and infrastructure is visible (Dario Amodei, Anthropic). If the price of "intelligence" approaches zero, and the price of access and coordination approaches a premium, the question arises: who controls access gates and value distribution networks.

Organizationally, AI shifts weight from "human uses tool" to "human coordinates agents." Already today, models perform a low single-digit percentage of global economy tasks, but grow mainly through composition and process orchestration (Sam Altman, OpenAI). In software engineering, a milestone is visible: the prospect that in the coming 12-18 months, most code in large technology companies may be generated by AI, reversing classic roles and development cycles (Mark Zuckerberg, Meta). AI agents, capable of executing entire processes and collaborating with each other, become organizational resources that must be planned, trained, and audited just like human teams (Satya Nadella, Microsoft). This in turn raises the bar for aspirations: superintelligence can become "almost as capable as the most efficient human organizations," redefining what scale and pace of action means (Greg Brockman, OpenAI). Empiricism already confirms this: coding assistants like Comate based on ERNIE achieve wide adoption, and a significant portion of production code is created with their help

(Haifeng Wang, Baidu). Structurally, companies transition from hierarchical, fixed structures to fluid, project teams that gather around problems and disperse after solving them (Mustafa Suleyman, Microsoft AI). New roles emerge – "AI superstars and champions" – which are knowledge carriers and transformation catalysts at the entire organization level (Brad Lightcap, OpenAI). Simultaneously, a vision of automated research laboratories operating "on GPU" appears, where most research and engineering is performed by systems, and humans manage goals, ethics, and quality control (Jakub Pachocki, OpenAI). This provides incredible possibilities but also raises the question of "who controls the controllers": automated research systems can endow "incredible power and responsibility" to small groups of decision-makers (Jakub Pachocki, OpenAI).

Developmentally, requirements for humans shift from proficiency in individual tools to meta-skills: learning, creativity, adaptation, and resilience (Demis Hassabis, Google DeepMind). In the short horizon, however, pragmatics becomes most important – proficiency in using AI tools and the habit of "learning how to learn" in partnership with models (Sam Altman, OpenAI; Jakub Pachocki, OpenAI; Szymon Sidor, OpenAI). Employers seek people who can take a higher-level view and design action paths instead of just executing steps, because humans remain the architect of purpose. Simultaneously, "natural language" becomes the new universal programming language: conversational interface replaces part of traditional technical layers, and flow logic is expressed in prompts and plans (Shundong, Baidu). This shift in tools is not just a matter of work comfort – it is a gateway to learning acceleration. AI can "tell us new things about the world," generating hypotheses and prioritizing experiments (Jakub Pachocki, OpenAI). In biology, a decade jump in one year is possible, which would be unimaginable under traditional grant and laboratory conditions (Dario Amodei, Anthropic). From finding drugs for rare diseases to climate change adaptation, AI catalyzes domains that previously needed years of painstaking work (Jakub Pachocki, OpenAI; Demis Hassabis, Google DeepMind). Symbolic is the AlphaFold example, which democratized access to protein structures – millions of freely available structures broke the infrastructure monopoly and accelerated work in thousands of teams (Pushmeet Kohli, Google DeepMind).

Socially, we live at a pace that may be "at least ten times faster" than the industrial revolution, which weakens institutions' and norms' ability to absorb change (Demis Hassabis, Google DeepMind). Therefore, "rule negotiation" for AI use at the social level becomes crucial before standard and behavior trajectories become path-dependent (Sam Altman, OpenAI). In this context, some institutions, like traditional colleges, may not fulfill their role for the majority – reaction time and curricula do not keep up with practice (Sam Altman, OpenAI). Simultaneously, "the value of being a real person" increases in a world of unlimited model-generated content: authenticity, verifiability, and responsibility become reputational assets (Sam Altman, OpenAI). In the thickening network of relationships, the phenomenon of attachment to systems – from tools to companions – appears, requiring broad conversation about boundaries, responsibility, and mental health (Jakub Pachocki, OpenAI). "Digital companions" can easily lead to "dark and strange places" if we design them without clear barriers and supervision (Demis Hassabis, Google DeepMind). The tragic story of an elderly lonely man manipulated by a chatbot shows these are not only abstract concerns – they are real risks of vulnerable interactions (Horwitz, 2025). Added to this is the bias and discrimination thread: models learn from bias-infected data, so without built-in balancing mechanisms they can replicate or even amplify injustice in recruitment, credit, or content generation (Jerome Pesenti, Sizzle AI; Charlie Bell, Microsoft). The scale of AI use multiplies side effects, so proper governance becomes a first-order function, not an add-on.

