



From execution to judgement: Reconfiguring higher education policy and outcome-based education for the integration of youth in the GenAI economy

Carlos L. Guardiola Ortuño* , TecnoFor, Spain (cguardiola@gmail.com)

*Corresponding author

Abstract

The emergence of generative artificial intelligence (GenAI) has substantially reshaped corporate processes, organisational structures, and human capital requirements, specifically impacting entry-level roles. This research uses a methodology that integrates four international frameworks: ISCO-08, O*NET, JRC-Eurofound, and CEDEFOP, to propose an original ‘Four Axes Task and Job Classification Framework for Entry-Level Profiles’ (Cognitive Complexity, Digital Intensity, Autonomy, and Social Dimension). By deconstructing jobs into tasks, the study identifies how GenAI increasingly automates routine cognitive activities, such as information processing, report drafting, and error debugging, that traditionally served as foundational training for recent grads. To assess task exposure and substitutability, this research maps entry-level vacancies from leading job portals against the proposed framework using a structured coding approach. Findings are then compared with international labour market reports to contrast theoretical expectations with observed corporate outcomes.

The analysis reveals emerging barriers to youth employment. First, a ‘Seniority Bias’, meaning that companies prefer experienced professionals to manage AI outputs over hiring juniors. Second, the automation of entry-level tasks eliminates the ‘training phase’ incentive, as the marginal cost of AI subscriptions and token consumption is significantly lower than the cost of on-the-job training. Finally, a ‘triple transmission-belt’ effect shows a chronological decoupling between fast technological innovation, the pace of corporate adoption, and slower university curricular updates.

The study concludes that, within an outcomes-based education approach, the value proposition for recent grads must shift from operational execution to strategic judgement and supervision. To remain relevant, higher education must address the gap created by the automation of traditional entry-level jobs, nurturing ‘New Collar’ specialists capable of using critical thinking to validate algorithmic outputs.

Keywords: Artificial Intelligence, generative artificial intelligence, digital transformation, labour market, productivity, professional competencies, youth employment

1. Introduction

While European youth employability has partially recovered from the pandemic shock, structural fragilities persist in the education-to-employment transition. These vulnerabilities are evident in youth unemployment rates and the prevalence of NEETs—those Not in Education, Employment, or Training. In October 2025, unemployment among individuals under 25 stood at 15.2% in the EU. Although this reflects significant national heterogeneity and cohort-based segmentation,¹ it remains considerably lower than the 2020 pandemic peak. By 2024, the NEET rate for the 15–29 age bracket was 11.0% across the EU, rising to 14.6% for those aged 25–29, the average for university graduates to enter the labour market.²

Within this landscape, the deployment of generative artificial intelligence (GenAI) tools has transitioned from gradual to mass adoption since the November 2022 launch of OpenAI’s ChatGPT. The integration of GenAI into corporate operations is not a marginal trend; market evidence suggests rapid uptake driven by strategic corporate commitments and massive venture capital investment. Firms are using accessible GenAI integration via productivity suites (Microsoft Copilot, Google Gemini), software development environments (Cursor, GitHub Copilot), automation platforms (n8n, Make), and multimedia tools (Adobe Firefly, Midjourney), among others. According to McKinsey, 79% of 1,993 surveyed companies globally use GenAI (McKinsey, 2025), while a Joint Research Centre study estimates that 30% of European

employees incorporate GenAI into their workflow (Gonzalez Vazquez et al., 2025).

Historically, new technologies contributed to job displacement. The automation of specific tasks required specialists to upskill, while simultaneously driving net employment growth by increasing demand for professionals proficient with new tools (Acemoglu & Restrepo, 2019). The digital transformation of the banking sector serves as a pertinent example and can be illustrated with the case of Banco Santander and BBVA—consistently ranked in the top three banks in Spain. Since the mid-2010s, the shift toward online self-service models rendered traditional, branch-heavy growth strategies less profitable. Spain reached a peak of over 45,000 bank branches in 2008, a figure that dropped to 17,239 by 2025 (Arbeloa et al., 2025). However, institutions like those mentioned expanded their workforces during this period. In Santander's case, the entity had 170,961 employees and 13,390 branches according to its 2008 annual report (Santander, 2008), compared to 201,304 employees in the third quarter of 2025 and 7,389 branches, representing a staff increase of 17.75% and a decrease in the number of branches of 44.82% (Santander, 2025). On the other hand, BBVA had 111,936 employees and 7,787 branches in 2008 (BBVA, 2008), rising to 126,997 employees and 5,657 branches, respectively, in the third quarter of 2025, representing a staff increase of 13.45% and a decrease in branches of 27.35% (BBVA, 2025). These examples demonstrate how large entities integrating digital transformation and talent into their strategy have adapted through technology with a positive net employment result.

Parallel to these substitution processes, senior professionals were released through redundancy or early retirement schemes, specifically those whose competencies were no longer valuable to the organisation. Senior employment data reveals a difficult reality, particularly in Spain, where 41.9% of people over 45 are job seekers, and 57% of the unemployed collective exceeds age 45 (SEPE, 2025). While the average unemployment rate for those over 55 in the EU is 4.4%, in Spain it is more than double at 9.56% (SEPE, 2025).

A novelty introduced by GenAI is that the net job increase might be at risk. According to the cited McKinsey report, 32% of surveyed executives believe that AI will lead to workforce reductions. This is consistent with the EY barometer, where 42% of professionals fear AI will render their jobs irrelevant (EY, 2025), and the World Economic Forum, which projects a trend reversal by 2027, estimating a 16% net job destruction due to AI adoption (WEF, 2023). Furthermore, GenAI adoption presents a new challenge: it not only maintains the dynamic of employment transformation combined with the substitution of senior professionals whose skills are no longer required, but could also become a barrier to the incorporation of young professionals. They face the automation of tasks typically required of recent graduates, while their lack of experience prevents access to other roles.

This research aims to determine if it is necessary to elevate entry-level profiles from operational execution towards superior capabilities in supervision, editing, and judgement. If so, universities must adapt to rapid technological innovation cycles that dictate the transformation of processes and professional capabilities.

To address these systemic challenges, this study investigates the structural reconfiguration of the labour market by posing three fundamental research questions. First, to what extent is the adoption of GenAI reconfiguring professional profiles? Second, how does the automation of routine cognitive tasks, traditionally used as foundational training, impact the employability of recent graduates? Finally, how can higher education institutions detect shifts in market demand and realign their curricula towards the development of emerging competencies?

The term 'disruptive technology' is deliberately avoided in this research, out of respect for the late Professor Clayton Christensen. He characterised disruptive technologies as those enabling pioneers to offer new attributes that the market initially considers irrelevant because they fall short of mainstream expectations. Eventually, these create new categories or markets and become desired by the public. Disruption occurs when dominant companies attempt to update their offerings too late and lose their competitive advantage (Bower & Christensen, 1995). In the case of AI, this definition is clearly not met. It is neither rejected by consumers, who have used AI assistants since Siri's launch in 2011 nor ignored by incumbents.

1.1 Literature Review: A Shift in How AI Impact Is Perceived

The evolution of how society and experts perceive the impact of AI on the labour market has transitioned from a focus on the automation of physical and routine tasks to a profound concern for the reconfiguration of cognitive work resulting from advances in GenAI's reasoning and LLMs. The analysis of these trends identifies the erosion of the initial stages of professional careers (Brynjolfsson, Chandar & Chen, 2025). This perception of impact has evolved through chronological stages, with the launch of ChatGPT in November 2022 serving as a turning point. Three timeframes are considered: the pre-GenAI period, the shock caused by the launch of ChatGPT observed in 2023, and the current phase of relative maturity in late 2025.

1.1.1 AI as a substitute for routine in the pre-ChatGPT era

In the years leading up to the emergence of LLMs, the perception of technological risk was predominantly framed around robotic automation. The consensus was that software advances effectively complemented workers in performing manual tasks that could be reduced to explicit, codifiable rules (Tolan et al., 2021). Examples include RPA (robotic process automation) tools used for invoice accounting or customer centre responses, among others. Technology was also perceived as complementing workers in non-routine tasks requiring complex problem-solving and interactive communication.

During that period, AI was viewed as a source of automation for jobs with a high level of routine and low cognitive or digital load. It was reasoned that it would ultimately increase labour demand, generate net employment, and lead to long-term improvements in job quality—like previous waves of innovation. The main concern resided in the displacement effect, where technology substituted human labour in specific tasks, reducing human contribution to

value. However, analysts considered this would be counteracted by a reinstatement effect in the form of new, cognitively elevated tasks (Acemoglu & Restrepo, 2019). AI and specialised software complemented ‘white-collar’ workers, while the true impact on job destruction was felt by ‘blue-collar’ workers in industrial or agricultural settings. Simply put, cognitive tasks were considered insurmountable limits for automation (Frontier Economics, 2018). This limit was expressed as the ‘Polanyi Paradox’, which conveys the idea that human beings know more about something than what they can explain as rules and processes—thus suggesting that tasks requiring flexibility, judgement, and common sense are intrinsically difficult to automate (Autor, 2015).

