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Automation, Artificial Intelligence, and Employment in the European Union: An Early-Stage Meta-Analysis of Macroeconomic Evidence

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Abstract

This paper provides a meta-analysis of macroeconomic, quantitative studies that seek to identify the causal impact of automation and artificial intelligence (AI) on employment in the European Union (EU). We contribute an EU-focused synthesis that concentrates on macro-level evidence, complementing a literature dominated by micro task-based analyses and broader cross-country discussions. Using an AI-assisted workflow for search, screening, and extraction with human oversight, we map the available evidence and report clear methodological and knowledge gaps. A central finding is that the automation and robotics literature is comparatively developed, while credible causal macro evidence on AI itself remains sparse and fragmented. We treat this scarcity as a result that motivates a concrete research agenda. Across the core empirical studies and selected grey literature, the net employment effect appears modestly positive on the order of 1.5 to 2.0 percent, but the distributional pattern is uneven. Risks concentrate among low-skilled and routine workers, older cohorts, and lagging regions, pointing to policy priorities in reskilling, education, and digital infrastructure. Methodologically, the paper demonstrates how LLM-assisted procedures can improve transparency, consistency, and scalability in early-stage evidence synthesis where conventional meta-regression is premature.

Keywords: Automation, Artificial Intelligence (AI), Employment, Labour Market, European Union (EU), Job Displacement, Workforce Polarization, Productivity, Wage Inequality, Skills, Regional Disparities, Reskilling, Technological Adoption, Meta-Analysis.

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Data Availability Statement

The data that supports the findings of this study are available in the appendix.

1. Introduction

Automation and AI technologies are transforming industries globally, with significant implications for employment. While these technologies promise increased productivity and new job creation, they also raise concerns about workforce displacement. Despite extensive research, there is no consensus on their net impact on employment. This paper conducts a meta-analysis of empirical studies to determine the effects of automation and AI on employment outcomes in the EU. Using an AI-assisted workflow that applies large language models to support literature screening and data extraction, with human oversight, we synthesize the available evidence on this policy issue.

A central goal of this paper is to address the primary research question: *What is the impact of automation and AI on employment within the EU, as evidenced by empirical research?* This question is particularly pertinent given the existing research gap, to our knowledge, no prior meta-analysis has specifically synthesized the causal effects of automation and AI on employment in the EU. Furthermore, while the literature abounds with experimental and survey-based studies examining the micro-level impacts of automation and AI on specific jobs and tasks, and numerous speculative discussions offer various perspectives, there is a relative scarcity of empirical research using macroeconomic data and variables to assess the broader employment effects. This meta-analysis focuses specifically on synthesizing these comparatively fewer, but crucial, macroeconomic studies that employ prehensive and data-driven perspective on this issue.

This paper makes three contributions. First, it provides the first EU focused scoping meta-analysis of macroeconomic quantitative studies that aim to identify the causal employment effects of automation and AI, thereby addressing a gap left by broader and predominantly non-EU syntheses. Second, it documents that while the automation and robotics evidence base is relatively mature, credible causal macro evidence on AI's labour market impacts in the EU remains sparse and fragmented, and we treat this scarcity as a central result that motivates a clear research agenda. Third, we introduce and validate an AI assisted workflow for evidence synthesis, combining large language model supported screening and extraction with human oversight and reporting inter rater reliability metrics to enhance transparency, scalability, and replicability in early-stage meta analytic research.

The paper proceeds with a literature review that identifies the research gap, a description of the methodology of the AI-assisted meta-analysis methodology, presentation of the results, a discussion of the findings and their implications, and concluding remarks.

Given the rapid evolution of artificial intelligence technologies and the relative scarcity of macroeconomic causal studies on their labour market impacts, this study should be understood as a meta-analysis which is an early-stage synthesis intended to map the current evidence landscape rather than deliver conclusive estimates. The aim is to assess the state of knowledge and highlight where gaps persist in empirical research on automation and AI in the European labour market. In doing so, this study also serves as a methodological demonstration, showcasing how AI-assisted workflows, including large language models used for screening, extraction, and evaluation can enhance meta-analytical research efficiency and consistency in underdeveloped fields of economics. This approach complements more traditional meta-analyses and offers a flexible framework for evidence synthesis in emerging domains where conventional techniques may be premature or infeasible (cf. Terzidis et al. 2019, Vivarelli 2014, and Guarascio et al. 2024).