At the individual level, the core is agency and meaning. Worker displacement is "raw and difficult" – it concerns biographies, not just indicators; its social and psychological costs are distributed across generations (Satya Nadella, Microsoft). People need not only income but also a sense that they are useful to others; therefore financial transfers alone cannot replace the role that work plays in identity structure (Sam Altman, OpenAI). Shifting work toward greater creativity and freedom sounds attractive, but for many it means increased uncertainty and requirement for comfort with ambiguity – which generates stress and resistance (Mustafa Suleyman, Microsoft AI). Simultaneously, new flexibility appears in the same space: people with high agency can, with AI support, faster turn intentions into results – from prototypes to ventures (Brad Lightcap, OpenAI). This fits into the broader "democratization of knowledge and privilege": tools that previously only a few had access to become common, shortening the distance between idea and execution for millions of potential creators (Mustafa Suleyman, Microsoft AI; Kevin Scott, Microsoft). However, on this trajectory lies parallel risk to mental health. Models used in crisis situations – despair, suicidal thoughts – can harm if they lack clinical context, supervision, and safe escalation protocols (Sam Altman, OpenAI; AIRT experts, Microsoft). There is also the phenomenon of "feeling useless" in confrontation with systems that seem more powerful, faster, and infallible – which easily affects self-assessment and motivation (Sam Altman, OpenAI). The counterbalance is practice: AI lowers the creation barrier, helping people become "maximum versions of themselves" – provided goals remain human and tools serve their realization (Mike Krieger, Anthropic). In health practice, the promise of better counseling appears – often surpassing the mediocrity of overworked systems and doctors – as well as support in diagnosing rare, complex conditions (Dario Amodei, Anthropic; Mustafa Suleyman, Microsoft AI). However, the key principle sounds simple: AI should remain a tool; humans – the source of purpose, meaning, and responsibility (Kevin Scott, Microsoft).

By joining these layers, we get a picture of economy and work where the cost of AI falls and the value of coordination and intention rises. Companies learn to build orchestras of agents, and people learn to conduct them through meta-skills and natural language. Society negotiates norms at an unprecedented pace, balancing between abundance and the risk of concentration, between democratization of knowledge and the threat of deepening inequality. Good distribution and responsibility rules – from access to computing power, through model audits, to the hygiene of human-AI relationships – will determine whether the potential translates into broad prosperity. The most important change, however, is internal: we are expanding our imagination about work as designing goals and systems, not just executing tasks. If we maintain the primacy of human meaning and agency, the deflation of intelligence can become inflation of opportunities.

Multi-dimensional synthesis of AI's impact on the labor market

To compare different observations, forecasts, and views on AI's impact on employment and the labor market, detailed consequences of AI use were analyzed and compared in the structure previously examined in scientific literature, consulting firm reports, and statements by AI creators and influential individuals – according to five dimensions of AI implementation consequences: economic, organizational, developmental, social, and individual. The results of this analysis are presented in Table 2.