During this stage, the polarisation hypothesis suggested that computing displaced mid-skilled jobs (routine tasks), while jobs at the extremes of the distribution, both high-skilled (abstract) and low-skilled (non-routine manual), continued to grow (WEF, 2020). In this context, companies still viewed AI as an emerging technology, often confined to highly specific applications.

1.1.2 The GenAI shock in 2023

The release of ChatGPT at the end of 2022 radically altered perceptions of technology’s impact on employment. In 2023, GenAI was viewed as a qualitative leap due to its unprecedented ability to understand and process human language, articulate knowledge, and generate multiple types of outputs (textual, images, videos, etc.), thereby fully entering cognitive and creative domains for the first time (Alavi & Westerman, 2023). Accordingly, perceived risk shifted abruptly towards high-skilled and high-wage jobs (Department for Education, 2023), previously considered protected by the Polanyi’s Paradox.

Estimates in 2023 suggested a scenario of dual crisis, where technological automation intertwined with the economic aftermath of the pandemic. Analysts and researchers anticipated in World Economic Forum reports an structural change in the labour market, as low and mid-skilled profiles, already at risk of substitution in the previous stage, would face intensified pressure relative to high-skilled roles. The key shift was a new consensus on how tasks related to reasoning, communication, and coordination could become more automatable than many physical tasks (WEF, 2023).

In this context, the standard hypothesis regarding technological change also re-emerged: AI is not only a threat of substitution but also an opportunity for augmentation or enhancement of human work. Early estimates indicated that most jobs and industries were only partially exposed and were more likely to be complemented by GenAI rather than substituted (EY, 2023).

Nonetheless, concern about job loss intensified among workers; according to a PwC survey, 35% of them expressed negative statements of AI impact (PWC, 2023). GenAI began to be perceived as a general-purpose technology capable of transforming organisational structures and business models. The statements of Emad Mostaque (CEO of Stability.ai) in an interview with Peter Diamandis saying, ‘there are no programmers in five years’ (Diamandis, 2023), correspond to this period.

Professor Yuval Noah Harari introduced a particularly interesting perspective at this point. He suggested that job

displacement no longer occurs within the same country or bloc (such as the EU). Instead, globalisation and technological advancement mean that jobs destroyed in Spain, for example, could be reoccupied in India. Therefore, although a net global employment growth effect might occur, a decrease in employment at the country or bloc level could not be ruled out (Harari, 2023).

1.1.3 Maturity, agentic AI, and the seniority bias in 2025

By the end of 2025, perceptions had evolved towards a more nuanced and systemic understanding of technological transformation, particularly with the introduction of Agentic AI—systems capable of acting autonomously, planning complex steps, and making independent decisions. This capability has led experts to argue that the impact is no longer merely a matter of tasks, but one that rewrites the foundational basis of jobs. This is because it not only automates tasks embedded in a role description but also renders that professional description meaningless (Hering & Rojas, 2025).

One of the most salient perceptions in 2025 is the explicit focus, for the first time, on youth employment at the initial stage of careers. Today, AI is considered highly effective at performing routine intellectual tasks typically assigned to junior profiles during organisational entry and training, i.e., activities such as report drafting, sectoral data analysis, document review, or error debugging (Green, 2024). The concern, therefore, is the combination of eliminating the first rungs of the professional ladder with the contraction of the base of the hierarchical pyramid in firms, making it more difficult for young graduates to acquire the experience required to progress to higher roles. By contrast, senior workers, who possess tacit knowledge accumulated through experience, are perceived as less vulnerable to substitution (Hosseini Maasoum & Lichtinger, 2025), as they provide judgement to evaluate the correctness of AI model outputs, review the steps an AI agent has planned, or precisely direct its research tasks.

An interesting theory introduced in 2025 is the concept of *hidden exposure*, defined as the ‘Iceberg Index’ (Chopra et al., 2025). This suggests that visible AI adoption in the technology sector represents only the tip of the phenomenon, while a much larger mass of latent cognitive automation extends across administrative, financial, and professional functions throughout the economy. Estimates suggest that this exposure is significantly greater than what traditional economic indicators can capture, because practical automation diffuses faster than employment reference systems can measure. However, the research already anticipates that 11.7% of labour market tasks are currently automatable (Chopra et al., 2025).

In terms of work organisation, the *platformisation* of regular work has consolidated. The perception is that AI not only automates tasks but also facilitates algorithm-based management, whereby machines, beyond collecting data for monitoring, have become capable of directing and evaluating human performance (Gonzalez Vazquez et al., 2025). This may constitute a source of efficiency and, therefore, productivity gains, but it also poses risks to employee autonomy and the quality of working conditions.

The combination of advances in Agentic AI with evidence from corporate adoption points to a pragmatic reality. Estimates

Table 1: Evolution of expected AI impact on employment (2020–2025). Source: [WEF 2020](#), [WEF 2023](#), [WEF 2025](#)

Reference Indicator	Context 2020	Context 2023	Context 2025
Net Employment Balance	+12 million (global)	Slightly positive	Concern over net destruction
Focus of Automation	Physical and basic administrative tasks	Cognitive and recording tasks	Reasoning, content, and autonomous agents
Critical Skills	Data analysis, resilience	Creative thinking, AI literacy	Agent orchestration, AI literacy (+70% demand)
Corporate Adoption	Incipient (Big Data/Cloud)	75% of companies in progress	88% of companies functionally integrated
Junior Context	Affected by COVID recession	Initial uncertainty in technology and consultancy	Structural barrier; 66% reduction in hiring

for 2025 indicate net employment growth, although there is broad acceptance that a hybrid configuration, where AI executes and humans supervise, will be the end state for many roles ([WEF 2025](#)). The impact of investments in training and reskilling in adapting to this new context should also not be underestimated. [Table 1](#) summarises the forecasts for these three cycles.

Yet those were projections and predictions; now is the time to assess the real impact on the labour market.

2. Methods

By defining a job as an aggregation of objectives, responsibilities, and tasks, this research aims to verify whether GenAI adoption is reconfiguring the professional profiles demanded by the market, with a focus on roles for recent graduates. This requires reviewing the shift from ‘role-based’ to ‘task-based’ job definitions to identify tasks that have become obsolete when GenAI can perform them at a near-zero marginal cost.

The methodological focus on tasks rather than job titles is a deliberate response to the specific nature of generative AI. Because GenAI operates by augmenting or substituting discrete cognitive sub-routines, such as information processing, text elaboration, or data synthesis, its primary impact occurs at the task level. Consequently, traditional ‘role-based’ definitions fail to capture the granular erosion of tasks, more precisely, those ‘training tasks’ that typically justify junior-level employment. Subsequently, the research will investigate how this automation of tasks and the reconfiguration of job roles have impacted employment, both generally and in the specific case of recent graduates.

This article assumes a fundamental analytical distinction between ‘professional roles’ and ‘professional tasks’. Task-based approaches model technological change as substitution and complementarity at the task level within occupations, followed by organisational reallocation ([Sostero, 2025](#)). For clarity, the following terms are used:

1. **Productivity** refers to workers performance, measuring their capacity to produce results over time at a specific cost.
2. **Entry-level roles** refer to positions typically occupied by recent graduates or young people with limited or no experience. For those, productivity is largely inferred from credentials and employability signals (ability to learn, execute, coordinate, and be accountable).
3. **Routine cognitive tasks** are mental activities that are codifiable, repeatable, and structured (e.g., report writing,

data extraction, classification, document completion), distinguishing them from non-routine cognitive tasks, which require situated judgement, social negotiation, responsibility, or decision-making capacity.

4. **Cognitive work** is the set of tasks involving symbolic processing and information (text, data, decisions) whose primary output is applicable knowledge or coordination.
5. **Employability** is a measure of the probability of labour market entry and stability, approximated by indicators such as hiring rates, duration of unemployment, evolution of job vacancies, salary expectations, and others.

This research aligns with the ‘task-based’ tradition pioneered by Autor, Levy, and Murnane ([2003](#)), which posits that technological change reconfigures labour by shifting the demand for specific activities within an occupation. While the model established the foundational routine vs. non-routine dichotomy, this study adopts and expands upon the JRC-Eurofound Task Framework ([Fernández Macías & Bisello, 2020](#)), which is an institutional framework developed and used in the EU Space. It will be used as a primary methodological anchor because it provides the multidimensionality (content, methods, and tools) required to map the exposure of cognitive tasks to AI agents.

