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RESHAPING LABOUR MARKET NEEDS THROUGH ARTIFICIAL INTELLIGENCE: CHANGING SKILL DEMAND, GREEN SKILLS, AND SECTORAL HETEROGENEITY

Abstract

Purpose – This paper examines how artificial intelligence (AI) is reshaping labour-market skill needs, focusing on the change in employer skill demand, the resilience of green skills, and sectoral heterogeneity in the European Union. Design/methodology/approach – Three hypotheses are tested against official statistics from Eurostat and the International Labour Organization for the last available decade (2014–2024); absolute and percentage change and compound annual growth rates are computed and triangulated with recent scholarly literature. Findings – Employment of ICT specialists rose by about 61% (to 4.9% of total employment) and hard-to-fill ICT vacancies doubled; employment in the environmental goods and services sector grew by about 60%, led by renewable energy (+92%); and high-AI-exposure services expanded roughly three times faster than lower-exposure sectors. All three hypotheses are confirmed. Practical implications – Education and labour-market policy should treat digital, green, and AI-complementary skills as a single, integrated agenda, since the binding constraint is the supply of skills. Originality/value – The paper integrates the digital, green, and sectoral dimensions within one twin-transition framework using harmonised official statistics.

Key words: *artificial intelligence, digital skills, green skills, labour market, skills mismatch, sectoral employment*

JEL classification: *J24, J21, O33, Q56, C10*

ОБЛИКОВАЊЕ ПОТРЕБА ТРЖИШТА РАДА ПОД УТИЦАЈЕМ ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ: ПРОМЕНА ТРАЖЊЕ ЗА ВЕШТИНАМА, ЗЕЛЕНЕ ВЕШТИНЕ И СЕКТОРСКА ХЕТЕРОГЕНОСТ

Апстракт

Сврха – Рад испитује како вештачка интелигенција (ВИ) преобликује потребе тржишта рада за вештинама, са фокусом на промену захтева послодаваца за вештинама, отпорност зелених вештина и секторску хетерогеност у Европској унији. Дизајн/методологија/приступ – Три хипотезе тестирају се на званичним статистикама Евростата и Међународне организације рада за последњу расположиву деценију (2014–

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2024); израчунавају се апсолутна и процентуална промена и просечна годишња стопа раста (CAGR), а резултати се триангулишу са савременом литературом. Резултати – Запосленост ИКТ стручњака порасла је за око 61% (на 4,9% укупне запослености), а удео предузећа са тешко попуњивим ИКТ радним местима се удвостручио; запосленост у сектору еколошких добара и услуга порасла је за око 60%, предвођена обновљивом енергијом (+92%); сектори високе изложености ВИ расли су отприлике три пута брже од сектора ниже изложености. Све три хипотезе су потврђене. Практичне импликације – Образовне политике и политике тржишта рада треба да третирају дигиталне, зелене и ВИ-комплементарне вештине као јединствену, интегрисану агенду, будући да је ограничавајући фактор понуда вештина. Оригиналност/вредност – Рад обједињује дигиталну, зелену и секторску димензију у оквиру јединственог концепта „двојне транзиције“, користећи хармонизоване званичне статистике.

Кључне речи: *вештачка интелигенција (ВИ), дигиталне вештине, зелене вештине, тржиште рада, неусклађеност вештина, секторска запосленост*

Introduction

In less than a decade, artificial intelligence (AI) has moved from a specialised technological field to a general-purpose technology that is reshaping how work is organised, valued, and demanded. The rapid development of large language models and generative AI tools after 2022 further accelerated this process, shifting the focus of public and scholarly debate from the question of "will AI replace jobs" to the more subtle question of "how is AI changing the content of jobs and the structure of skills that employers demand." The relevance of the topic at this particular moment stems from a twofold circumstance: on the one hand, the speed of technological diffusion outpaces the speed at which education systems and labour market policies adapt; on the other hand, this transformation is unfolding simultaneously with the green transition, which raises the question of how two parallel, potentially competing or complementary, pressures on skills, the digital and the ecological, relate to one another. For developing and transition economies such as Serbia, this question also carries strategic significance, since the competitiveness and inclusiveness of the labour market depend on the timely adjustment of skills.

The key trends framing this debate can be summarised along three lines. The first is the automation of routine tasks, documented in the earlier wave of robotisation and digitalisation, which exerted pressure primarily on medium-skilled, procedural jobs and contributed to labour market polarisation. The second is the emergence of generative AI, which, unlike previous waves, affects cognitive, clerical, and highly educated profiles to a greater extent, thereby altering the traditional assumption about who is "exposed" to technology (Eloundou et al., 2024). The third line is the change in the demanded skills structure: demand for technical and digital competencies is rising, but so is demand for so-called soft and transversal skills (analytical reasoning, management, creativity, collaboration), while the importance of formal qualifications is being redefined in favour of concrete, demonstrable skills. In parallel, "green skills" are becoming a subject of

particular attention as a component of the sustainable transition, while the question of their autonomous durability relative to increasingly dominant digital competencies remains open (Erceg & Zoranović, 2020).

The subject of this paper is an analysis of the way in which artificial intelligence transforms the needs of the labour market, viewed through the prism of skills rather than solely through the number of jobs. The aim of the paper is to determine, drawing on scholarly literature and official statistical sources (the International Labour Organization, ILO, and Eurostat), in which direction employers' requirements are changing, what the status of green skills is in the age of AI, and how uniform or differentiated AI's impact is across sectors. Accordingly, the paper is guided by three research questions: (1) How are employers' requirements regarding employees' skills changing under the influence of AI? (2) How relevant do "green skills" remain in the era of AI transformation? and (3) How differently does AI affect individual industries and sectors?

On this basis, the following hypotheses are formulated:

H1: Under the influence of artificial intelligence, employers' requirements are systematically shifting from routine and procedural skills toward technical, digital, and higher cognitive-social skills, accompanied by a declining importance of formal qualifications in favour of concrete (demonstrable) skills.

H2: Green skills retain their relevance in the labour market, but their demand increasingly depends on complementarity with digital and technical competencies; their significance is therefore not autonomous but conditioned by the coupling of the green and digital transitions.

H3: The impact of artificial intelligence on the labour market is sector-differentiated, in sectors with a high share of routine tasks the substitution effect prevails, whereas in sectors with analytical, technical, and interpersonal tasks the effect of augmentation and increasing skill complexity prevails.

