Mind the AI Gap

A Stage-Based Human Capital Framework for the Fourth Industrial Revolution

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Introduction

- **IA as a catalytic technology of the industrial revolution**

Artificial intelligence is widely considered one of the key catalytic technologies of the Fourth Industrial Revolution due to its capacity to transform production, decision-making, and organisational systems across sectors (Damioli et al., 2025). Its transversal nature enables the automation and optimisation of increasingly complex cognitive and productive processes (Park, 2018; Ross & Maynard, 2021).

- **Human capital as a key factor in the deployment of industrial revolutions**

Industrial revolutions depend not only on technological breakthroughs, but also on the availability of specialised human capital capable of developing, adapting, and implementing new technologies (Mokyr, 2021). Throughout history, the diffusion of transformative technologies has relied on workers possessing advanced technical and scientific knowledge (Kranzberg, 1967; Wang et al., 2020).

Introduction

- **Core Occupations of Industrial Revolutions: Knowledge Elites**

Each industrial revolution generates a “knowledge elite” composed of highly specialised occupations that drive technological change and facilitate its integration into productive systems (Squicciarini & Voigtländer, 2014). In the case of AI, occupations such as Data Scientists, AI Engineers, and Knowledge Engineers are becoming central to the development and deployment of intelligent systems (Su et al., 2021).

- **Technological and industrial revolutions unfold through cumulative phases**

Industrial revolutions evolve through cumulative and incremental phases, ranging from technological experimentation to diffusion and consolidation within the economy (Pérez, 2002; Schot & Kanger, 2018). As technologies mature, the occupational and skill requirements associated with them also evolve, shifting from exploratory profiles towards implementation, maintenance, and governance functions.

Research Gap

- Existing research has extensively analysed the relationship between AI and labour market but **limited attention has been paid to the intersection of these two dimensions**; that is, to how **occupational structures** associated with the knowledge elites **that drive industrial revolutions evolve across the different phases** of technological deployment

- This gap is particularly relevant as these occupational configurations enable the diffusion and operationalisation of transformative technologies across production systems and the different deployment stages privilege different forms of expertise and occupational specialisation

Contributions

General contribution

This paper develops a dynamic framework linking the deployment phases of artificial intelligence with the evolution of occupational structures associated with the "knowledge elite" of the Fourth Industrial Revolution. In doing so, it moves beyond static approaches to AI occupations and highlights how human capital requirements evolve throughout the technological lifecycle.

Specific contributions

1. **Development of an AI occupational taxonomy**
   The paper identifies and systematises AI-related occupations and skills through the ESCO framework,
2. **Phase-based analytical framework**
   It proposes a dynamic model connecting AI deployment phases — ideation, implementation, and governance — with changing occupational relevance and task structures.
3. **Empirical evidence on the current stage of AI diffusion**
   The study provides qualitative evidence showing that firms are currently in the early implementation and deployment phase,

Methodology

Phase 1	First version of the list of AI occupations	Systematic process for the identification and classification of occupations and skills linked to artificial intelligence (AI).	European Classification of Skills, Competences, Qualifications and Occupations (ESCO) database. Analysis of 3,039 occupations and 13,939 associated professional competences.
Phase 2	Contrast I: of the list of occupations	Comparison with lists and taxonomies of other reference organisations.	-Basque Artificial Intelligence Center (BAIC) -Association to promote the use of data and Artificial Intelligence in companies and SMEs in the Spanish industry (IndesIA) -International Professional Organisation of Competence Evaluation in France (OPIIEC).
Phase 3	Contrast II: of the list of occupations and identification of skills of AI occupations.	-Interviews with enterprises and companies -Focus groups with professionals from vocational training centres -Interviews with companies and experts	-2 VET centres -25 companies, classified in two groups: AI solution developers (8) and implementers (17). -4 experts
Phase 4	Skill of the AI occupations	Assignment of skills linked to each profile	-European Classification of Skills, Competences, Qualifications and Occupations (ESCO) database. -International Professional Organisation for the Evaluation of Competence in France (OPIIEC).
Phase 5	Linking occupational profiles with phases of AI deployment	Creation of the model Validation	-2 VET centres -25 companies, classified in two groups: AI solution developers (8) and implementers (17). -4 experts

Results: Occupational Taxonomy

Generators	Enablers	Generators/Enablers
Robotics engineer	Database Integrator	Software developer
Data Scientist	DB Designer	Data analyst
AI Engineer	Cloud Architect	Knowledge Engineer
Computer Vision Engineer	Data warehouse designer	Data Engineer
IoT Developers	Database Administrator	
Embedded software developers	User experience analyst	
Software developers for mobile devices	User interface designer	
	Integration engineer	
	Data quality specialist	
	Cloud systems engineers	
	ICT business analysts	
	Devops Engineer	

Results: Skills Taxonomy-Data Analyst

Data analyst: import, inspect, clean, validate, model or interpret data sets in relation to the company's business objectives. They ensure that data sources and repositories provide consistent and reliable data. Data analysts use various algorithms and IT tools, as required by the situation and the current data. They may produce reports in the form of visualisations, such as graphs, charts and dashboards.