2.1 Qualifying entry-level work for recent graduates

The analysis of descriptive frameworks provides the foundations to measure the potential impact of GenAI on those entering the labour market for the first time upon completing higher education. The ambition is to find a description of entry-level jobs based on *tasks* instead of *positions* or *job titles*—as GenAI’s impact occurs precisely at the task level. This evolution primarily responds to the growing complexity of modern work environments, characterised by:

- Professional roles that do not directly match the heterogeneity of tasks.
- Dynamic environments, which combine structural variability in corporate configuration with remote working.
- Globalisation, which delocalises workers from managers and from the end-user or clients for whom the work is performed.

A task-based approach to employment, deconstructing it into its constituent tasks, allows for the study of the impact of technological

Table 2: Summary of international frameworks integrated for the task-based analysis of entry-level profiles

Model	Author	Area	Suitability
JRC-Eurofound	Joint Research Centre (European Commission) and Eurofound (Fernández Macías & Bisello, 2020)	Job content in tasks and exposure to technology	Provides an operational taxonomy of tasks and technological exposure metrics to build axes and compare occupations/entry-level roles in the EU.
ISCO-08	International Labour Organization (ILO) (ILO 2012)	International standard classification of occupations	Provides the common language to standardise occupations, allowing for comparability and mapping of entry-level roles.
O*NET	U.S. Department of Labor and National Center for O*NET Development (Peterson et al., 1997)	High-granularity occupational descriptors	Provides micro-detail (tasks and capabilities) to operationalise the axes of cognitive complexity and digital/tool intensity, useful for inferring GenAI exposure by task type.
CEDEFOP	EU Agency (cedefop.europa.eu)	Information to measure the digital intensity of tasks	Provides evidence on skills demand (including digital) and training-labour market mismatch, reinforcing the argument of university-market decoupling and the characterisation of entry-level roles by skill requirements.

changes on the real nature of skilled work. Therefore, the first step consists of verifying whether existing taxonomies that define employment identify exactly what is expected of a recent graduate and how GenAI might render their contribution superfluous (Tolan et al., 2021).

To this end, four international classifications were selected: the JRC-Eurofound Task Framework of the European Commission, the ISCO-08 classification (adapted in Spain as INE CNO-11), the O*NET system of the U.S. Department of Labor, and CEDEFOP intensity metrics.

2.1.1 Epistemological foundations of a task-based approach

A task-based approach considers *tasks* as the minimum unit of job analysis. Within the JRC-Eurofound Task Framework, tasks are defined as discrete pieces of work that require a competence and, when grouped, constitute an occupation (Fernández Macías & Bisello, 2020). This allows for the deconstruction of employment into dimensions that transcend the sector of activity, educational background, or years of experience. Instead, the focus is placed on what workers do, how they perform it, the tools they use, and their contribution to an organisation’s productive cycle. This European framework specifically indicates market acceptance of competence specialisation by tasks as a more accurate measure of potential impact on success than traditional views—based on educational background and degree achieved (Fernández Macías & Bisello, 2020).

The need for integrating diverse frameworks responds to a dual priority: first, to categorise what is accepted in the market as cognitive work and how inexperienced and experienced cognitive work differ. Second, to unify a criterion to identify the nature of jobs offered to university graduates upon their entry into the labour market. As seen in Table 2, ISCO-08 provides a statistical hierarchy for international comparability; O*NET offers descriptive granularity on tasks understood as work activities; JRC-Eurofound Task Framework provides the theoretical classification basis for tasks according to the object they operate on (ideas, things, or people)—something essential for differentiating the cognitive from the physical workload in graduate jobs; and CEDEFOP provides a scale of digital intensity³—allowing the assessment of how feasible the impact is on the substitution of people by systems.

2.1.2 Physical tasks and cognitive tasks

The JRC-Eurofound Task Framework decomposes jobs into tasks with three basic dimensions: the content of the task (including purpose), the way in which this task is organised, and the tools necessary to carry it out. This classification is significant, as it allows for the identification of GenAI’s preliminary impact on the employment of recent graduates—depending on whether the impact is technical, organisational, or cognitive. Unfamiliarity with corporate tools or processes is not a priori an obstacle for candidates, as onboarding programmes based on best practices typically address these knowledge transfers (Díaz-Muñoz & Andrés-Reina, 2024).

Therefore, the key lies in the cognitive aspect. JRC-Eurofound defines task content by the type of processing and the objects involved: physical tasks operate on material objects, intellectual tasks on ideas, and social tasks on interpersonal relationships (Fernández Macías & Bisello, 2020). Entry-level jobs for recent graduates may involve all three; however, GenAI’s primary impact is on the cognitive task (Abendroth-Dias et al., 2025). Indeed, intellectual tasks are defined by activities such as processing or elaboration of information, problem-solving with different levels of complexity, planning, or learning. The framework also integrates a series of indicators to quantify these tasks, capturing their frequency and relative difficulty based on accessing and elaborating documentation, performing calculations, applying mathematical or scientific knowledge, etc. These activities coincide with the capabilities demonstrated by consumer-level tools⁴ such as ChatGPT, Google Gemini, or Perplexity, which operate following user prompts (Green, 2024).

Regarding the other two dimensions, physical and social, they must not be excluded from the tasks associated with recent graduates. Physical tasks are particularly relevant, as, although traditionally associated with manual labour, many entry-level professions for individuals with studies in engineering, health sciences, or natural sciences incorporate a significant physical component. In JRC-Eurofound Task Framework, physical content is categorised into three levels:

- 1. **Strength** tasks, referring to the capacity to exert physical energy to manipulate loads and people.

2. **Dexterity** tasks, referring to the ability to perform precise and coordinated movements.
3. **Navigation** tasks, referring to the ability to move objects or oneself in unstructured or dynamic spaces.

2.1.3 Physical or digital tools to measure digital intensity

The classification of tools used to perform tasks allows for the categorisation of the *digital intensity* of a role. While JRC-Eurofound Task Framework considers non-digital machinery to include hand tools and industrial equipment, digital tools comprise computing and communication equipment and specialised software. Crucially, the entire digital transformation process experienced during the first decades of the 21st century has impacted the content of tasks even in traditionally manual occupations, such as physiotherapy or dentistry. This is to the extent that, no matter how routine a task is, digital intensity has increased—even if only in the mediation between operator subject, in reporting, or monitoring. This implies that GenAI and automation tools can assume digital support and elementary mediation functions that complement essentially manual tasks (Abendroth-Dias et al., 2025). Thus, considering CEDEFOP framework further allows for the measurement of the digitalisation level of tasks. The digital intensity indicator adopts three values:

1. **Basic level.** Use of common tools frequently used in non-work environments, such as internet browsing, email, basic text drafting, presentations, and simple spreadsheets.
2. **Intermediate level.** Includes working with complex spreadsheet functions (charts, macros, pivot tables, advanced formulas), or handling sector-specific solutions like accounting software, multimedia editing, or project management programmes.
3. **Advanced level.** Includes database tools, programming environments, cloud platforms, graphic design, etc.

This intensity gradient is fundamental for classifying the tasks involved in the employment of recent graduates. For example, a

graduate in Economics or Business Administration in a junior analyst role will be affected by a medium digital intensity, whereas a Computer Science graduate in a DevOps department will use advanced environments. This intensity classification allows for contrasting, on the one hand, the level of AI impact on the task: the simpler it is, the easier it is to incorporate GenAI solutions. On the other hand, it allows for assessing the adequacy of the education received: the greater the digital intensity introduced in the curriculum, the better prepared the students will be.

2.1.4 Depth of work activities

O*NET Content Model (Peterson et al., 1997) allows for a deeper analysis of the theoretical framework of GenAI's impact on the work of recent graduates. This system is proposed by the U.S. Department of Labor and organises occupational information into domains describing job characteristics and worker competencies with over 2,000 detailed activities, grouped into 41 generalised work activities (GWAs). For differentiating between physical tasks, threatened by robotisation, and cognitive tasks, threatened by GenAI, this is a relevant analytical framework. For instance, under the category 'Mental Processes', O*NET identifies tasks such as data analysis, understanding information, problem-solving, creative thinking, etc. The relationship between GWAs and JRC-Eurofound tasks seems clear. In the physical domain, O*NET also includes descriptors on the context in which the work occurs, or the requirements of the workers, including equivalences for fine manipulation, its frequency, the need for balance, or limb coordination.