2. Theoretical Framework: Technological Displacement and Complementarity

This study is grounded in two key economic theories of technological change: the technological displacement hypothesis and the complementarity (or task-based) perspective. The displacement view, tracing back to Keynes (1930) and extended by Acemoglu and Restrepo (2019, 2020), suggests that automation reduces labour demand by replacing human workers-especially in routine tasks. In contrast, the complementarity perspective argues that technological progress creates new tasks and roles for human labour, particularly in high-skill sectors, potentially offsetting job losses (Acemoglu & Restrepo, 2019).

The theory of technological unemployment, as initially posited by Keynes (1930), suggests that automation leads to job losses as machines replace human labour. This perspective has gained renewed traction with contemporary advances in robotics and AI. Acemoglu and Restrepo (2020) demonstrated the displacement effects of industrial robots in the United States, finding that each additional robot per 1,000 workers reduces employment and wages. These effects are particularly concentrated in manufacturing-heavy regions, impacting low- and medium-skilled labour. Georgieff and Hyee (2022) provide cross-country evidence supporting this view, showing a negative correlation between AI exposure and growth in hours worked in occupations requiring limited digital skills. They argue that while partial automation can increase productivity, the direct displacement of workers often outweighs potential benefits for those unable to adapt. Du (2024) further emphasizes the potential for automation and AI to reshape employment structures, discussing skill-biased technological change and its implications for income inequality. While highlighting the disproportionate risks for low-skilled workers, the author underscores the importance of proactive policies such as education, training, and innovation to mitigate these effects.

Countering the technological unemployment narrative, proponents of automation and AI emphasize their potential for job creation and economic growth. The reinstatement effect, as articulated by Acemoglu and Restrepo (2018, 2019), suggests that automation creates new tasks where human labour retains a comparative advantage, potentially offsetting displacement and even increasing labour demand. This echoes historical precedents, such as the Industrial Revolution, where initial job losses were eventually followed by innovation and new employment opportunities. Empirically, Liu (2024) found a negative correlation between AI adoption and unemployment rates across multiple sectors, suggesting that technological progress can stimulate new economic opportunities. Georgieff and Hyee (2022), while acknowledging displacement in some areas, also found that in occupations with high computer use, AI exposure is associated with employment growth, attributed to productivity gains in non-automatable tasks. Du (2024) also highlights the emergence of new high-tech sectors requiring advanced skills, which create new employment opportunities. However, the key point of contention is whether these job creation effects are sufficient to offset the potential displacement effects, a question our meta-analysis directly addresses.

These frameworks help explain the heterogeneity observed in empirical findings. For instance, the observed polarization in labour markets such as job losses in routine-intensive sectors and gains in knowledge-intensive sectors can be seen as a reflection of skill-biased technological change (SBTC), a recurring theme in both theoretical and empirical research (Autor, Levy, & Murnane, 2003; Vivarelli, 2014). Moreover, analysis of the latent structure of reported effects points to two main sources of variation that can be examined empirically: a structural-temporal gradient-capturing differences between single-country and EU-wide settings and changes over time-and a methodological axis-capturing variation linked to the strength and type of identification. Viewed through the displacement versus task-based complementarity lens, this mapping helps explain why estimates tend to be more negative in routine-intensive, manufacturing-oriented contexts and more offsetting where AI/ICT intensity and non-routine task content are higher (Acemoglu & Restrepo, 2019; Autor, Levy, & Murnane, 2003; Georgieff & Hyee, 2022; Vivarelli, 2014). Positioning the meta-analysis within these theoretical perspectives links disparate empirical results to broader economic models and provides a structured account of how automation and AI shape employment patterns in the EU; the empirical section that follows evaluates heterogeneity along these two axes (see also Ugur et al., 2018; Guarascio et al., 2024).

3. Literature Review

The impact of automation and artificial intelligence on the labour market has become a central topic of discussion in economics, sociology, and policy circles. The increasing prevalence of automated systems and AI technologies across various sectors sparked a wide-ranging debate about their potential consequences for employment. While some predict widespread job displacement and technological unemployment, others argue that these technologies will primarily augment human capabilities, create new types of jobs, and drive economic growth.