Table 2. From economy to human: comparison of AI implementation consequences according to three types of sources

Issue	Scientific sources	Consulting reports	Statements by AI creators and influential persons
Economic consequences			
Productivity and efficiency growth	Present: research indicates work efficiency and employment quality growth with differentiated net effects on jobs	Present: MGI estimates of \$2.6-4.4 trillion annually from generative AI macroeconomic growth effects	Present: AI lowers cost of intelligent work, shifts profitability boundaries and supports "radical abundance"
Substitution vs augmentation occupational exposure	Present: substitution of routine tasks and creation of high-competency roles mixed short-term effect	Present: IMF, OECD, WEF – high exposure of mental work, complementarity vs automation	Present: rapid automation of part of tasks and increased value of tool-complemented work
Inequality and polarization wages, industries	Present: risk of inequality growth and structural pressure in affected sectors	Present: premium growth for complementary competencies and regional and industry polarization	Present: very unequal outcomes between companies and regions without new redistribution rules
Value redistribution and benefit concentration	Partially: indications of benefit redistribution requiring public policies	Present: risk of benefit concentration in high-productivity sectors and large centers	Present: concentration of power and capital around models, data, infrastructure

Issue	Scientific sources	Consulting reports	Statements by AI creators and influential persons
Intelligence deflation price drop	Not present: lack of reference	Not present: lack of reference	Present: computational intelligence cost heading to very low level
AI price wars	Not present: lack of reference	Not present: lack of reference	Present: standardization and cost drops pushing market toward price wars
Organizational consequences			
Operating model rebuilding	Partially: need to redefine roles and work organization for AI	Present: change in operation model, work architecture, governance and risk	Present: transition from tool use to agent coordination in processes
Adoption-monetization gap	Not present: lack of this concept directly	Present: value gap through immature processes, data, roles and security	Partially: indirectly through emphasis on orchestration and operational maturity
Governance, compliance and model audits	Present: need for supervision roles and AI competencies emerges	Present: full model lifecycle, drift monitoring, risk and compliance	Present: question who controls the controllers and need for agent supervision
New roles around AI	Present: upskilling, new role categories supervision, AI gov	Present: AI product owners, model custodians, data stewards	Present: AI champions, orchestration and agent management roles
Human-AI hybrid teams	Present: indications of work quality and collaboration changes	Present: hierarchy flattening, risk integration, compliance from design	Present: fluid project teams, agent and human coordination

Issue	Scientific sources	Consulting reports	Statements by AI creators and influential persons
Code automation and process agents	Partially: lack of emphasis on code, more general automation	Present: use of generative AI in knowledge-intensive processes	Present: majority of code generated by AI agents realize entire processes
Developmental consequences			
Skills-first and micro-certifications	Partially: adaptation of academic programs and counseling	Present: skills-first paradigm and rapid competency update cycles	Partially: emphasis on meta-skills and tool proficiency
Reskilling, upskilling on mass scale	Present: need for requalification and new AI competencies	Present: 90% of technological roles evolving company development programs	Present: learning how to learn and practical tool proficiency
Tool proficiency and NL as programming language	Partially: general AI preparation, less about NL as language	Partially: designing human-AI interaction and working with data	Present: conversational interface and planning become main way of working
AI as research and discovery accelerator	Not present: lack of this thread in labor market research	Partially: mentions of innovation and productivity acceleration	Present: AlphaFold, rapid hypotheses, experiments, jumps in biology
Education and youth market entry	Present: program adaptation and positive impact on employability	Present: mapping key future competencies in reports	Partially: emphasis on development paths and agency in learning with AI
Social consequences			
Communication mechanization and relationship flattening	Partially: general changes in work relations	Present: contact automation, spontaneity loss, need for standards	Present: system attachment phenomenon and relational risks