The paper is structured into four parts. Following this *introduction*, in which the subject, aim, and hypotheses are defined, comes the *theoretical framework and literature review*, organised thematically around the change in skill demand, automation and digital competencies, green skills, and sectoral differences. The third chapter, *research and discussion*, presents the statistical analysis of data from official institutions (ILO and Eurostat), by which the stated hypotheses are empirically tested against comparative indicators. Furthermore, the discussion of results is elaborated. The paper concludes with a *conclusion*, in which the findings are synthesised, the status of the hypotheses is assessed, and implications for education and employment policies under the twofold, digital and green, transition are formulated.

2. Theoretical Background and Literature Review

2.1. Changing Skill Demand Under the Influence of AI

Empirical studies based on online job-posting data consistently show that AI changes the *structure* of demanded skills, not merely their volume. Alekseeva et al. (2021), analysing a database of online vacancies (Burning Glass Technologies) for the U.S. labour market over the period 2010–2019, document a dramatic increase in

demand for AI skills across almost all industries and occupations, with the highest concentration in IT, engineering, science, and management; they also find that AI skills carry a wage premium of about 11% within the same firm and 5% within the same job title (quantitative analysis of a large sample of vacancies). Green (2024), within the OECD series of papers on AI, estimates the effects of AI on skill demand in occupations that do not require specialised AI skills, and finds that in occupations highly exposed to AI the most sought-after skills are managerial and business skills (project management, finance, administration), indicating the complementarity of AI with coordination and reasoning skills (method based on online vacancies). Eloundou et al. (2024) develop a framework for assessing occupations' exposure to large language models and estimate that about 80% of the U.S. workforce could have at least 10% of their tasks affected by this technology, with a reversed pattern relative to earlier waves of automation, greater exposure is shown by better-paid and more educated occupations based on research that combine human expertise and GPT-4 task classification.

The consensus in the literature is that AI is rapidly rising demand for technical and interdisciplinary skills and that it operates primarily in an augmentation mode, alongside complementary managerial and analytical skills. The main disagreement concerns the direction of the distribution of exposure. While generative AI appears to affect highly skilled cognitive profiles as well (Eloundou et al., 2024), studies based on vacancies emphasise that demand and wage premiums still rise most for narrowly specialised AI competencies (Alekseeva et al., 2021). The extent to which measured "exposure" translates into actual changes in jobs also remains open.

2.2. Automation, Digital, and Technical Skills

The conceptual foundation is the thesis of the automation of routine tasks and its distributional consequences. Acemoglu and Restrepo (2020), analysing local U.S. labour markets, provide robust evidence of the negative effect of industrial robots on employment and wages: one additional robot per thousand workers reduces the employment-to-population ratio by about 0.2 percentage points and wages by about 0.42% (quantitative analysis across commuting zones). This finding confirms that technological substitution is not neutral but affects particular skill profiles. Felten et al. (2021) construct a measure of occupational exposure to artificial intelligence (AIOE), linking ten AI applications to 52 human abilities, and show that exposure differs markedly across occupations, with the possibility of aggregation to the industry (AIIE) and geographic levels as a quantitative approach based on cross-linking abilities and applications. On the side of skill-structure adjustment, Wang et al. (2024), using panel data for 31 Chinese provinces (2010–2019) and fixed-effects, mediation, threshold, and spatial econometric models, find that AI promotes growth in high- and medium-skilled employment while reducing low-skilled employment, with non-linear effects and spatial spillovers across regions (open access, Heliyon).

The literature agrees that technology systematically "upgrades" demanded skills (skill upgrading) and displaces routine, low-skilled tasks, confirming the polarisation framework. Disagreements arise over the *net* effect on employment, while earlier work on robotisation emphasises substitution and losses (Acemoglu & Restrepo, 2020), more recent studies of AI emphasise recomposition and increasing skill complexity (Wang et

al., 2024). The common conclusion is that digital and technical skills are becoming a basic condition of employability across a wide range of occupations.

2.3. Green Skills and Sustainability in the Context of AI Transformation

Research on green skills shows that they are qualitatively different from non-green skills but also increasingly intertwined with digital competencies. Consoli et al. (2016), in a foundational study based on U.S. occupational data (ONET), find that green jobs make more intensive use of higher cognitive and interpersonal skills and are characterised by higher levels of education, work experience, and training than non-green jobs (quantitative occupational profiling). Gasparini et al. (2025) critically re-examine official taxonomies of green occupations and skills, combining ONET and ESCO with a regional input-output model of investments in energy technologies in the Netherlands, and find that only a minority of occupations relevant to the energy transition can be strictly classified as "green," while the majority rest on non-green skills, with digital competencies proving more decisive than narrowly "green" expertise. Bone et al. (2025), analysing about eleven million online vacancies in the United Kingdom (2018–mid-2024), record that the number of vacancies with at least one green skill grew by about 67%, and show that employers increasingly apply "skill-based hiring" for both green and AI jobs, with a decline in requirements for formal university education (a quantitative time series of vacancies).

The consensus is that green skills remain relevant and increasingly in demand, but that their operational value increasingly depends on their coupling with digital and technical skills within the "twin transition". Literature disagreements exist over measurement: taxonomy-based approaches (which identify "green occupations") risk underestimating the role of non-green and digital skills in achieving the green transition (Gasparini et al., 2025). The open question is whether green skills constitute an independent demand category or an increasingly complementary layer within a broader digital-technical skills base.

2.4. Sectoral and Industry Differences in the Impact of AI

The literature emphasises that AI's impact is highly heterogeneous across sectors. Gmyrek et al. (2023), in an ILO working paper, estimate the global exposure of occupations to generative AI using task descriptions from the ISCO-08 classification and the GPT-4 model, and conclude that for most occupations augmentation is more likely than full automation, with the greatest exposure among clerical jobs and more pronounced effects in higher-income countries; the refined version of the index (ILO Working Paper 140, 2025) introduces "exposure gradients" and estimates that about one quarter of the global workforce is in the zone of potential transformation due to generative AI (an institutional report methodologically based on task assessment). Felten et al. (2021), with their industry-specific measure (AIIE), empirically confirm that exposure to AI differs significantly across industries. Wang et al. (2024) add the dimension of sectoral and regional structure, showing that AI operates through the optimisation of industrial structure and produces spatial spillovers, whereby the effects are not uniform but depend on the attained level of economic development.