3.1 Meta-Analyses on the Employment Effects of Automation and AI

Empirical research examining the macroeconomic impact of automation and AI on employment presents an ambiguous picture, revealing a division between the potential for productivity gains and the risk of job displacement. Several meta-analyses sought to synthesize this evidence. Terzidis et al. (2019), in a meta-analysis of 91 studies, found that automation and trade generally benefit wages and employment in advanced economies. However, their analysis revealed a significant skill bias, with technology primarily benefiting high-skilled workers, thus potentially increasing labour market polarization. This skill-biased impact is a recurring theme in the literature. Vivarelli (2014) in his meta-analysis similarly argued that technological progress, while driving growth in knowledge-intensive sectors, can simultaneously displace workers in routine-intensive occupations, disproportionately affecting low- and medium-skilled individuals. Ugur et al. (2018) further emphasized the importance of distinguishing between process innovations (often labour-saving) and product innovations (more likely to be employment-enhancing). Their meta-regression analysis highlighted the heterogeneous net employment effects of innovation, noting that these effects are generally small and influenced by factors like labour market and product market regulation.

However, the magnitude of job displacement due to automation remains unclear. Guarascio et al. (2024), in their meta-analysis of 33 studies focusing specifically on robotization, found negligible aggregate effects on employment and wages. They attributed this to compensatory mechanisms, such as the creation of new complementary jobs and increased efficiency, which offset initial job losses. This finding contrasts somewhat with studies focusing on broader forms of automation and AI, such as those by Terzidis et al. (2019) and Vivarelli (2014), where a more pronounced skill-biased impact and labour market polarization are observed, suggesting that the specific type of technology considered may play a crucial role in determining employment outcomes. Klump et al. (2023) further contribute to this nuanced picture by examining the wage effects of industrial robots, finding limited direct impacts on overall wage levels but modest and less observable effects of skill-biased effects when disaggregated by sector and skill group. They observed that automation in manufacturing tends to be associated with more negative wage effects, while non-manufacturing industries may experience slightly more positive outcomes. This highlights the importance of considering sectoral and skill-specific impacts, though the overall magnitude of these effects remains limited. Dagli (2021) further supports the idea of a more moderate impact, concluding that the overall effect of technology on employment is moderately positive.

These meta-analyses, while providing valuable insights, differ in their methodologies, scope (e.g., focus on robots vs. broader automation), and the specific time periods and regions considered. For example, while Terzidis et al. (2019) included a large number of studies spanning various advanced economies, Guarascio et al. (2024) focused specifically on robotization and a smaller set of studies. These differences in methodology and scope may explain some of the discrepancies in their findings. Critically, none of these meta-analyses explicitly focus on synthesizing the causal impact of automation and AI on employment within the EU using a rigorous selection of macro-level studies, which is the specific contribution of our research.

3.2 Grey Literature Insights into the Impact of Automation and AI on Employment in the EU

Grey literature, including reports and publications from organizations like the OECD, ILO, PwC, and WEF, provides insights into the practical implications of automation and AI on labour markets, particularly within the EU. These reports often focus on current trends, sectoral dynamics, and policy considerations, complementing academic research. This section synthesizes key findings from this grey literature, focusing on the ongoing debate regarding the impact of automation and AI on employment. While some reports emphasize the potential for productivity gains and limited aggregate employment effects, others highlight concerns about sectoral job displacement, increasing inequality, and the need for proactive policy interventions. This review of grey literature contributes to answering the research question.

Several reports suggest that the aggregate employment impact of AI has been relatively limited so far, with a primary effect of task reorganization rather than widespread job displacement (OECD, 2021). This perspective aligns with findings from European Central Bank (Albanesi et al., 2023), which found evidence of employment growth in AI-exposed occupations across several European countries, particularly benefiting younger and more skilled workers, consistent with the Skill Biased Technological Change (SBTC) framework. However, this aggregate view masks significant sectoral and regional variations. The International Labour Organization working paper (Carbonero et al., 2018) highlights job displacement in manufacturing-heavy regions due to robot adoption, partially offset by job creation in the service sector. The consulting firm PwC (Hawksworth et al., 2018) further emphasizes these sectoral differences, identifying distinct "waves of automation" with varying impacts across sectors like financial services, logistics, and manufacturing. These variations underscore the importance of considering sectoral context when assessing the impact of automation and AI. Moreover, the International Labour Organization working paper (Gmyrek et al., 2023) highlights that these effects are not evenly distributed across demographic groups, with women and low-income workers facing greater automation risks, exacerbating existing inequalities.