Table 3 shows a classification of some entry-level jobs using the equivalence of the two models to prove the feasibility of mapping equivalences. This enables the research to link GenAI's impact on employment while providing the foundations to validate whether low-intensity intellectual tasks are being massively substituted, thus depriving recent graduates of entry-level employment.

However, it is possible to include one more category to broaden the scope of the classification.

Table 3: Classification of selected entry-level jobs for recent graduates

O*NET Domain	JRC-Eurofound Model	Examples of Entry-Level Jobs for Recent Graduates
Mental Processes	Intellectual Tasks	Data Analysis Market Research Business Consulting Medical Diagnosis Software Design and Development Creation of Advertising Campaigns
Interacting with Others	Social Tasks	Customer Service Sales Team Management Teaching Care Public Relations
Physical Activities	Physical Tasks	Fieldwork Industrial Work Factory Work Physiotherapy Healthcare Work

2.1.5 Occupational structure and autonomy

A third method for classifying employment resides in the occupational structure that aggregates tasks towards the definition of a job position, which is ultimately published on a job portal as an open vacancy. Vacancies serve as the nexus where employers and applicants connect in the labour market. The International Standard Classification of Occupations, ISCO-08, organises professions according to the required level and specialisation of competencies. The concept of competence level does not refer solely to formal qualification but is defined as a correlation between complexity, job responsibilities, and required experience. Levels 3 and 4 (ILO, 2012) are the most relevant within the scope of this research:

- 1. **Competence level 3** represents applied and procedural technical specialisation. It involves the application or control of operational processes and requires theoretical, factual, and technical knowledge in a specific area; however, employees at this level require supervision from higher-level professionals. It includes the capacity to present reports and results and to interact with people through teamwork or service provision. These roles typically require 1 to 3 years of training after secondary education, and professional experience is accepted as potentially equivalent to formal education.
- 2. **Competence level 4** represents a higher degree of technical and functional complexity. Performance at this level demands problem-solving, decision-making, and creative capacity based on knowledge and experience. Generally, it requires a period of study at higher education institutions of between 3 and 6 years, equivalent to bachelor's or master's degrees. It also includes the ability to interpret complex texts and communicate sophisticated ideas through written or oral means.

ISCO-08 links the competence level to the complexity of tasks; for recent university graduates, the most relevant groups are Group 2 (scientific and intellectual professionals, associated with Level 4) and Group 3 (technicians and associate professionals, requiring Level 3). In Spain, this framework is adapted as CNO-11,⁵ maintaining the same hierarchical and pyramidal structure. This allows for the translation of specific occupations in sectors with a different granularity, such as Management (1), a whole branch like computer science (27), or a profession like economist (2810).

2.1.6 Finding job openings

A final consideration involves how active job seekers engage with vacancies. An examination of a sample of five leading job-search portals in Spain selected by website traffic data available⁶ shows that each platform has adopted a different approach to search features and filtering criteria, guided primarily by user-experience considerations. As shown in Table 4, educational attainment, field of study, and previous experience are not consistently included as available filters for results, meaning these descriptors might not be relevant to finding a job.

2.2 The impact of artificial intelligence on the labour market

Sectoral data reveals a complex and, in many respects, contradictory reality. When different regional contexts are considered, the realised impact of AI on employment appears unequal and variable, depending on the source analysed.

Globally, the World Economic Forum refines its estimates towards 2030, projecting a scenario of high dynamism but also substantial friction. The most recent data points to the creation of 170 million jobs, mainly driven by digitisation and information processing, versus the disappearance of 92 million (WEF, 2025). This would imply a net increase of 7% in formal global employment. Nevertheless, this optimism is tempered by the fact that these figures imply a structural rotation of the labour market of 22%, meaning that one in five current jobs will undergo drastic changes. This indicates that the reconfiguration of job roles through the redefinition of tasks is a reality.

Other sources, such as Goldman Sachs, suggest that the task-level impact could be more profound, estimating that 18% of work globally could be automated (Briggs & Kodnani, 2023). This displacement, however, is framed as a productivity driver that could raise global GDP by 7% annually in the long term, assuming that displaced workers are reintegrated into new occupations arising from the technology itself.

The US labour market offers immediate data on how AI is beginning to filter the workforce. Data based on ADP payroll records show that, since the massive adoption of GenAI, workers in the initial stages of their careers (22–25 years old) in highly exposed occupations have suffered a relative 13% drop in their employment. In contrast, roles for senior workers in these same sectors have remained stable or have even grown (Brynjolfsson, Chandar & Chen, 2025).

Table 4: Comparative analysis of search features and filtering criteria across leading job portals

Site	Main Search Feature	Educational Background Filters	Years of Experience Filters
Glassdoor.es	Natural Language Search and Location	No	Yes
Indeed.es	Natural Language Search and Location	Yes	No
Infojobs.net	Natural Language Search and Location	Yes	Yes
Randstad.es	Natural Language Search	No	Yes
LinkedIn Jobs	Natural Language Search and Location	No	Yes

In the European Union, attention shifts to the *platformisation* of work and the transformation of specific sectors. One third of European workers already use AI tools for their daily tasks, with particularly high adoption in Denmark, Belgium, and the Netherlands. JRC research indicates that, so far, AI has not significantly reduced employment in large European companies but has increased productivity, especially in the service sector (Abendroth-Dias et al., 2025).

However, critical warnings do exist. Morgan Stanley analysts have warned that the European banking sector could face the loss of up to 200,000 jobs by 2030 due to AI and branch closures. Estimates suggest that the sector could cut 10% of its workforce in the next four years, primarily affecting central services, compliance, and risk management divisions.⁷ Institutions such as ABN Amro have already announced⁸ plans to cut 25% of their staff over the next three years, citing cost-saving and digitalisation measures.

Analysis of the Spanish market shows one of the clearest gaps between the ‘risk of disappearance’ and ‘effective creation’. According to Randstad Research, the adoption of GenAI in Spain will lead to a net loss of approximately 400,000 jobs over the next decade (Randstad, 2024). Nevertheless, contrasting projections with reality, data from the joint research⁹ by Adecco Group and Infoempleo indicate that 89.6% of Spanish companies report that AI has not yet had a significant impact on their workforce, either in hiring or in layoffs. There is, however, latent concern, as 74% of Spanish workers believe that companies will ultimately require fewer staff in the long term due to this technology.

Despite these points of tension, consultancies such as Oxford Economics¹⁰ caution against the narrative of AI-driven mass layoffs—which may be obscuring a justification for corporate restructurings aimed at increasing net profits. According to their reports from early 2026, in the first eleven months of 2025, only about 55,000 layoffs in the United States were directly attributed to AI, representing barely 4.5% of the total registered, compared with over 245,000 cuts linked to traditional market conditions. This suggests that, for the moment, AI functions more as a factor reconfiguring future hiring, constraining the entry of junior profiles, than as a tool for immediate mass layoffs.

Taken together, this indicates that AI is redefining professional positions through task reconfiguration. The variability of the data arises because most studies measure ‘exposure’ or ‘potential’,

rather than realised ‘outcomes’, which depend on each firm’s strategy, regulation, and employees’ abilities. Even so, Table 5 summarises the main figures published by research sources on expected job creation and destruction.

However, although these are analysts’ expectations, market reality, published as press releases from corporate sources, suggests job destruction in internationally prominent organisations. Table 6 compiles press reports linking AI to job destruction, citing corporate sources:

3 Results

3.1 Four-axes task and job classification framework for entry-level profiles

As a result of integrating different task-classification frameworks, this research proposes a multidimensional model that classifies job descriptions available to recent graduates. The model uses the following axes:

- **Axis X. Cognitive complexity and task content.** This axis measures the transition from purely physical to intellectual tasks. It draws on the JRC’s content taxonomy and the GWA descriptors from O*NET.
 - Low level: predominance of physical navigation and strength tasks.
 - Medium level: combination of physical dexterity and information processing.
 - High level: predominance of intellectual problem-solving and planning tasks.
- **Axis Y. Tool sophistication and digital intensity.** Based on CEDEFOP and the JRC’s tool dimension, this axis rates the role’s technological dependence.
 - Non-digital: jobs where physical machinery or manual tools are used.
 - Basic digital: communication tools and simple word processing.
 - Advanced digital: employment of complex sectoral software, programming, and mass data management.
- **Axis Z. Autonomy and organisational method.** This axis reflects the quality of the graduate’s labour integration, using JRC autonomy indicators and O*NET cognitive supervision requirements.