Issue	Scientific sources	Consulting reports	Statements by AI creators and influential persons
Trust, transparency, labeling, explainability	Present: ethics and responsible implementations	Present: transparency and explainability requirements as trust condition	Present: rule negotiation and need for agent supervision
Regional polarization and SMEs	Present: risk of inequality expansion	Present: benefit concentration and need for inclusive programs for SMEs	Partially: warnings about unequal outcomes and concentration
Bias and discrimination in data	Present: ethical implications and bias risk	Present: standards and bias minimization policies	Present: risk of replication, injustice amplification
Pace of change vs institutions and norms	Partially: mentions of system preparation	Present: role of standards and governance at system scale	Present: change 10x faster than industrial revolution, need for norm negotiation
Digital companions and social risks	Not present: lack of reference	Partially: trust and usage boundary themes	Present: system attachment, vulnerable interaction risks
Human consequences			
Anxiety, stress, algorithmic monitoring	Present: adaptation pressure and uncertainty	Present: APA, BCG – anxiety grows without support and dialogue	Present: increased uncertainty and comfort requirement with ambiguity
Work meaning and agency	Partially: work quality and agency themes	Present: importance of development paths and psychological safety	Present: transfers won't replace meaning human source of purpose and responsibility

Issue	Scientific sources	Consulting reports	Statements by AI creators and influential persons
Occupational displacement and transition costs	Present: substitution and requalification pressure	Present: reskilling programs, mentoring, evaluation criteria and work relief	Present: harsh and difficult biographical and generational costs
Knowledge and counseling democratization	Partially: improved access to educational counseling	Partially: broader access to tools and competencies in organizations	Present: lower creation barriers and maximum versions of self with tools
Vulnerable groups and exclusion	Present: people with disabilities, graduates vulnerable to changes	Partially: inclusive development programs in companies	Partially: AI usage risks in crises and need for safe protocols
Mental health and AI in crises	Partially: general stress and overload risks	Present: role of support and implementation projects reducing stress	Present: risks in crisis situations and potential for better clinical counseling

Note. "Present" means the issue is clearly described or supported by examples and estimations. "Partially" means indirect or fragmentary mentions. "Not present" means no references in the adopted source category within the source content.

Own elaboration.

In the dimension of **economic consequences**, most issues overlapped across scientific, consulting, and AI creator sources: productivity and efficiency growth, varied occupational exposure to AI depending on work characteristics, wage inequality, and regional and industry polarization. Only price drops and price war issues in the AI world were not subjects of scientific research or considerations in consulting reports. This is not surprising – these issues primarily concern AI creators and influential people in this industry, often major shareholders and CEOs of corporations, who must constantly seek funds for system development and balance operational costs with user revenues while meeting market expectations. The issue of value redistribution and benefit concentration appears interesting – noted in all three types of sources, though in scientific sources they appear as research conclusions while among AI creators the strategic character of this issue is visible.

In the **organizational dimension**, a significant portion of threads is common to all three source groups: the need for governance, compliance and model audits, creating new roles around AI, and working in hybrid human-AI teams emerges, though science more often signals direction while consulting and creators describe practical implementation mechanisms. Consulting reports clearly emphasize the "value gap" between rapid adoption and monetization (immature processes, data, roles, security), while creator statements strongly highlight the transition from "tool use" to "agent coordination" and mass code automation, which scientific research addresses rather indirectly. Consequently, consensus concerns the direction of change (redefinition of operating model and roles), while differences relate to pace, scale, and descriptive language: consulting focuses on operational readiness and risk, creators on agent orchestration and rapid revaluation of production cycles.

In the **developmental area**, consulting reports and earlier text consistently indicate transition to the skills-first paradigm, acceleration of competency refresh cycles, and mass reskilling/upskilling, while science confirms the need for requalification and education adaptation, though less often framing this in terms of micro-certifications and new validation standards. AI creators particularly emphasize meta-skills (learning, creativity, planning) and "natural language" as the new work programming interface, as well as AI's role as research and discovery accelerator – a thread not usually exposed in labor market literature and mentioned more generally in reports. Convergence occurs regarding the thesis of growing tool proficiency and positive impact of adapted education on youth market entry, though the scale and examples of acceleration are most strongly illustrated in creator statements.