While concerns about job displacement persist, the grey literature also emphasizes the potential for AI-driven productivity gains and job creation. Another report by PwC (2024) ‘AI Jobs Barometer’ reports a significant wage premium for AI-related skills, indicating growing demand for technical expertise. Another OECD study (2023) links AI adoption to increased productivity in knowledge-intensive sectors, suggesting that AI can augment human capabilities and create new roles. World Economic Forum (2023) in their vital study further emphasizes the emergence of new AI-related professions, such as AI specialists and data analysts. A working paper by European Central Bank (Albanesi et al., 2023) reinforces this view by highlighting how AI-driven task augmentation has primarily benefited high-skilled workers, fostering job creation in areas requiring human-AI collaboration. However, a key question remains: do these productivity gains and new job opportunities sufficiently compensate for potential job displacement? This is a central question that our meta-analysis seeks to address.

3.3 Research Gap and the Need for a Meta-Analysis

While the preceding review highlighted the extensive body of research on the relationship between technology and employment, a critical gap persists in the literature: a synthesis of the causal macroeconomic effects of automation and AI technologies on aggregate employment within the EU. This meta-analysis offers a powerful approach to address this limitation by statistically combining the results of multiple studies, thereby increasing statistical power and providing a more precise and reliable estimate of the overall effect.

Furthermore, much of the existing literature comprises micro-level studies examining the impact of automation on specific tasks or within individual firms, or speculative discussions based on theoretical models, case studies, or macroeconomic projections. While these contributions are valuable for understanding specific mechanisms or potential future trends, they do not provide a comprehensive understanding of the aggregate employment effects at the macroeconomic level. Our meta-analysis addresses this limitation by specifically focusing on empirical studies that utilize macroeconomic data and methodologies to assess the broader labour market dynamics.

Moreover, there is a lack of a dedicated meta-analysis focusing specifically on the EU. The EU's unique labour market institutions, social welfare systems, and strong emphasis on digital transformation make it a crucial context for investigation. These specific characteristics may influence the relationship between automation/AI and employment in ways that differ from other regions.

To summarize, while previous meta-analyses such as Terzidis et al. (2019), Vivarelli (2014), and Guarascio et al. (2024) have provided important insights into the employment effects of automation, these studies have varied significantly in terms of scope, geographic coverage, and methodological rigor. Notably, none of these analyses focused explicitly on the causal macroeconomic effects of automation and AI on employment within the European Union.

In contrast, this study adopts a meta-analysis approach tailored to an emerging research area such as the causal labour market effects of automation and artificial intelligence. The use of this approach is justified not only by the limited number of qualifying empirical studies, but also by the high degree of methodological heterogeneity and geographical imbalance observed in the literature. These features make a full statistical meta-regression inappropriate at this stage and instead call for a mapping and structuring of the available evidence base.

Furthermore, this study introduces a novel own AI-assisted methodology, demonstrating the feasibility of using large language models to support systematic screening, data extraction, and classification tasks in meta-research. This methodological innovation responds to growing interest in improving the efficiency and transparency of literature synthesis (Reason et al., 2024; Lam Hoai & Simonart, 2023).

Finally, this work addresses persistent policy and research gaps. It documents the regional disparities in technological adoption within the EU, the uneven distribution of AI-related employment effects, and the insufficient causal evidence on AI itself as distinct from automation more generally. These gaps have critical implications for labour market forecasting, inequality, and digital policy across the EU. The study therefore aims not only to synthesize what is known, but to inform future empirical research agendas and policy development.

4. Methods

This study adopts a meta-analysis framework, appropriate for synthesizing fragmented evidence in emerging research areas. Unlike traditional statistical meta-analyses, which require a large number of methodologically similar studies, scoping reviews aim to map the range and characteristics of available research, identify gaps, and inform future inquiry. Given the limited number of qualifying causal studies on AI and employment in the EU, and the substantial heterogeneity in research design, outcome measures, and data sources, a full meta-regression is neither feasible nor methodologically appropriate. Instead, this study offers a structured, AI-assisted synthesis, a replicable early-stage approach suitable for underdeveloped economic domains (DeSimone, 2021).

4.1 AI-assisted meta-analysis

Meta-analyses are indispensable tool for synthesizing evidence from multiple studies to inform policy, practice and further research (Uman, 2011; Field & Gillett, 2010). However, the conventional meta-analysis process is time-consuming and resource intensive. Artificial intelligence, and specifically large language models (LLMs), open a doorway to possibly immense improvement. Generative AI has already demonstrated capabilities in increasing research productivity (Tomczyk et al., 2024) and holds significant potential for streamlining meta-analysis workflows (Lam Hoai & Simonart, 2023; Michelson et al., 2020; Reason et al., 2024). Therefore, this section outlines a structured workflow proposal designed to integrate generative AI into meta-analysis.