The literature agrees that there is no single "story" about AI's impact, outcomes vary by sector, task type, skill level, and geography, with routine and administrative sectors carrying a higher risk of substitution, while analytical, technical, and interpersonal ones predominantly record augmentation. The main difference in academic analyses is between approaches and methodologies applied: exposure studies (Gmyrek et al., 2023; Felten et al., 2021) estimate potential, whereas econometric studies (Wang et al., 2024) measure realised effects, which explains part of the divergence in conclusions. The common implication is that adaptation policies must be sector-differentiated.

2.5. Recent Empirical Evidence and the Regional Context

Recent empirical work reinforces and extends these themes. Analyses that separate tasks from jobs find that AI adoption reshapes the task content of work more than it eliminates whole jobs (Bonney et al., 2024), while reviews of automation technologies conclude that their employment effects are heterogeneous and contingent on skill level and sector (Filippi et al., 2023; Chun & Shin, 2025). Evidence on the dual character of AI shows that it simultaneously creates and displaces labour demand (Choi & Leigh, 2024), and a systematic review of generative AI confirms that the transformation of jobs, rather than their wholesale substitution, is the dominant expected outcome (Salari et al., 2025). On the green side, occupation- and flow-based evidence documents an ongoing greening of the labour market driven by changing occupational content and worker reallocation (Bachmann et al., 2026), consistent with the twin-transition reading advanced in this paper.

For the regional and Serbian context, the digital dimension of this transformation is well documented: digitalisation has been shown to raise economic growth, productivity, and employment (Arsić, 2020), while the Serbian labour market has undergone marked structural transformation, including along gender lines (Stanković, 2016), a dimension echoed by international evidence on the uneven exposure of women to AI. The coupling of the digital and green agendas is increasingly examined through regenerative-economy frameworks, both for Serbia specifically (Manasijević, 2024) and in terms of the broader principles linking sustainability to business practice (Sessa, 2025).

3. Research and Discussion

This subtitle subjects the three hypotheses formulated in the introduction to an empirical test against comparative indicators drawn exclusively from official statistical sources. It proceeds hypothesis by hypothesis: after a methodological note (3.1), Sections 3.2–3.4 present, for each hypothesis, the relevant tables and figures together with a discussion that reads the statistics against the scholarly literature. Section 3.5 synthesises the evidence and states, for each hypothesis, whether the official data confirm, partially confirm, or contradict it.

3.1 Methodological Note: Sources, Period, and Data Limitations

The analysis relies on two families of official sources. The first is Eurostat, the statistical office of the European Union, from which harmonised indicators for the aggregate "European Union – 27 countries (from 2020)" (EU-27) are drawn. The second is the International Labour Organization (ILO), whose institutional estimates and its

joint work with the International Renewable Energy Agency (IRENA) are used for the global picture and, in particular, for dimensions that Eurostat does not measure directly (occupational exposure to generative AI; worldwide renewable-energy employment).

The analysis covers the last ten available years. The operational window is 2014–2024 wherever the series allows (ICT specialists; enterprise recruitment of ICT specialists; employment by economic activity). For indicators with a shorter or interrupted coverage the exact period is stated at each table: individuals' digital skills (2015–2019 under the 2015 framework and 2021–2025 under the 2021 framework), and employment in the environmental goods and services sector (EGSS), for which the latest available year at the time of writing is 2022.

For the first hypothesis, H1 (a shift of employer demand towards digital, technical, and AI-complementary skills) the analysis uses employed ICT specialists (Eurostat *isoc_sks_itspt*), individuals' level of digital skills (*isoc_sk_dskl_i* / *isoc_sk_dskl_i21*), and enterprises' recruitment of and hard-to-fill vacancies for ICT specialists (isoc_ske_itrcrn2); the latter is read as a demand-side proxy for the skills mismatch that the ILO documents on the supply side. For the second hypothesis, H2 (the resilience of green skills) it uses employment in the EGSS (env_ac_egss1), broken down by environmental domain, complemented by the global ILO-IRENA renewable-energy employment estimate. For the third hypothesis, H3 (sectoral heterogeneity) it uses employment by NACE Rev. 2 economic activity (Eurostat Labour Force Survey, lfsa_egan22d), aggregated to NACE sections and grouped into "higher" and "lower" exposure sectors following the occupational-exposure literature.

For every indicator three simple trend measures are reported: the absolute change and the percentage change over the period, and, where meaningful, the compound annual growth rate (CAGR = (V_t / V_0) ^ $(1/n)$ - 1). Sectoral employment reported at the NACE two-digit (division) level was aggregated to the NACE section level (A-U) by the author; the "no-response" category and the very small sections T (household employers) and U (extraterritorial organisations) are excluded from the sectoral figure but not from the economy-wide total.

Regarding limitations, four caveats apply. First, break in series where the EU digital-skills indicator was redefined in 2021 (the DSK2 framework is not comparable with the pre-2021 DSK framework), so the two sub-periods must not be chained. Second, unit heterogeneity, where EGSS employment is measured in full-time equivalents (FTE) whereas total employment is measured in persons; the EGSS employment share reported here therefore relates FTE to persons and should be read as an approximation. Third, provisional and estimated values, i.e. the most recent Eurostat observations (notably 2024–2025) are partly estimated and may be revised. Fourth, and most important for interpretation, the official statistics measure employment stocks and skill supply, not the causal effect of AI as such; movements in these series are consistent with, but do not by themselves prove, an AI-driven mechanism. The discussion is framed accordingly, and the statistical signal is triangulated with the scholarly literature throughout.

3.2 The Shift of Employer Demand Towards Digital, Technical, and AI-Complementary Skills

Analysis of H1 holds that, under the influence of artificial intelligence, employers' requirements are shifting systematically from routine and procedural skills towards

technical, digital, and higher cognitive-social skills. Three official indicators speak to the demand side of this claim: the weight of ICT specialists in employment, the digital-skill endowment of the population, and the difficulty enterprises report in recruiting ICT specialists.