Table 5: Expected impact of job destruction

Source	Scope / Horizon	Job Creation	Destruction / Risk	Net Result
WEF (2025)	Global (2030)	170 million	92 million	+78 million
WEF (2023)	Global (2023–2027)	69 million	83 million	–14 million
Randstad Research	Spain (10 years)	1.61 million	2.00 million	–400,000
Oxford Economics	USA (Nov 2025)	n/a	55,000 (attributed)	Neutral (AI as excuse)
Morgan Stanley	European Banking (2030)	n/a	212,000 (risk)	Negative (projection)
McKinsey	Organisations (2025)	13% of companies	32% of companies	Negative (perception)
Goldman Sachs	Global (Long term)	Redistribution	18% of total work	Positive (in GDP terms)

- Routine work: repetitive tasks with defined processes, constant supervision, and zero decision-making capacity.
- Autonomous work: capacity for self-regulation of work pace and content.
- Direction of others: capacity for self-autonomy and management of others' work.
- **Axis W. Social dimension.** This last axis complements the model by including human interaction, drawing from JRC model, which defines these as tasks that operate on people and relationships. O*NET provides fundamental descriptors for graduates in service, education, and management areas; often, this social dimension constitutes the 'non-routine' component that shields skilled jobs from mechanical automation. Its relative weight in a recent graduate's role allows for distinguishing high-interaction profiles from isolated technical profiles. It is operationalised through two components:
 - Interpersonal skills: difference between basic communication and elevated skills such as persuading, negotiating, or mentoring.
 - Social interaction: related to activities of selling, influencing, assisting, and caring for others.

The rationale for selecting the specific analytical categories (X, Y, Z, and W) is grounded in the necessity to move from a 'role-based' to a 'task-based' approach, as GenAI's impact occurs precisely at the unit level of tasks. The resulting model integrates the statistical structure of ISCO/CNO with the descriptive depth of O*NET and the conceptual basis of JRC–Eurofound and CEDEFOP.

Specifically, Cognitive Complexity (X) and Digital Intensity (Y) are essential to measure the substitutability of 'Routine Cognitive Tasks' that GenAI now performs at near-zero marginal

cost. Autonomy (Z) is crucial to identify the 'Seniority Bias', as it highlights how the reduction of supervised tasks, typically assigned to juniors, creates a structural barrier to entry. Finally, the Social Dimension (W) is included as it identifies the 'Social Shielding' that protects high-interaction roles from mechanical automation. By integrating these dimensions, the model provides a more granular and multi-faceted diagnostic tool than traditional job titles alone, capturing the reality of human-AI competition in entry-level positions.

This model goes beyond the labels traditionally associated with job vacancies for recent graduates and complements job definitions by incorporating the reality of cognitive effort, manual dexterity, technological mastery, operational freedom, and the need to interact with others.

Furthermore, it directly supports outcome-based education (OBE) by providing a precise taxonomy to define what graduates can do in the emerging GenAI economy. A proper OBE approach places students at the centre of the learning process while ensuring alignment with labour-market relevance and the achievement of clearly specified competencies (Tam 2014).

The framework contributes to this goal in two ways. First, it strengthens constructive alignment by identifying the routine cognitive tasks that are increasingly automated by GenAI. This enables universities to shift learning outcomes away from purely operational execution towards higher-level capabilities such as judgement, oversight, and supervision, thereby reinforcing the principle that educational activity should be directed towards clear and meaningful ends. Second, it facilitates curriculum development and improvement by allowing academic programmes to be mapped against its classification axes. This makes it possible for curriculum designers and programme leads to develop validation checklists and to benchmark learning outcomes against a shared reference framework of occupation.

Table 6: Empirical evidence of AI-linked job cuts: Corporate outcomes reported in media (2024–2026)

Company	Professionals Affected	Source
Accenture	1,100	Financial Times, 25th September 2025
Alphabet (Google)	1,000	Business Insider, 16th January 2024
Amazon	30,000	Reuters, 27th October 2025
BT Group	55,000	The Guardian, 15th June 2025
Cisco	5,900	Reuters, 15th August 2024
Dell	12,000	Reuters, 26th March 2025
IBM	8,000	The Wall Street Journal, 6th May 2025
Klarna	3,000	BBC, 28th August 2024
Meta	1,000	Bloomberg, 13th January 2026
Microsoft	15,000	Fortune, 2nd July 2025
Salesforce	4,000	CNBC, 2nd September 2025
SAP	8,000	Reuters, 24th January 2024
UPS	48,000	The Wall Street Journal, 28th October 2025

Table 7 presents a sample of entry-level jobs with no experience required, targeting graduates, obtained from job offers at [Glassdoor.es](#),¹¹ [Indeed.es](#),¹² [Infojobs.net](#),¹³ [Randstad.es](#),¹⁴ and [LinkedIn Jobs](#)¹⁵ during December 2025, along with their classification following the proposed classificatory model.

To ensure transparency and replicability in the analytical procedure, a systematic coding strategy was applied to classify the entry-level roles within the Four-Axes Framework. For Axis X (Cognitive Complexity), roles were coded as ‘High’ when their primary GWAs align with O*NET’s ‘Mental Processes’ and JRC-Eurofound’s descriptors for intellectual tasks. For Axis Y (Digital Intensity), assignments followed the CEDEFOP three-tier scale: ‘Basic’ for general productivity tools, ‘Intermediate’ for sector-specific software, and ‘Advanced’ for roles requiring

programming or complex data management environments. Axis Z (Autonomy) was coded by cross-referencing ISCO-08 competence levels; ‘Routine’ corresponds to Level 3 tasks requiring constant supervision, while ‘Supervised Autonomous’ aligns with Level 4 tasks involving independent decision-making. Finally, Axis W (Social Dimension) used O*NET interpersonal descriptors, where ‘High’ identifies roles where social negotiation, persuasion, or mentoring are core professional requirements rather than incidental activities.

This multidimensional approach anticipates complex phenomena such as the routinisation of intellectual work, or the mismatch between technological training and the actual use of digital tools in the workplace. The model accounts for three trends:

Table 7: Multidimensional mapping of a sample of entry-level jobs into the four-axes task and job classification framework (December 2025)

Entry-Level Job	X Cognitive Complexity	Y Digital Intensity	Z Autonomy	W Social Interaction
Chemical Lab Technician	Medium	Basic Digital	Routine	Basic
Civil Engineer	Medium	Advanced Digital	Routine	Basic
Clinical Pharmacist	High	Basic Digital	Supervised Autonomous	High
Clinical Psychologist	High	Basic Digital	Supervised Autonomous	High
Copywriter / Content Writer	High	Basic Digital	Supervised Autonomous	High
Cybersecurity Analyst	High	Advanced Digital	Routine	Basic
Data Journalist	High	Advanced Digital	Autonomous	High
Elementary School Teacher	High	Basic Digital	Autonomous	High
Financial Auditor	High	Advanced Digital	Routine	Basic
HR Professional (Recruitment...)	Medium	Basic Digital	Supervised Autonomous	High
Industrial Engineer	Medium	Basic Digital	Routine or Supervised Autonomous	Medium
Journalist	High	Basic Digital	Autonomous	Medium
Junior Business Analyst	High	Advanced Digital	Supervised Autonomous	High
Junior Consultant	High	Basic Digital	Supervised Autonomous	High
Junior Data Analyst	High	Advanced Digital	Supervised Autonomous	Basic
Junior Financial Analyst	High	Advanced Digital	Supervised Autonomous	High
Junior Project Manager	Medium	Basic Digital	Direction of Others	High
Lawyer	High	Advanced Digital	Routine	High
Logistics Coordinator	Medium	Advanced Digital	Routine	High
Mechanical Engineer	High	Advanced Digital	Routine or Supervised Autonomous	Basic
Medical Resident	High	Basic Digital	Supervised Autonomous	High
Nursing	Medium	Basic Digital	Supervised Routine	High
Secondary School Teacher	High	Basic Digital	Supervised Autonomous	High
Shift Supervisor	Medium	Basic Digital	Direction of Others	High
Social Worker	High	Basic Digital	Supervised Routine	High
Software Developer	High	Advanced Digital	Supervised Autonomous	Medium
Technical Architect	Medium	Advanced Digital	Routine or Supervised Autonomous	Medium
UX/UI Designer	High	Advanced Digital	Supervised Autonomous	High

- **Social shielding trend.** Profiles such as Nursing or Social Work, which at the entry stage carry a heavy load of protocol adherence under supervision, exhibit a very high social dimension. Given their low digital intensity, digital tools are typically a complementary monitoring instrument; these roles are highly resistant to automation.
- **Digital bottleneck trend.** Disciplines such as Architecture or Civil Engineering at junior levels are often concentrated in the high digital intensity quadrant but remain subject to strong regulatory constraints or senior supervision. In this setting, GenAI may have the greatest impact, as the recent graduate largely operates as a tool user.
- **Autonomy trend.** Notably, healthcare professions (Doctor/ Psychologist) and teaching roles grant high autonomy, despite residency or supervision, much earlier than corporate professions, where organisational method is strictly hierarchical and routine in the early year.