To structure the integration of generative AI, we developed an AI-assisted workflow for meta-analysis. This workflow assumes using custom chat-based AI agents, as well as large language models directly, i.e. locally or through API connection. Table 1 outlines the division of tasks between human researchers and generative AI across six key phases of meta-analysis. As shown, the workflow is based on human-AI collaboration through the entire process. In the Defining phase, while researchers direct the project and define research questions, AI supports brainstorming and refining these questions. For Search, human researchers conduct database searches and prepare datasets, complemented by AI tools for semantic search and generating search strings. During Screening and Selection, humans devise and iteratively refine prompts for classification, while AI assists by suggesting criteria, and most importantly, classifying and extracting data from abstracts. In Data Extraction, researchers decide on data to be extracted and prepare workflows, while AI performs the extraction itself. For Data Analysis, researchers review and interpret findings, with AI supporting the writing of analysis scripts. Finally, in the Writing Phase, while researchers write the report, AI provides support for paper outlining. This task division highlights a model where AI tools augment, rather than replace, the researcher's role at each stage of the meta-analysis process, significantly improving productivity of the entire process.

Table 1. Task split between human researcher and LLM on each step of meta-analysis

Task group	Human	Generative AI
Defining	• Directing the research project, creating research questions; • Defining inclusion and exclusion criteria;	• Support brainstorming and ideation; • Support refining and wording research questions; • Writing search strings;
Search	• Running databases search; • Creating and preparing datasets;	• Semantic search tools; • Writing search strings;
Screening and selection	• Devising prompts for classification and extraction tasks; • Iterative testing prompts;	• Suggesting and reviewing inclusion/exclusion criteria; • Delete duplicates;

	• Selecting papers; • Download papers (pdfs storage);	• Classification and extraction of data from abstracts;
Data Extraction	• Decide on data to be extracted; • Prepare data extraction workflows and scripts; • Verify extracted data;	• Extracts data from papers;
Data analysis	• Review data analysis; • Interpret findings;	• Write scripts or code for data analysis;
Writing	• Write the report or paper;	• Support paper or report writing;

Source: own elaboration.

Screening abstracts against predefined inclusion and exclusion criteria is a particularly labour-intensive and time-consuming stage in meta-analysis. However, large language models (LLMs) offer a significant opportunity to dramatically enhance efficiency in this task. Indeed, studies indicate substantial workload reductions using AI-based tools for abstract screening (Chai et al., 2021). Moreover, empirical observations from our development process highlight the remarkable time savings: screening 30 abstracts took approximately 55 minutes (human reviewer 1) and about 35 minutes (human reviewer 2), while GPT-4o accomplished the same task in about 1.5 minutes. These, while not admissible, indicate a possible productivity increase in the magnitude of 23-37 times. Our quick test was run on a sample of 30 abstracts, while in actual meta-analyses screeners need to review thousands. Beyond speed, human screeners often experience tiredness and reduced focus after extended periods, increasing the likelihood of errors in this demanding and detail-oriented task. In contrast, AI offers consistent and rapid processing, potentially minimizing errors associated with human fatigue. Our approach to LLM-based screening involves several key steps. First, researchers establish clear inclusion and exclusion criteria. Second, a step-by-step screening process is designed to guide the LLM. Crucially, specific prompts are developed and iteratively refined to ensure accurate classification. We propose employing a Boolean classification system, categorizing abstracts as "yes," "no" (e.g. relevant or irrelevant to the meta-analysis research questions) based on their alignment with the criteria. Edge cases could be classified as "maybe" and later reviewed by human researchers to maintain oversight. Furthermore, prompts can be designed to extract specific data points concurrently with the classification decision. For instance, the LLM can be instructed to identify the study's country and research method used. That data can be later used to exclude unfitting studies from the meta-analysis.

Data extraction, the systematic collection of specific information like effect sizes and outcome measures from selected studies, is another critical phase in meta-analysis. Traditional manual data extraction is not only time-consuming but also prone to human error (Ortiz et al., 2021). Generative AI offers a promising solution to enhance both the efficiency and accuracy of this process. Recent research indicates that AI-driven data extraction can achieve impressive accuracy rates, reaching up to 99% in some tasks (Reason et al., 2024). For optimal results in large-scale data extraction, we recommend adopting a methodology similar to that of Reason et al. (2024). Their approach emphasizes sequential extraction in structured segments, ensuring both systematic data retrieval and high precision.