Table 1. Employed ICT specialists, EU-27, 2014–2024

Year	ICT specialists (% of total employment)	ICT specialists (thousand persons)
2014	3.4	6,334.5
2015	3.5	6,555.0
2016	3.6	6,919.5
2017	3.7	7,181.2
2018	3.8	7,570.4
2019	4.0	7,880.4
2020	4.3	8,442.4
2021	4.5	8,920.3
2022	4.6	9,370.1
2023	4.8	9,749.5
2024	4.9	10,189.9
Change 2014–2024 (abs.)	+1.5 pp	+3,855.4
Change 2014–2024 (%)	+44.1%	+60.9%
CAGR 2014–2024	3.72%/yr	4.87%/yr

Source: Eurostat, Employed ICT specialists (isoc_sks_itspt), unit "% of total employment" and "thousand persons", EU-27. Data extracted 12 July 2026. 2024 values are provisional. pp = percentage points; CAGR = compound annual growth rate. Calculations by the author.

Table 2. Individuals with at least basic overall digital skills, EU-27 (share of individuals aged 16–74)

Year	Basic or above-basic overall digital skills (%)	Measurement framework
2015	53.7	2015 framework (DSK)
2016	54.3	2015 framework (DSK)
2017	55.3	2015 framework (DSK)
2019	56.1	2015 framework (DSK)
2021	53.9	2021 framework (DSK2)
2023	55.6	2021 framework (DSK2)
2025	60.4	2021 framework (DSK2)

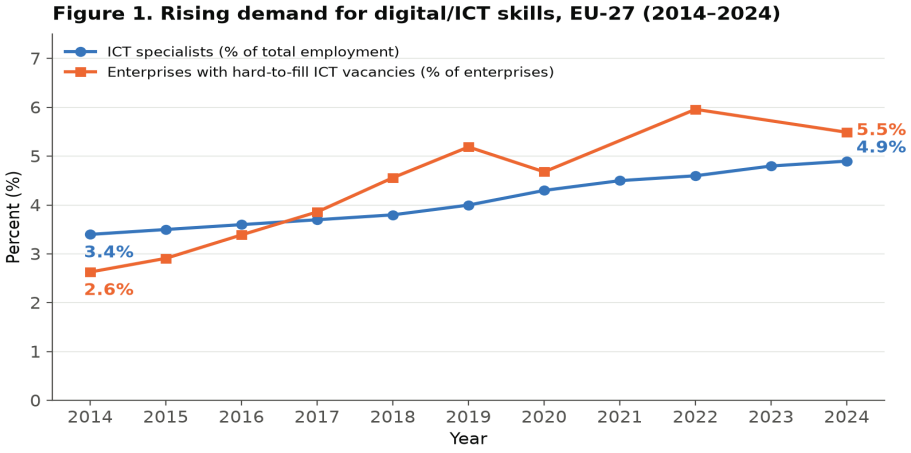
Source: Eurostat, Individuals' level of digital skills: isoc_sk_dskl_i (2015–2019) and isoc_sk_dskl_i21 (2021–2025), indicator "basic or above-basic overall digital skills", all individuals, EU-27. Data extracted 12 July 2026. Note the 2021 break in series: the two frameworks are not directly comparable.

Table 3. Enterprises and the recruitment of ICT specialists, EU-27, 2014–2024

Year	Enterprises that recruited / tried to recruit ICT specialists (%)	Enterprises with hard-to-fill ICT vacancies (%)
2014	7.08	2.63
2015	7.58	2.91
2016	7.92	3.39
2017	8.09	3.86
2018	8.49	4.56
2019	8.97	5.19
2020	8.47	4.68
2022	9.49	5.96
2024	9.55	5.49
Change 2014–2024 (abs.)	+2.5 pp	+2.9 pp
Change 2014–2024 (%)	+34.9%	+108.7%

Source: Eurostat, Enterprises that recruited or tried to recruit ICT specialists (isoc_ske_itrcrn2), enterprises with 10+ persons employed, all activities except finance, EU-27. Data extracted 12 July 2026. The survey is not conducted every year (no observation for 2013, 2021, 2023). Calculations by the author.

Figure 1. Rising demand for digital/ICT skills, EU-27 (2014–2024)



Source: author's elaboration on Eurostat isoc_sks_itspt and isoc_ske_itrcrn2 (EU-27), extracted 12 July 2026.

The three indicators converge on the same direction of travel. The number of ICT specialists in the EU-27 rose from 6,334.5 thousand in 2014 to 10,189.9 thousand in 2024, an absolute increase of about 3,855.4 thousand persons (60.9%, CAGR 4.87% per year), while their share of total employment climbed from 3.4% to 4.9% (Table 1, Figure 1). Because total employment grew by only 10.4% over the same decade (Section 4.4), ICT employment expanded roughly six times faster than the labour market as a whole. This is

the clearest possible statistical fingerprint of a structural re-weighting of demand towards technical and digital competencies, and not merely of general employment growth.

The supply of digital skills in the population moved in the same direction but far more slowly. Under the 2015 framework the share of individuals with at least basic overall digital skills rose only from 53.7% (2015) to 56.1% (2019); under the redefined 2021 framework it moved from 53.9% (2021) to 60.4% (2025), a gain of 6.5 percentage points (Table 2). Two readings follow. First, digital-skill supply is improving but remains a binding constraint: even on the most recent figure roughly four in ten adults still lack basic digital skills. Second, the gap between rapidly rising specialist demand (Table 1) and slowly rising general skill supply (Table 2) is precisely the condition under which recruitment difficulties should intensify, which is what Table 3 shows.

The share of enterprises that recruited or tried to recruit ICT specialists rose from 7.1% (2014) to 9.6% (2024, +34.9%), and, more tellingly, the share reporting hard-to-fill ICT vacancies more than doubled, from 2.6% to 5.5% (+108.7%, peaking at 6.0% in 2022). Read together, these figures describe a demand curve for digital talent shifting out faster than supply can follow: a labour-market tightness that operates as the demand-side counterpart of the qualification mismatch the ILO documents on the supply side.