3.2 Impact of GenAI on the employment of recent graduates

The United States has been the epicentre of GenAI implementation, and it is where the most immediate effects on hiring structures are observed. By the end of 2025, the US labour market shows contradictory signals: while the overall economy adds jobs, the technology sector and professional services are undergoing substantial restructuring directly linked to AI (Brynjolfsson, Chandar & Chen, 2025; Chopra et al., 2025). The situation for graduates from the 2024 and 2025 cohorts is particularly complex. The unemployment rate for young university graduates aged 20 to 24 stood at 9.5% in September 2025, doubling the general adult unemployment rate (4.3%) (Hosseini Maasoum & Lichtinger, 2025). In fields highly exposed to AI, such as basic software engineering and analytical support, employment for early-career employees has fallen by 13%. At the same time, employers are raising the entry threshold; 66% of companies admit to having reduced the hiring of junior profiles because AI now performs the support tasks that previously justified these positions. Furthermore, there is a perception of technological blockage in recruitment, with 73% of applicants reporting the feeling that AI-based candidate filtering systems automatically discarded their applications due to how they measure position matching, with no option for a first interview (Brynjolfsson, Chandar & Chen, 2025; Hosseini Maasoum & Lichtinger, 2025).

The European Union shows a pattern marked by regional disparity and a regulatory framework (the EU AI Act) that attempts to balance innovation with job protection. In 2025, 20% of EU companies use some form of AI, a notable increase compared with 8.1% in 2023 (Abendroth-Dias et al., 2025). Notably, in 2025, AI is being used for management tasks; 31% of European companies that use AI employ it for the organisation of administrative processes, a function that traditionally employed many Business Administration or Economics graduates in their first years. Furthermore, 15.1% of EU workers use GenAI tools for daily work, primarily for text drafting and translation, which has boosted

productivity but has also increased stress due to algorithmic surveillance and automated schedule management. The impact on European graduates' labour-market integration is evident in the analysis of employment platforms. Job offers for entry-level profiles fell 45% below their five-year average in the first quarter of 2025 (Hering & Rojas, 2025). This figure is alarming, as it is even lower than the levels recorded during the pandemic lockdown, suggesting that companies prefer to maintain smaller, more senior workforces supported by AI tools, rather than investing in the training of new talent.

Spain occupies an intermediate position in adoption, but with structural vulnerabilities that could amplify AI's substitution effects. In the first quarter of 2025, 21.1% of Spanish companies with more than 10 employees use AI, placing the country slightly above the EU average. This adoption is led by large companies (44%), while micro-enterprises lag (13.4%). The sectors with the highest integration are information and communications (46.6%) and scientific and technical activities (26.1%) (Fernández Cerezo, Hidalgo & Izquierdo, 2025). Despite this adoption, the Bank of Spain points out that 80% of companies believe that AI will not affect their total employment volume in the short term, although those that already use it tend to expect a positive impact on productivity and internal efficiency. For Spanish university students aged 22 to 29, the unemployment rate fell to 12% in 2024, a positive figure compared with previous years, but one that conceals a problem of underemployment and overqualification that AI could aggravate (SEPE, 2025). Although 77.6% of graduates work in positions commensurate with their qualifications, the remaining 22.4% remain trapped in low-skilled roles.

GenAI has proven to be an efficient technology in performing tasks that previously constituted the bulk of a junior employee's or university intern's work, such as taking or summarising meeting minutes, conducting literature searches, accessing data and preparing reports, testing and debugging source code errors, attending to clients, drafting contracts, or generating basic content for social media. As these are among the first tasks to be automated, this implies the elimination of what labour sociologists refer to as 'training tasks'. Without these lower-responsibility duties, companies lose the incentive to hire profiles without experience, since the training cost of a junior employee—previously offset by their routine task contribution—is now higher than the \$30 USD monthly subscription to an AI system that performs those same tasks instantly. This creates a gap in which only experienced profiles capable of supervising AI are demanded, leaving recent graduates in an employability limbo.

3.3 The demand for new collars

Despite the destruction of traditional roles, demand for certain skills is growing at an accelerating pace. Based on vacancies published on its network, LinkedIn estimates that demand for AI literacy increased by 70% between 2024 and 2025 (LinkedIn, 2025). Companies are not only seeking computer engineers but also what are described as 'new collar' professionals or hybrid specialists: people trained in traditional areas (law, medicine, economics) who possess the technical capacity to orchestrate AI agents and

apply critical thinking to validate algorithm results (Klein, 2025; Hosseini Maasoum & Lichtinger, 2025).

Those who possess these skills are receiving a significant wage premium. In 2025, the salary of a professional with proven AI competencies is, on average, 56% higher than that of a colleague in the same position without these skills (WEF, 2025). This wage gap has doubled compared with the previous year (when it was 25%), indicating that the market is aggressively valuing the capacity to augment human work with AI.

Thus, vulnerability to AI does not depend on the level of education but on the nature of the tasks to be performed (Gmyrek et al., 2025). Table 8 covers exposure patterns for different entry-level profiles, according to the classification in the proposed four axes.

Research from cited sources agrees in pointing out that GenAI is becoming a filter that makes access to the first job difficult for recent graduates. The automation of basic tasks previously performed by juniors has caused 66% of companies to reduce their plans to hire entry-level profiles. This does not necessarily mean that employment disappears, but that the first step to entry is slightly higher. Those graduating in 2026 compete not only with other graduates from their cohort but also with a technology that performs their initial tasks at a marginal cost that tends towards zero.

Current evidence suggests that rather than a scenario of job reduction, we are facing a massive reassignment, with the note from Y. N. Harari that this reassignment may not necessarily occur in the same country where the cut took place. As mentioned, the speed of technology incorporation into productive sectors, and its capacity for job transformation, is superior to both the capacity of universities to train professionals and the adaptation of active professionals. The data from 2024 and 2025—following the massive adoption of GenAI in companies—suggest a triple transmission belt engine. There is one speed for the incorporation of technology into the market, another for its adoption within companies, and a third for the adaptation of the education for professionals. Higher education remains valuable, and University graduates have lower unemployment rates than the average (SEPE, 2025), but its

relative value decreases if not complemented by skills in human interaction, autonomy, or technological orchestration—which are those demonstrated to be the foundations of the ‘new collar’.

This growing demand for ‘new collar’ roles requires a strategic realignment within the Triple Helix Model to address the ‘triple transmission-belt’ effect that decouples technological change, corporate adoption, and curricular renewal. In a knowledge-based economy, development arises from the interaction between wealth generation (industry), novelty production (academia), and policy coordination (government) (Leydesdorff, 2010).

Ultimately, for young people aged 24 to 26, GenAI has ceased to be a tool to incorporate or not into their profession as part of the digital intensity of a job. It is the very environment in which they must demonstrate their value. Those who depend on traditional cognitive skills or the certification of their degree will face an increasingly higher barrier to entry and an accelerated risk of obsolescence. The responsibility now falls on educational institutions to close the gap between academic training and the reality of an economy that no longer counts on young people learning on the job—because it is no longer profitable.

4. Discussion and Conclusions

GenAI’s automation of entry-level *training tasks* introduces systemic friction by weakening the traditional pathways through which graduates acquire practical experience, creating structural barriers to youth employment as discussed. Addressing this challenge requires coordinated action across the actors of the Triple Helix (Leydesdorff, 2010). If knowledge functions as a mechanism of coordination, higher education institutions must adapt to the hybrid competencies associated with *New Collar* roles, combining domain expertise with AI orchestration and critical judgement, designing curricula that prioritise strategic judgement over operational ability. Thus, the Four-Axes Task and Job Classification Framework serves as a diagnostic tool to support this alignment, enabling stakeholders to coordinate their functions while sustaining higher education as a bridge between technological transformation and labour-market integration in a Schumpeterian era of *creative destruction* (Leydesdorff, 2010).