Essential skills	Optional skills
Analysing data intelligence	Data storage and digital systems
Apply statistical analysis methods	Analysing and managing risks
Apply data quality processes	Create data models
Define data quality criteria	Build and maintain a positive relationship with the client
Perform data extraction	Manage quantitative data
Perform analytical mathematical calculations	Manage knowledge
Set up data processes	Manage data and cloud storage
Manage data	Manage data collection systems
Integrating ICT data	Manage business software
Interpreting current data	Manage a project
Handle data samples	Manage a business proposal
Standardise data	Reporting analysis results
Performing data cleansing	Leading an agile and innovative approach
Collect ICT data	Launch and run a study
Use databases	Provide visual data presentations
Using data processing techniques	Collect and analyse project-related information
	Collect data for forensic purposes
	Make data-driven decisions
	Use English in a professional context
	Use office tools
	Using spreadsheet software

Results: mapping occupations onto the phases of AI deployment

Phase of AI deployment	Occupation	Occupation Category	Dominant task cluster	Secondary cluster
Ideation & design	Computer Vision Engineer	Generator	Knowledge creation & modelling	Data engineering
	Data Scientist	Generator	Knowledge creation & modelling	Data engineering
	AI Engineer	Generator	Knowledge creation & modelling	Software & system development
	Knowledge Engineer	Generator / Enabler	Knowledge creation & modelling	Data engineering & management
Implementation & integration	Embedded Systems Software Developer	Generator	Software & system development	Integration & deployment
	Industrial Mobile Software Developer	Generator	Software & system development	Integration & deployment
	Robotics Engineer	Generator	Integration & deployment	Operation & optimisation
	IoT Developer	Generator	Integration & deployment	Data engineering
	Database Integrator	Enabler	Data engineering & management	Integration & deployment
	Database Designer	Enabler	Data engineering & management	Software & system development
	Cloud Architect	Enabler	Integration & deployment	Software & system development
	Data Warehouse Designer	Enabler	Data engineering & management	Integration & deployment
	Cloud Systems Engineer	Enabler	Integration & deployment	Operation & optimisation
	Integration Engineer	Enabler	Integration & deployment	Software & system development
	Software Developer	Generator / Enabler	Software & system development	Integration & deployment
	Data Analyst	Generator / Enabler	Data engineering & management	Knowledge creation
	Data Engineer	Generator / Enabler	Data engineering & management	Integration & deployment
Maintenance & governance	Database Administrator	Enabler	Operation & optimisation	Data engineering & management
	UX Analyst	Enabler	Interaction, business & governance	—
	User Interface Designer	Enabler	Interaction, business & governance	Software & system development
	ICT Business Analyst	Enabler	Interaction, business & governance	Knowledge creation
	Data Quality Specialist	Enabler	Data engineering & management	Operation & optimisation
	Cloud DevOps Engineer	Enabler	Operation, testing & optimisation	Integration & deployment

Results: Key Findings

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- **Current stage of AI diffusion**
  Most firms are still in an exploratory phase of AI adoption focused on organising data infrastructures and understanding potential use cases rather than implementing advanced AI systems at scale. AI deployment therefore remains both a technological and organisational challenge.

- **Growing importance of hybrid profiles**
  The findings highlight the increasing relevance of hybrid occupations capable of translating business needs into AI solutions. Profiles such as ICT Business Analysts and Knowledge Engineers are becoming critical for connecting organisational problems with technological possibilities.

- **Fluid and interdisciplinary occupations**
  AI-related occupations remain highly hybridised and interdisciplinary, with overlapping technical and organisational functions. This reflects the early stage of AI diffusion, where experimentation still dominates over occupational specialisation.

Preliminary Conclusions

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- AI deployment is cumulative, incremental and non-linear (capacity, infrastructure, data-driven culture...)
- Data-driven culture remains weak in most of the firms
- AI deployment depends on both elite expertise (core and peripheral occupations) and workforce adaptation
- Education systems must combine university and VET strengths
- AI-related skills should be embedded across the education system
- Future research should explore regional knowledge elites and absorptive capacity