These patterns align closely with the empirical literature. Studies of online vacancies find a broad-based rise in demand for AI and digital skills across almost all industries, concentrated in IT, engineering, science, and management, and carrying a distinct wage premium (Alekseeva et al., 2021). More recent vacancy-based work confirms that digital skills command a measurable pay premium, consistent with genuine scarcity rather than mere credential inflation (Garcia-Lazaro et al., 2025). Worker-level evidence from Germany similarly shows that exposure to AI is associated with shifts in task and skill composition and with wage effects that vary by the type of skills a worker holds (Engberg et al., 2025). The direction of adjustment is also consistent with Wang et al. (2024), who find that AI raises high- and medium-skilled employment while compressing low-skilled employment. At the same time, the literature qualifies a naive "more technical skills" reading: in occupations highly exposed to AI the most sought-after competencies are often managerial and analytical rather than narrowly technical (Green, 2024), and generative AI extends exposure to highly educated, cognitive profiles rather than sparing them (Eloundou et al., 2024). Where the official statistics and the literature diverge is on interpretation: Eurostat can show that specialist demand and recruitment difficulty are rising, but it cannot, on its own, separate an AI-specific effect from the broader digitalisation of the economy. On balance, the EU evidence supports H1 in its core claim, a systematic tilt of demand towards digital and technical skills, while leaving the finer point about the declining value of formal qualifications to be established by the vacancy-level studies (Bone et al., 2025).

3.3 The Resilience of Green Skills Under AI Transformation

H2 holds that green skills retain, and even increase, their relevance in the labour market, although their demand increasingly depends on complementarity with digital and technical skills. The most direct official measure of green employment is Eurostat's environmental goods and services sector (EGSS), which counts the labour input devoted to environmental protection and resource management across the whole economy.

Table 4. Employment in the environmental goods and services sector (EGSS), EU-27, 2014–2022

Year	EGSS employment (thousand FTE)	EGSS as % of total employment*
2014	4,165.0	2.22
2015	4,316.0	2.28
2016	4,393.0	2.28
2017	4,625.0	2.37
2018	4,795.0	2.43
2019	5,091.0	2.55
2020	5,307.0	2.70
2021	5,903.0	2.98
2022	6,673.0	3.29
Change 2014–2022 (abs.)	+2,508.0	+1.07 pp
Change 2014–2022 (%)	+60.2%	-
CAGR 2014–2022	6.07%/yr	-

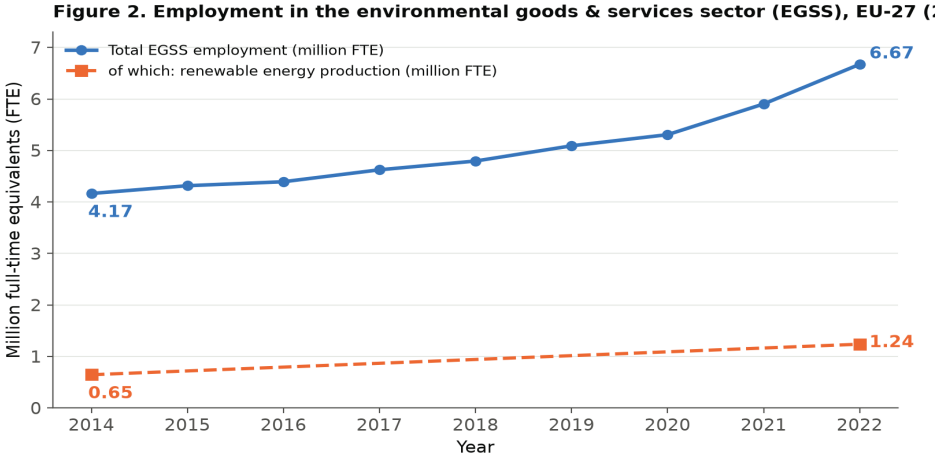
Source: Eurostat, Employment in the environmental goods and services sector (env_ac_egss1), unit full-time equivalents (FTE), EU-27; total employment from Eurostat lfsa_egan22d. Data extracted 12 July 2026.
**The share relates EGSS employment measured in FTE to total employment measured in persons and is therefore an approximation (see 3.1). Calculations by the author.*

Table 5. EGSS employment by environmental domain, EU-27, 2014 vs 2022 (thousand FTE)

Environmental domain	2014 (k FTE)	2022 (k FTE)	Change (%)	CAGR
Total EGSS	4,165	6,673	+60.2%	6.07%/yr
Environmental protection (CEPA, total)	2,571	3,826	+48.8%	5.09%/yr
- of which waste management (CEPA 3)	1,103	1,961	+77.8%	7.46%/yr
Resource management (CReMA, total)	1,594	2,847	+78.6%	7.52%/yr
- of which renewable energy production (CReMA 13A)	646	1,239	+91.8%	8.48%/yr
- of which heat/energy saving & management (CReMA 13B)	790	1,411	+78.6%	7.52%/yr

Source: Eurostat, env_ac_egss1 (EU-27), classification of environmental activities CEPA/CReMA. Data extracted 12 July 2026. Calculations by the author.

Figure 2. Employment in the environmental goods & services sector (EGSS), EU-27 (2014–2022)



Source: Author's elaboration on Eurostat env_ac_egss1 (EU-27), extracted 12 July 2026.

Green employment did not merely hold its ground during the decade of accelerating digitalization, it expanded strongly. EGSS employment in the EU-27 rose from 4,165 thousand FTE in 2014 to 6,673 thousand FTE in 2022, an increase of about 2,508 thousand FTE (+60.2%, CAGR 6.07% per year), lifting its share of total employment from 2.22% to 3.29% (Table 4, Figure 2). Against a whole-economy employment growth of about 10.4% over 2014–2024, EGSS employment grew several times faster, the opposite of what a 'crowding-out by digital skills' narrative would predict.

The domain breakdown (Table 5) shows that the growth is led precisely by the energy transition. Employment in renewable-energy production (CReMA 13A) almost doubled, from 646 to 1,239 thousand FTE (+91.8%), heat and energy saving (CReMA 13B) rose by 78.6%, and total resource-management employment increased by 78.6%; waste management (CEPA 3) grew by 77.8%. The EU picture is consistent with the global one: the ILO and IRENA estimate that worldwide renewable-energy employment reached a record 16.2 million jobs in 2023, up from 13.7 million in 2022 (an 18% year-on-year rise), with the EU accounting for about 1.8 million (ILO & IRENA, 2024).