While the proposed AI-assisted workflow enhances the efficiency of evidence synthesis, it is particularly valuable in nascent fields where research is still maturing. In such contexts, it provides a structured yet flexible alternative to formal meta-regression, supporting evidence mapping, gap identification, and policy-relevant aggregation of findings.

4.2 Data collection

A systematic search strategy was employed to identify relevant studies examining the impact of automation and AI on employment within the EU. Multiple databases and search methods were used to ensure broad coverage of the existing literature, following recommendations for comprehensive literature syntheses (DeSimone et al., 2021; Gusenbauer & Haddaway, 2020; Martín-Martín et al., 2021; Mongeon & Paul-Hus, 2016). String searches were conducted in EBSCOhost, Scopus, and Web of Science. Complementary manual searches were performed in Google Scholar, Semantic Scholar, and Google to identify additional relevant publications and grey literature. These searches aimed to identify any potentially relevant studies not captured by the database searches. We also consulted the reference lists of included studies and known relevant publications.

The search strategy focused on identifying studies examining the impact of automation and AI on employment. Keywords related to automation and AI were combined with keywords related to employment using Boolean operators (AND, OR). Initial searches yielded many results, indicating the need for refinement. We therefore excluded broader terms like "work" and "workforce," limited the publication year to 2010-2024, added terms related to causal research, and included only relevant publication types (article, proceeding paper, book chapters). Search was conducted on 1.11.2024. This refined search strategy resulted in 2566 results from Web of Science, 7383 from Scopus, 2179 from EBSCOhost.

The following lists of synonyms were used to ensure comprehensive coverage of relevant terms:

- Automation and AI: automation, artificial intelligence, AI, robotics, machine learning, automated systems, autonomous systems, intelligent systems, industry 4.0, computerization, robotization, digitalization, technological change.
- Employment: employment, jobs, job displacement, job loss, job creation, labour market, unemployment, skills.
- Impact: impact, influence, effect.

Duplicate records were identified and removed using a combination of DOI, title, and abstract matching. The initial search process identified 12,128 records. Following the removal of duplicates, the dataset was refined to 9,717 unique records. For the analysis presented in Part II, which examines the impact of AI and automation on employment in the EU, 15 academic articles were selected for review. Similarly, for the analysis in Part III, focusing on the impact of AI and automation on labour migration and migrants within and to the EU, a curated selection of relevant studies was reviewed.

4.3 Screening

Following the data collection phase, a three-level screening process was implemented to select studies relevant to our research question. This process combined the efficiency of LLM-based screening with the judgment of human reviewers to ensure the inclusion of relevant studies, efficiency and transparency of decisions made.

Level 1 screening was conducted using OpenAI's GPT-4o model. The LLM was tasked with classifying abstracts based on three key criteria: thematic fit, causal study design, and quantitative methodology. Complex prompts were developed and tested on a small sample of studies before application to the database. Each criterion was assessed separately to reduce the cognitive load on the LLM and increase accuracy. The following definitions were used:

- Thematic Fit: An abstract has thematic fit if it discusses the relationship between automation and AI on employment.
- Causal Study: Studies that seek to measure the impact of one variable (AI adoption or automation technology, X) on another (job displacement, employment levels, or labour market conditions, Y), with a clear focus on causal inference.
- Quantitative: Studies employing quantitative data and methods. These studies typically include numerical data analysis, econometric or statistical modelling, and the use of quantitative indicators. Studies that use real-world data to support their analysis.

Level 2 screening involved a combination of LLM-based data extraction and human filtering of data. OpenAI's GPT-4o Mini model was used to extract the following information from abstracts that passed Level 1 screening:

- location including studies focused on any of European markets, excluding markets outside of EU, global studies or without any geographical focus
- studied period including studies involving 2010-2024 period
- industry (criterion forfeited)
- technology studied including studies focused on automation, AI, industry 4.0, robotics, excluding studies on other technologies, digital transformation
- effect size measures including studies that measure impact of automation or AI on employment; excluding studies that do not measure the impact (e.g. qualitative, discussion or review papers)
- economic indicators used including studies that employ known economic indicators (e.g. unemployment rate, vacancies, productivity metrics, automation investment levels, Gini coefficient and others); excluding studies that do not use economic metrics.

Specific prompts were designed and tested on smaller sample of papers for each data point to ensure accurate extraction. The extracted data was then used to filter studies based on our inclusion criteria. Human reviewers then examined the LLM's extracted data and made final decisions regarding inclusion based on these extracted data points. Discrepancies were resolved through discussion.