Table 8: Exposure of a sample of entry-level professions

Entry-Level Job	X	Y	Z	W	Impact	Explanation	Evidence
Business Analysts	H	AD	S/A	H	High	GenAI performs data consolidation and basic analysis in seconds	The Big 4 consulting firms have reduced their hiring of recent graduates by up to 29% (Business Insider, Aug 2025)
Software Developers	H	AD	S/A	M	High	GenAI’s ability to write code from natural language (vibe coding) reduces the need for programmers in maintenance or monitoring duties	In the UK, offers for recent graduates in STEM profiles fell by 46% (Gov.uk, Jul 2025)
Copywriter / Content Writer	H	BD	S/A	H	High	The Digital Marketing and content writing sector has massively integrated GenAI.	34.7% of companies use GenAI for marketing tasks (Eurostat, Dec 2025)
Cybersecurity Analyst	H	AD	R	B	Low	The demand for expert cybersecurity profiles is growing exponentially	32% growth is projected in this area over the next 5 years (Forbes, Aug 2024).
Nursing	M	BD	S/R	H	Low	GenAI does not impact occupations requiring physical dexterity, empathy, and decision-making in unstructured environments	40% growth is expected for nurse practitioners in the next decade. (Bureau of Labour, Aug 2025).

Until now, professional profiles have typically been defined through a top-down logic: employers specify goals and expected outcomes, which are then operationalised as responsibilities. These, in turn, manifest as tasks, for which specific competencies and levels of specialisation are required, ultimately framed by a descriptive job title, a seniority level, and a remuneration scheme. The adoption of GenAI is, however, rewriting professional profiles bottom-up. By automating and reshaping day-to-day work, GenAI reconfigures job descriptions not from goals or abilities, but from the actual things to do. This forces employers to revise responsibilities, competency requirements, and pay structures when a role becomes partially or wholly empty of content. The more tasks GenAI renders redundant, the greater the likelihood that a professional profile disappears entirely.

The labour market is undergoing this reconfiguration of professional profiles, driven by three core conclusions from this research:

1. **Value shifts from execution to judgement.** Entry-level profiles must be upgraded in value, because recent graduates can no longer base their proposition on tasks that GenAI performs more efficiently and at a lower cost. The graduate's contribution must move from operational execution (drafting, basic code debugging, literature searches...) towards supervision, editing, and strategic judgement. Rather than acting as draft producers, junior profiles must become operators with judgement. Their value increasingly lies in verification, domain knowledge, procedure design (prompts), and operational accountability for machine-generated outputs. The 'new collar' paradigm reflects demand for hybrid specialists who combine traditional training (law, medicine, economics) with the technical capacity to orchestrate AI agents and apply critical thinking to validate algorithmic outputs (Klein, 2025; Hosseini Maasoum & Lichtinger, 2025).
2. **Investment in training junior employees is benchmarked against the marginal licence cost.** One of the most critical conclusions of this research is that GenAI performs particularly well on tasks traditionally assigned to junior employees or interns. As these foundational tasks are automated, the on-the-job training period that has historically been embedded in entry-level roles and considered an investment by companies contracts or disappears. Employers lose the incentive to hire inexperienced profiles because the training cost of a junior employee—previously offset by their contribution to routine tasks—now exceeds the cost of an AI subscription¹⁶ that executes those same tasks instantly. This creates a gap in which only experienced profiles capable of supervising AI are in demand, leaving recent graduates structurally vulnerable if they cannot demonstrate supervision skills from day one.
3. **There is a chronological decoupling between technology–company–university.** The underlying problem can be conceptualised as a triple transmission-belt engine operating at different speeds. The pace at which

new technologies emerge and consolidate outstrips the capacity to define jobs and, subsequently, professions, and to update official curricula. This prevents recent graduates from evidencing competencies aligned with current business requirements. University degrees are insufficient if not complemented by the competencies employers demand and by expertise in the technologies that define market reality: today, GenAI; tomorrow, another system.

Yet how can new capabilities and technologies be integrated into curricula without passing through the certification process required to modify them? A traditional response has been to extend the educational pathway through Short Degrees or Lifelong Learning courses. However, recent evidence from Eurydice's 'The European Higher Education Area in 2024' report suggests this produces three adverse effects. First, it increases the financial burden on students in a context where relative public funding has declined and the 'cost-of-living crisis' directly impacts the EHEA. Second, the proliferation of intermediate programs—often ranging from 60 to 120 ECTS—effectively delays labour-market entry by one or two years. Third, the accumulation of these credentials, which often lack a shared design and clear readability across borders, contributes to overqualification and complicates the transition to employment for recent graduates whose practical experience remains limited (Eurydice, 2024).

The context faced by recent graduates demands more than operational execution based on certified knowledge acquired through a degree. Their ability to join the labour market actively and contribute effectively to the objectives of employing organisations requires evidence of a combination of higher-level capabilities, greater autonomy, and stronger interpersonal interaction with others (colleagues, managers, clients...). The University cannot escape this reality if it is to remain both a custodian of knowledge and a bridge to the labour market. However, two crucial questions remain unresolved: how to cultivate judgement in the absence of substantive workplace experience? And how to gain on-the-job training when, in the first place, access to a job is precisely what is at stake?

Notes

- 1 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Unemployment_statistics#Youth_unemployment.
- 2 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Statistics_on_young_people_neither_in_employment_nor_in_education_or_training.
- 3 <https://www.cedefop.europa.eu/en/tools/skills-intelligence/digital-skills-intensity?year=2021#1>.
- 4 Technologies accessible to the mass consumer are those available for end-users, where neither knowledge nor training are considered criteria to discriminate the market segments they target.
- 5 https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177033&menu=ultiDatos&idp=1254735976614.

- 6 Website traffic data obtained from third party tools: ahrefs.com, semrush.com, and similarweb.com.
 - 7 <https://www.ft.com/content/71e12f85-1edb-4156-8cb5-3fe8aef36d93>.
 - 8 <https://www.reuters.com/business/world-at-work/dutch-bank-abn-amro-cut-5200-jobs-by-2028-2025-11-25/>.
 - 9 <https://www.adecogroup.com/-/media/project/adecco-group/adecogroup/spain-content/2025-press-releases/2025-12-02-ndp-informe-infoempleo-adecco-ia-transformacion-digital.pdf>.
 - 10 <https://fortune.com/2026/01/07/ai-layoffs-convenient-corporate-fiction-true-false-oxford-economics-productivity/>.
 - 11 https://www.glassdoor.es/Empleo/espa%C3%B1a-empleos-SRCH_IL.0,6_IN219.htm?seniorityType=entrylevel.
 - 12 <https://es.indeed.com/jobs?q=&l=Espa%C3%B1a&sc=0kf3Aattr%28QC5F%7CEXSNN%7CHFDVW%252COR%29attr%28VDTG%7%29%3B&from=searchOnDesktopSerp&vjk=d71609f7f35c0a62>.
 - 13 https://www.infojobs.net/ofertas-trabajo?keyword=&educationIds=147,125,150,140,130,120&segmentId=&page=1&sortBy=PUBLICATION_DATE&onlyForeignCountry=false&sinceDate=ANY&experienceMin=_0_YEARS&experienceMax=_0_YEARS.
 - 14 <https://www.randstad.es/candidatos/ofertas-empleo/ex-no-se-requiere-experiencia-previa/>.
 - 15 https://www.linkedin.com/jobs/search/?currentJobId=4359137372&f_E=1%2C2&geoId=105646813&origin=JOB_SEARCH_PAGE_JOB_FILTER&refresh=true&sortBy=R.
 - 16 See for example: <https://openai.com/business/chatgpt-pricing/>, <https://claude.ai/upgrade>, <https://gemini.google/subscriptions/>, <https://github.com/features/copilot/plans>.
- References**
- Abendroth Dias, K. et al. (2025). In E. Navajas Cawood, M. Vespe, A. Kotsev, & R. Van Bavel (Eds.), *Generative AI outlook report – exploring the intersection of technology, society and policy*. Publications Office of the European Union. <https://data.europa.eu/doi/10.2760/1109679>
- Acemoglu, D., & Restrepo, P. (2019) Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Alavi, M., & Westerman, G. (2023). How generative AI will transform knowledge work. *Harvard Business Review*, 7.
- Arbeloa, E. et al. (2025). *La accesibilidad presencial a los servicios bancarios en España: Informe de seguimiento 2024*. Banco de España. <https://doi.org/10.53479/39078>
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: an empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333. <https://doi.org/10.3386/w8337>
- BBVA (2008). *Cuentas Anuales Correspondientes al ejercicio anual terminado el 31 de diciembre de 2008*. Comisión Nacional del Mercado de Valores. <https://www.cnmv.es/portal/consultas/ifa/listadoifa?id=0&nif=A-08188807&lang=es>
- BBVA (2025). *Informe Trimestral 3T25*. BBVA Accionistas e Inversores. <https://accionistaseinversores.bbva.com/informes/informe-3t25-home/>
- Bower, J. L., & Christensen, C. (1995). Disruptive technologies: Catching the wave. *Harvard Business Review*, 73(1), 43–53.
- Briggs, J., & Kodnani, D. (2023). *The Potentially Large Effects of Artificial Intelligence on Economic Growth*. Goldman Sachs Economic Research. <https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html>
- Brynjolfsson, E., Chandar, B., & Chen, R. (2025). Canaries in the Coal Mine? Six Facts About the Recent Employment Effects of Artificial Intelligence. *Digital Economy*.
- Chopra, A. et al. (2025). The iceberg index: Measuring skills-centered exposure in the AI economy. <https://doi.org/10.48550/arXiv.2510.25137>
- Department for Education. (2023). *The impact of AI on UK jobs and training*. Gov.UK <https://www.gov.uk/government/publications/the-impact-of-ai-on-uk-jobs-and-training>
- Díaz-Muñoz, R., & Andrés-Reina, M. P. (2024). Onboarding: Key to perception of the company as a great place to work. *Rect@: Revista Electrónica de Comunicaciones y Trabajos de ASEPUMA*, 25, 21–36. <https://doi.org/10.24310/recta.2024.25.1.02>
- Diamandis, P. (2023, Jun 29th) *Why AI Matters and How to Deal With The Coming Wave* w/ Emad Mostaque / EP #52 Peter H. Diamandis. YouTube https://www.youtube.com/watch?v=ciX_iFGyS0M
- EY (2023). *If AI holds the answers, are CEOs asking the right strategic questions?* EY CEO Survey – July 2025. https://www.ey.com/en_gl/ceo/if-ai-holds-answers-are-ceos-asking-right-questions
- EY (2025). *From concerns to confidence: The workforce's response to AI*. EY European AI Barometer 2025. https://www.ey.com/en_lu/insights/ai/ey-european-ai-barometer-2025
- European Commission / EACEA / Eurydice (2024). *The European Higher Education Area in 2024: Bologna Process Implementation Report*. Publications Office of the European Union.
- Fernández Cerezo, A., Hidalgo, I., & Izquierdo, M. (2025). *La adopción de la inteligencia artificial en las empresas españolas: un primer análisis basado en la EBAAE*. Boletín Económico del Banco de España 2025/T2 06, <https://doi.org/10.53479/39705>
- Fernández Macías, E., & Bisello, M. (2020). A taxonomy of tasks for assessing the impact of new technologies on work. *JRC*