The literature helps interpret why this expansion supports, rather than contradicts, the AI transformation story. Green jobs have long been shown to be skill-intensive, drawing more heavily on higher cognitive and interpersonal skills and on formal education than comparable non-green jobs (Consoli et al., 2016). Crucially, recent work finds that the green transition rests less on narrowly 'green' expertise than on the coupling of green and digital competencies: re-examining official taxonomies, Gasparini et al. (2025) conclude that digital skills are often more decisive than strictly green ones for the energy transition, while systematic evidence from manufacturing identifies a common core of digital, specialised-technical, and resilience skills required for the 'twin'

green-digital transition (Hofmann Trevisan et al., 2024). Vacancy-based evidence points the same way: the number of UK job advertisements requiring at least one green skill grew by roughly 67% between 2018 and mid-2024, and employers increasingly hire for green and AI roles on a skills basis rather than by formal degree (Bone et al., 2025). The official EU statistics and the literature therefore agree on the central point of H2, green skills are resilient and rising, and they jointly refine it: the demand is real but increasingly hybrid, realised through the twin transition rather than as an autonomous 'green' category. H2 is thus confirmed in its first clause and supported in its conditional clause about complementarity with digital and technical skills.

3.4. Sectoral Heterogeneity in the Impact of AI

The H3 holds that AI's impact on the labour market is sector-differentiated: substitution should predominate where routine tasks are concentrated, and augmentation and rising skill complexity where analytical, technical, and interpersonal tasks prevail. Employment by economic activity (NACE Rev. 2) over 2014–2024 provides a direct test of whether the labour market has in fact diverged across sectors, and in the direction the exposure literature predicts.

Table 6. Employment by economic activity (NACE Rev. 2 section), EU-27, 2014 and 2024

NACE section	2014 (thousand persons)	2024 (thousand persons)	Abs. change	% change	CAGR
J – Information and communication	5,207.5	8,026.2	+2,818.7	+54.1%	+4.42%
M – Professional, scientific, and technical	9,726.3	12,515.9	+2,789.6	+28.7%	+2.55%
L – Real estate activities	1,475.0	1,839.6	+364.6	+24.7%	+2.23%
R – Arts, entertainment, and recreation	2,916.1	3,618.6	+702.5	+24.1%	+2.18%
E – Water supply; sewerage, waste management	1,451.3	1,738.7	+287.4	+19.8%	+1.82%
D – Electricity, gas, steam, and air conditioning	1,411.4	1,688.1	+276.7	+19.6%	+1.81%
Q – Human health and social work	19,540.0	23,344.3	+3,804.3	+19.5%	+1.79%
I – Accommodation and food service	8,337.9	9,953.1	+1,615.2	+19.4%	+1.79%
P – Education	13,346.4	15,422.4	+2,076.0	+15.6%	+1.46%
H – Transportation and storage	9,663.9	11,146.4	+1,482.5	+15.3%	+1.44%
S – Other service activities	4,511.6	5,159.6	+648.0	+14.4%	+1.35%
F – Construction	12,568.2	14,243.3	+1,675.1	+13.3%	+1.26%
N – Administrative and support services	7,587.6	8,536.9	+949.3	+12.5%	+1.19%
O – Public administration and defence	13,262.4	14,381.2	+1,118.8	+8.4%	+0.81%

K – Financial and insurance activities	5,271.7	5,626.2	+354.5	+6.7%	+0.65%
G – Wholesale and retail trade; repair	26,566.6	27,752.0	+1,185.4	+4.5%	+0.44%
C – Manufacturing	30,657.1	31,689.2	+1,032.1	+3.4%	+0.33%
B – Mining and quarrying	707.7	567.1	-140.6	-19.9%	-2.19%
A – Agriculture, forestry, and fishing	9,872.9	6,876.0	-2,996.9	-30.4%	-3.55%

Source: Eurostat, Employment by sex, age and economic activity (lfsa_egan22d), persons aged 15+, both sexes, EU-27; two-digit divisions aggregated to NACE sections by the author. Data extracted 12 July 2026. Sorted by percentage change (descending). 2024 values are provisional.

Table 7. Employment change in higher- vs lower-AI-exposure sector groups, EU-27, 2014–2024

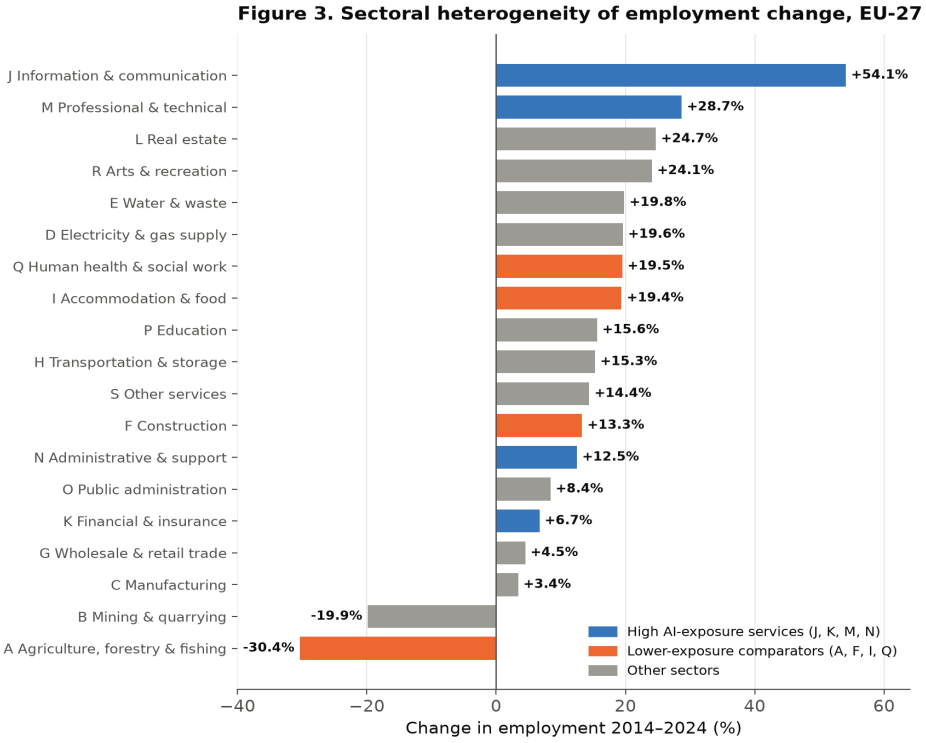
Sector group	2014 (thousand persons	2024 (thousand persons	Abs. change	% change	CAGR
Higher-exposure services (J, K, M, N)	27,793.1	34,705.2	+6,912.1	+24.9%	+2.25%
Lower-exposure comparators (A, F, I, Q)	50,319.0	54,416.7	+4,097.7	+8.1%	+0.79%
Whole economy (all NACE)	187,644.4	207,172.7	+19,528.3	+10.4%	+0.99%

Source: author's elaboration on Eurostat lfsa_egan22d (EU-27), extracted 12 July 2026. The higher-exposure grouping follows the occupational-exposure literature (Felten et al., 2021; Gmyrek et al., 2023, 2025); it is indicative, not an official Eurostat classification.