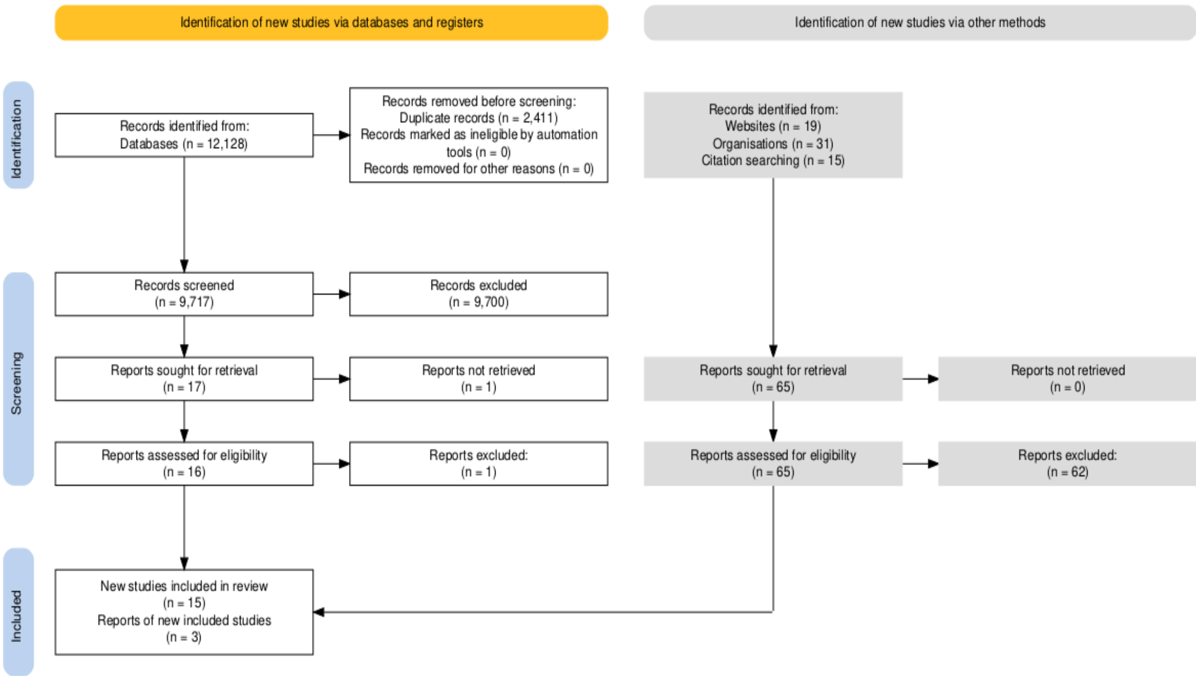
Level 3 screening was performed by two independent human reviewers. Reviewers assessed both the abstract and the full text of studies that passed Level 2 screening to ensure they met all inclusion criteria. A key focus at this stage was to confirm that the studies examined the impact of AI on job displacement at a macro-level rather than micro-level analyses and that the studies focused on causal inference and used econometric indicators. Discrepancies between reviewers were resolved through discussion or consultation with a third reviewer.

The screening and filtering process allowed to select studies relevant to the meta-analysis. The database reduction process was as follows:

- Starting number of papers in the database: 9,717 papers in the database
- After level 1 screening: 1,149 papers in the database
- After level 2 screening: 83 papers in the database
- After level 3 screening (final number of papers): 15 papers in the database.

Additionally, we identified 65 sources of grey literature through manual search of websites and organizations and included 3 of them in the study. The same screening criteria were applied as for papers. The study selection process is illustrated in the PRISMA flow diagram (Figure 1) (Haddaway et al., 2022).

Figure 1. PRISMA Flow diagram of studies search and screening



Source: Own elaboration based on Haddaway et al. (2022) software.

4.4 Inter-Rater Reliability for Human and AI Evaluations

To evaluate the consistency between human and AI evaluations, we examined inter-rater reliability across three separate evaluation tasks such as thematic fit, study causality, and study "quantitativeness" - in which three human evaluators and one AI system coded each academic abstract as "Yes" (1) or "No" (0) based on specific instructions. For each of the three tasks, we performed Krippendorff's alpha analyses at two levels:

- All Coders Individually: Comparing the three human evaluators and the AI simultaneously.
- Human Consensus vs. AI: Pooling the human evaluators' responses (e.g., averaging or majority vote) into a single "human" code, then comparing it with the AI's code.