In the **social dimension**, trust, transparency, content labeling, and model explainability are common denominators across all three source categories, as are bias and discrimination risks and concerns about regional polarization and SME challenges. Consulting reports most strongly emphasize communication mechanization and the need for interaction quality standards, while creators add two emphases: unprecedented pace of change requiring "rule negotiation" and risks associated with attachment to systems and "digital companions," less present in scientific research. The overall picture shows agreement on the role of governance and inclusive programs, with differences in exposing new social phenomena and the speed at which institutions are forced to adapt norms.

At the **individual level**, all three types of sources confirm the presence of anxiety, stress, and adaptive pressure – including elements of algorithmic monitoring – as well as real costs of occupational displacement, while simultaneously indicating the importance of support programs and development pathways. Consulting reports particularly emphasize the impact of well-designed implementations – mentoring, on-the-job training, clear criteria – on agency and well-being, while creators raise themes of work meaning, knowledge democratization, and "lower barriers to creation," but also risks to mental health in crisis situations and the necessity for safe protocols. Convergence concerns the need to maintain agency and clear learning pathways, while divergences involve language and emphasis: science more often catalogs risks and vulnerable groups, consulting focuses on organizational interventions, and creators emphasize the potential for "maximum versions of oneself" provided human purpose and responsibility are maintained.

CONCLUSIONS

The article shows that AI's transformational impact on employment is multi-dimensional and consistent with the vision outlined in the introduction – from labor market restructuring and occupational polarization, through rebuilding organizational operating models, to changing competency requirements and work experience at the individual level as well as social relations around trust and transparency. In the economic-organizational view, AI raises productivity and shifts process profitability boundaries but requires new operational governance – AI model governance, audits, roles around data – and faces a gap between rapid adoption and slower monetization, strongly emphasized by both consulting reports and AI technology creator statements. From developmental and socio-human perspectives, it accelerates transition to the skills-first paradigm, increases demand for meta-skills and tool proficiency, but simultaneously reveals risks of inequality, bias, adaptive stress, and the need for institutional safeguards for vulnerable groups and relationship quality at work.

These conclusions are embedded in AI's longer history, where high expectations have twice been accompanied by AI winter periods, including after criticism in the 1973 Lighthill report and the collapse of the expert systems era, reminding us that subsequent waves of enthusiasm may slow due to scientific, technical, and institutional barriers. Current progress is unprecedented, but the further trajectory may slow due to lack of qualitative breakthrough toward AGI, explainability and responsibility challenges, hardware-energy limitations, and legal-regulatory factors, including lack of mature standards and implementation practices at scale. In particular, while intensive work on quantum computers continues, review consensus remains cautious about near-term useful advantages for practical AI tasks, reinforcing the thesis that the pace and utility of breakthroughs may remain limited in a multi-year horizon. Simultaneously, it should be emphasized that productivity and work quality shifts already achieved are confirmed in field studies, as well as the introduction of architectures based on multi-agent AI collaboration, which redefine roles, production cycles, and work coordination methods, with real impact on tasks, positions, and career paths described throughout the article.

While this analysis provides a comprehensive overview of AI's current transformational impact on employment, several critical research directions warrant further investigation. Long-term longitudinal studies examining AI's effects on labor market structures over 10–20-year horizons would provide valuable insights into persistent versus transitory employment shifts. Comparative research across different geographic regions could illuminate how varying institutional frameworks, educational systems, and policy interventions shape labor market adaptation to AI. Empirical evaluation of reskilling and upskilling program effectiveness remains essential for evidence-based workforce development strategies. Additionally, systematic research on AI's psychological impact on workers – including stress, job satisfaction, and mental health outcomes – requires sustained attention through longitudinal cohort studies. The development and testing of ethical AI governance frameworks that balance innovation with worker protection represents another crucial research frontier. Finally, as AI-driven productivity gains materialize, research exploring alternative wealth redistribution models and their economic and social consequences will become increasingly vital for ensuring equitable outcomes in the AI era.

Research unambiguously indicates that AI will not replace humans, but humans collaborating with AI will replace those who do not. This makes the ability to adapt and continuously learn the most valuable competency of the 21st century.

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