The decade's employment growth is strikingly uneven across sectors (Table 6, Figure 3). At one extreme, information and communication (J) expanded by 54.1% (CAGR 4.42%) and professional, scientific and technical activities (M) by 28.7% (CAGR 2.55%); at the other, agriculture (A) contracted by 30.4% and mining (B) by 19.9%, while manufacturing (C, +3.4%) and wholesale and retail trade (G, +4.5%) barely moved. The within-J detail is even more revealing: computer programming and consultancy (division J62) more than doubled, from about 2,354 to 4,981 thousand persons, a direct labour-market imprint of digitalisation and AI adoption.

Aggregating sectors into indicative exposure groups sharpens the contrast (Table 7). The higher-exposure services (J, K, M, N) added about 6.9 million jobs (+24.9%, CAGR 2.25%), growing more than twice as fast as the whole economy (+10.4%) and about three times faster than the lower-exposure comparator group of agriculture, construction, accommodation, and health (+8.1%, CAGR 0.79%). This is the pattern H3 anticipates: the analytically and technically intensive service sectors expanded and up-skilled, consistent with an augmentation regime in which AI raises the productivity of, and demand for, higher cognitive-technical labour.

Figure 3. Sectoral heterogeneity of employment change, EU-27 (2014–2024)



Source: author's elaboration on Eurostat lfsa_egan22d (EU-27), extracted 12 July 2026. Colour groups are indicative (see Table 7).

The data also reveal an important nuance that a simple 'high-exposure grows, low-exposure shrinks' reading would miss. Exposure and growth are not identical. Within the high-exposure group, financial and insurance activities (K) grew only 6.7%, far below ICT and professional services, consistent with the substitution of routine back-office and clerical tasks, the very tasks the ILO identifies as most exposed to generative AI. Administrative and support services (N) likewise grew modestly (+12.5%). Conversely, several lower-exposure sectors grew briskly for reasons largely unrelated to AI: human health and social work (Q, +19.5%) reflects population ageing and rising care demand, and construction (F, +13.3%) reflects the investment cycle. Agriculture's steep decline is a long-run structural and mechanisation trend that predates AI. The sectoral signal is therefore consistent with H3, but it reflects the joint operation of AI-related task effects and non-AI structural forces (demography, the business cycle, and long-run sectoral shift).

This reading matches the literature. Felten, Raj, and Seamans (2021) show that exposure to AI differs markedly across industries, and the ILO's global exposure estimates find that clerical occupations carry the highest exposure while, for most occupations, transformation (augmentation) is more likely than outright automation; about one in four workers worldwide

is in an occupation with some generative-AI exposure, with the highest-exposure category concentrated in high-income countries (34% of employment) far more than in low-income countries (11%) (Gmyrek et al., 2023; Gmyrek et al., 2025). The baseline substitution logic evidenced for industrial robots (Acemoglu & Restrepo, 2020) plausibly underlies the weak growth of routine-intensive activities such as manufacturing and parts of finance, whereas the recomposition and skill-upgrading emphasised by Wang et al. (2024) matches the surge in ICT and professional services. Where the official statistics add value is in showing that these divergent effects are already visible in realised EU employment stocks, not merely in estimates of potential exposure. H3 is thus confirmed: AI's labour-market impact is sector-differentiated, with augmentation predominating in analytical-technical services and substitution pressure concentrated in routine-intensive activities, even though the observed employment outcomes also embed non-AI structural drivers.

3.5. Synthesis of Findings

Taken together, the official statistics tell a consistent story across the three hypotheses. On H1, the EU data show an unmistakable re-weighting of demand towards digital and technical skills: ICT specialists grew from 3.4% to 4.9% of employment and from 6.3 to 10.2 million persons (+60.9%), roughly six times faster than total employment, while the doubling of hard-to-fill ICT vacancies against only slowly rising general digital-skill supply signals a persistent demand supply gap. H1 is confirmed in its core claim. On H2, far from being crowded out, green employment expanded by 60% (EGSS, 2014–2022), led by renewable-energy and energy-management jobs, and the global ILO-IRENA count reached a record 16.2 million in 2023; the literature clarifies that this resilience is increasingly realised through the twin green-digital transition. H2 is confirmed, with its complementarity clause supported. On H3, employment growth diverged sharply across sectors, higher-exposure analytical-technical services grew about three times faster than lower-exposure comparators, in a pattern of augmentation-versus-substitution that matches the exposure literature. H3 is confirmed, with the caveat that realised sectoral outcomes also reflect demography, the business cycle, and long-run structural change.

Two cross-cutting conclusions emerge. First, the three transformations are not separate: the same digital-technical skill base that drives H1 also conditions the green employment of H2 and shapes the sectoral divergence of H3, the labour market is being reorganised around a common digital-analytical core. Second, the binding constraint visible throughout the EU data is on the supply side: specialist demand, recruitment difficulty, and green-and-digital hybrid roles are all rising faster than the population's skills are adjusting. This frames the policy implication developed in the next chapter, that education and active-labour-market policy must treat digital, green, and AI-complementary skills as an integrated agenda rather than as competing priorities.

4. Conclusion

This paper set out to determine how artificial intelligence is reshaping the needs of the labour market when those needs are viewed through the prism of skills rather than the mere number of jobs. Guided by three research questions, how employer demand for skills is changing, whether green skills remain relevant, and how differentiated AI's

impact is across sectors, it combined a thematic review of the recent scholarly literature with an empirical analysis of official statistics from Eurostat and the International Labour Organization (ILO) for the last available decade. This concluding chapter draws the two strands together, states the status of each hypothesis, distils the overarching conclusions, and sets out the implications and limitations of the study.