- Working Papers Series on Labour, Education and Economy, European Commission.* <https://publications.jrc.ec.europa.eu/repository/handle/JRC120618>
- Frontier Economics (2018). The Impact of Artificial Intelligence on Work: an Evidence Review. *The British Academy, Digital Society.* <https://www.thebritishacademy.ac.uk/publications/impact-artificial-intelligence-work-evidence-review/>
- Gmyrek, P, et al (2025). Generative AI and jobs: A refined global index of occupational exposure, *ILO Working Paper 140.* <https://doi.org/10.54394/HETP0387>
- Gonzalez Vazquez, I., Fernandez Macias, E., Wright, S., & Villani, D. (2025). *Digital monitoring, algorithmic management and the platformisation of work in Europe.* Publications Office of the European Union. <https://doi.org/10.2760/9406086>
- Green, A. (2024). Artificial intelligence and the changing demand for skills in the labour market, *OECD Artificial Intelligence Papers*, No. 14. <https://doi.org/10.1787/88684e36-en>
- Harari, Y. N. (2023). Mustafa Suleyman & Yuval Noah Harari -FULL DEBATE- What does the AI revolution mean for our future? The Economist. <https://www.youtube.com/watch?v=7JkPWHr7sTY>
- Hering, A., & Rojas, A. (2025). *AI at Work Report 2025: How GenAI is Rewiring the DNA of Jobs.* Indeed Hiring Lab <https://www.hiringlab.org/2025/09/23/ai-at-work-report-2025-how-genai-is-rewiring-the-dna-of-jobs/>
- Hosseini Maasoum, S. M., & Lichtinger, G. (2025). Generative AI as Seniority-biased Technological Change: Evidence From US Resume and Job Posting Data. *SSRN.* <http://doi.org/10.2139/ssrn.5425555>
- ILO (2012). *International Standard Classification of Occupations 2008 (ISCO-08): Structure, group definitions and correspondence tables.* International Labour Organization. <https://www.ilo.org/publications/international-standard-classification-occupations-2008-isco-08-structure>
- Klein, B. (2025). Generative AI and labor market outcomes: Evidence from the United Kingdom. *SSRN.* <http://dx.doi.org/10.2139/ssrn.5516798>
- Leydesdorff, L. (2010). The knowledge-based economy and the triple helix model. *Annual Review of Information Science and Technology*, 44, 367–417. <https://doi.org/10.48550/arXiv.1201.4553>
- LinkedIn (2025). *AI Labor Market Update. Tracking AI adoption and skills in the U.S. economy.* LinkedIn <https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/PDF/ai-labor-market-update-header-sept-2025.pdf>
- McKinsey (2025). *The State of AI in 2025: Agents, Innovation, and Transformation.* McKinsey & Company. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai/>
- Peterson, N. G., Mumford, M. D., Borman, W. C., Jeanneret, P. R., Fleishman, E. A., & Levin, K. Y. (1997). O* NET Final Technical Report. Volume I [and] Volume II [and] Volume III. American Institutes for Research.
- PWC (2023). *Global Workforce Hopes & Fears Survey 2023.* PwC <https://www.pwc.com/gx/en/issues/workforce/hopes-and-fears/hopes-and-fears-2023.html>
- Randstad (2024). *IA y mercado de trabajo en España.* Randstad Research <https://www.randstadresearch.es/ia-mercado-trabajo-espana/>
- SANTANDER (2008). *Cuentas Anuales e Informe de Gestión correspondientes al ejercicio anual terminado el 31 de diciembre de 2008, junto con el informe de auditoría.* Comisión Nacional del Mercado de Valores. <https://www.cnmv.es/portal/consultas/ifa/listadoifa?id=0&nif=A39000013&lang=es>
- SANTANDER (2025). *Informe Financiero 2025. Enero – Septiembre.* SANTANDER Accionistas e Inversores. <https://www.santander.com/es/accionistas-e-inversores/informacion-economico-financiera#resultados-trimestrales>
- SEPE (2025). *Informe del Mercado de Trabajo de las Personas mayores de 45 años. Estatal.* Servicio de Empleo Público de España. <https://www.sepe.es/HomeSepe/es/que-es-el-sepe/comunicacion-institucional/publicaciones/publicaciones-oficiales/listado-pub-mercado-trabajo/informe-mercadotrabajo-estatal-mayores45.html>
- Sostero, M. (2025). Job Tasks in the EU: Implications for Skills and Labour Shortages. *Eurofound research paper, Publications Office of the European Union.* <https://doi.org/10.2806/5581302>
- Tam, M. (2014). Outcomes-based approach to quality assessment and curriculum improvement in higher education. *Quality Assurance in Education*, 22(2), 158–168. <https://doi.org/10.1108/QAE-09-2011-0059>
- Tolan, S., Pesole, A., Martinez Plumed, F., Fernandez Macias, E., Hernandez-Orallo, J., & Gomez Gutierrez, E. (2021). Measuring the occupational impact of AI: tasks, cognitive abilities and AI benchmarks. *Journal of Artificial Intelligence Research*, 71, 191–236. <https://doi.org/10.1613/jair.1.12647>
- WEF (2020). *The Future of Jobs Report 2020.* World Economic Forum. <https://www.weforum.org/publications/the-future-of-jobs-report-2020/>
- WEF (2023). *The Future of Jobs Report 2023.* World Economic Forum. <https://www.weforum.org/publications/the-future-of-jobs-report-2023/>
- WEF (2025). *The Future of Jobs Report 2025.* World Economic Forum. <https://www.weforum.org/publications/the-future-of-jobs-report-2025/>

To cite this article:

Guardiola Ortuño, C. L. (2026). From execution to judgement: Reconfiguring higher education policy and outcome-based education for the integration of youth in the GenAI economy. *Artificial Intelligence Advances in Education*, 1(1), 78–93. <https://doi.org/10.66818/aiaie.v1i1.915>

Submitted: 27 January 2026 **Accepted:** 22 March 2026 **Published:** 30 March 2026

Copyright:

© 2026 The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution-NoDerivatives 4.0 International License (CC BY-ND 4.0), which permits to copy and distribute the material in any medium or format only in an unadapted form, as long as the author is named. The license allows commercial use. See <https://creativecommons.org/licenses/by-nd/4.0/>.

Artificial Intelligence Advances in Education is a peer-reviewed open access journal published by SCS Journals.