The shift of employer demand towards digital, technical, and AI-complementary skills (H1), is confirmed. The convergence of the statistical indicators is unambiguous. In the EU-27 the number of ICT specialists rose from about 6.3 to 10.2 million between 2014 and 2024 (+60.9%), lifting their share of employment from 3.4% to 4.9%, roughly six times faster than total employment grew, while the share of enterprises reporting hard-to-fill ICT vacancies more than doubled (from 2.6% to 5.5%). These demand-side signals track the literature closely: vacancy-based studies document a broad, cross-industry rise in demand for AI and digital skills and a distinct wage premium for them (Alekseeva et al., 2021; Garcia-Lazaro et al., 2025; Popović et al., 2025), and worker-level evidence confirms that AI exposure reshapes task and skill composition (Engberg et al., 2025). The literature also refines the hypothesis in one respect: the most sought-after competencies in AI-exposed roles are frequently analytical and managerial rather than narrowly technical (Green, 2024), and generative AI extends exposure to highly educated cognitive profiles instead of sparing them (Eloundou et al., 2024). The official statistics can establish that demand is tilting decisively towards digital and technical skills, but not, on their own, isolate an AI-specific mechanism from broader digitalisation.

The resilience of green skills (H2) is confirmed, and its conditional clause about complementarity with digital and technical skills is supported. Far from being crowded out by the digital transition, employment in the environmental goods and services sector expanded by 60.2% between 2014 and 2022 (from 4.17 to 6.67 million full-time equivalents), with renewable-energy employment almost doubling (+91.8%); at the global level, the ILO and IRENA report a record 16.2 million renewable-energy jobs in 2023. The literature clarifies the nature of this resilience: green jobs are skill-intensive (Consoli et al., 2016), yet the transition increasingly rests on digital as much as on narrowly 'green' expertise (Gasparini et al., 2025) and demands a hybrid skill set characteristic of the 'twin' green-digital transition (Hofmann Trevisan et al., 2024; Bone et al., 2025). Green skills therefore endure not as an autonomous category but as an increasingly integrated layer within a broader digital-technical base.

The sectoral heterogeneity of AI's impact (H3) is confirmed, with an important qualification. Employment growth over 2014–2024 diverged sharply across sectors: information and communication grew by 54.1% and professional and technical services by 28.7%, while agriculture contracted by 30.4% and mining by 19.9%. Grouped by exposure, analytically and technically intensive services grew about three times faster than lower-exposure comparators (+24.9% versus +8.1%), matching the augmentation-versus-substitution logic of the exposure literature (Felten et al., 2021; Gmyrek et al., 2023, 2025) and the robot-substitution baseline (Acemoglu & Restrepo, 2020). The qualification is that realised employment reflects more than AI: the weak growth of finance points to the automation of routine back-office tasks, but the strong growth of health and social work reflects population ageing, and agriculture's decline is a long-run structural trend. Sectoral outcomes thus embed AI-related task effects together with demography, the business cycle, and structural change.

Two conclusions cut across the three hypotheses. The first is that the digital, green, and sectoral transformations are not separate phenomena but expressions of a single re-organisation of work around a common digital-analytical core. The same technical and cognitive skill base that drives the rise of ICT specialists (H1) also conditions the expansion of green employment (H2) and shapes which sectors grow and up-skill (H3). This is why the 'competition' between the digital and the green transition that the introduction posed as an open question is, on the evidence, better understood as a coupling: the two transitions draw on overlapping competencies and advance together rather than at each other's expense.

The second conclusion is that the binding constraint throughout the EU data lies on the supply side. Specialist demand, recruitment difficulty, and hybrid green-and-digital roles are all rising faster than the population's skills are adjusting, even on the most recent figures roughly four in ten adults still lack basic digital skills. The central labour-market risk identified by this paper is therefore not mass technological unemployment but a widening and persistent skills gap, whose distributional edge is sharp: the ILO's estimates show that exposure to generative AI is concentrated in higher-income countries and, within them, disproportionately in jobs held by women (Gmyrek et al., 2025). The transformation is real, but its costs and benefits are unevenly distributed.

These findings carry direct implications for policy. First, education and training systems should treat digital, green, and AI-complementary competencies as a single, integrated agenda rather than as competing priorities, embedding them across curricula rather than confining them to specialist tracks. Second, because employers increasingly hire on the basis of demonstrable skills and place less weight on formal degrees (Bone et al., 2025), credentialing should move towards modular, stackable, and verifiable qualifications, backed by genuine lifelong-learning infrastructure that reaches adults already in the workforce, the group least served by initial education. Third, active labour-market policy should be sector-differentiated: reskilling effort should be concentrated where substitution pressure is greatest (routine back-office and clerical roles in finance and administration, and routine manufacturing), while capacity is scaled in the expanding analytical-technical and care sectors. Fourth, the coupling of the two transitions argues for aligning green-transition and digital-skills strategies within a single 'just and twin transition' framework that anticipates the distributional effects across genders, regions, and levels of development. For transition economies such as Serbia, where the competitiveness and inclusiveness of the labour market depend on the timely adjustment of skills, the priority is to close the digital-skills gap early and to build the green-digital hybrid competencies on which future employment will increasingly rest.

The conclusions must be read against the study's limitations. The official statistics measure employment stocks and skill supply, not the causal effect of AI as such; the observed movements are consistent with, but do not prove, an AI-driven mechanism, and they embed non-AI structural forces. Several data caveats also apply: the EU digital-skills series has a break in 2021, EGSS employment is measured in full-time equivalents while total employment is in persons, the most recent observations are partly provisional, and the EU-27 aggregate conceals substantial cross-country heterogeneity. Because the diffusion of generative AI accelerated only after 2022, much of its labour-market imprint post-dates the available series and remains to be measured.

Three avenues for future research follow. First, causal, worker- and firm-level designs, of the kind pioneered on matched administrative data, are needed to separate

the AI-specific effect from general digitalisation and from structural change. Second, task-level tracking as generative AI diffuses would test whether the augmentation regime documented here persists or gives way to greater substitution among cognitive occupations. Third, the measurement of green-digital skill complementarity, through richer occupational taxonomies (ESCO/O*NET), and targeted country case studies, including transition economies, would ground the twin-transition thesis in the specific institutional and educational contexts where policy is made.

The evidence assembled in this paper supports a clear overall proposition: artificial intelligence is not primarily eliminating work but recomposing it, reorganising the labour market around a digital, analytical, and increasingly green skill core, and doing so unevenly across sectors and social groups. Whether this recomposition proves inclusive or divisive will depend less on the technology itself than on the speed and equity with which education and labour-market institutions adjust the supply of skills. That, rather than the question of how many jobs AI will destroy, is the decisive policy challenge of the coming decade.

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