Table 2. Consistency of abstracts classification and data extraction between team of three human evaluators and AI (GPT 4o and 4o-mini). Authors' own elaboration.

Type of task	Task	Simple consistency score	Krippendorff's alpha (three human evaluators and AI individually)	Krippendorff's alpha (human team and AI)
Classification	Thematic fit	93%	0.66	0.83
	Causality	97%	-0.04	-0.02
	Quantitative	93%	0.78	0.87
Extraction	Study Location	97%	0.9	0.9
	Studied period	70%	0.15	0.21
	Industry	80%	0.62	0.83

Source: own elaboration.

For thematic fit, the Krippendorff's alpha among all four raters (three humans + AI) was 0.66, indicating a moderate degree of inter-rater reliability. However, when the human evaluators' responses were pooled and compared with the AI, alpha increased to 0.83, reflecting a higher level of agreement once individual human variability was consolidated into a single consensus code. The simple agreement rate between the aggregated human response and the AI was 93%, suggesting that although the humans showed some internal differences, their collective decision aligned closely with that of the AI. In contrast, study causality ratings yielded notably low (negative) Krippendorff's alpha values. When analysing all four raters together, alpha was -0.043, and when comparing the pooled human response to the AI, alpha was -0.017. Nevertheless, the simple agreement rate in this task was 97%, indicating that humans and the AI rarely disagreed. The negative alpha values are largely attributable to the highly skewed distribution of ratings, where nearly all coders selected the same category (0 or 1), making the expected disagreement extremely small. Even a single divergent rating can inflate the observed disagreement above the expected level, mathematically resulting in a negative alpha. For the study "quantitativeness" assessment, alpha among all four raters was 0.78, indicating relatively strong agreement at the individual-coder level. When the human evaluators' responses were pooled, the alpha value increased to 0.87 in comparison to the AI's coding. The simple agreement between this aggregated human judgment and the AI reached 93%, suggesting that in determining whether a study is quantitative, the AI's decisions broadly aligned with the collective human perspective. Notably, when all the three classification criteria were pooled (thematic fit, causality, and quantitativeness) into a single inclusion/exclusion outcome, the final decisions made by humans and the AI matched 100% of the time. In other words, despite some variability in individual ratings, the ultimate acceptance or rejection of each abstract was fully concordant between the human team and the AI system.

Following the evaluation of abstract screening, we also assessed the inter-rater reliability of human and AI performance in data extraction tasks. We examined three distinct data extraction tasks: study location, studied period, and industry sector. Similar to the screening evaluations, three human evaluators and one AI system (GPT-4o mini) independently extracted data from abstracts, and we employed simple consistency rates and Krippendorff's alpha to measure agreement. For study location extraction, the simple consistency rate between human and AI coders was 97%, indicating very high agreement. This strong consistency was further supported by Krippendorff's alpha. When considering all four raters individually, alpha reached 0.9, meaning excellent inter-rater reliability. These results suggest that the AI system can perform study location extraction with a level of consistency comparable to, and highly aligned with, human evaluators. In contrast to study location, the studied period extraction task showed lower inter-rater reliability. While the simple consistency rate was 70%, indicating a moderate level of agreement, the Krippendorff's alpha values were considerably lower. For all four raters individually, alpha was 0.15, and for the human consensus versus AI, alpha was 0.21. These low alpha values suggest a weaker agreement among both human and AI coders in extracting the studied period. The discrepancy between simple consistency and Krippendorff's alpha in this task may indicate that while coders frequently chose the same categories, the agreement was not robust enough to account for chance, or that there was less clear consensus on what constitutes the 'studied period' within the abstracts. Significant improvements should be made in the extraction prompt. For the industry sector extraction task, we observed moderate to high inter-rater reliability. The simple consistency rate was 80%, suggesting good overall agreement. Krippendorff's alpha among all four individual raters was 0.62, indicating a moderate level of agreement at the individual coder level. Importantly, when comparing the pooled human response to the AI, Krippendorff's alpha increased to 0.83, reflecting a substantial improvement in agreement when individual human variability was accounted for.

Across these data extraction tasks, the AI system demonstrated varying degrees of alignment with human evaluators. For clearly defined and relatively objective information, such as study location, the AI achieved excellent inter-rater reliability, comparable to human consensus. However, for more subjective or context-dependent information, like studied period and, to a lesser extent, industry sector, the reliability was lower. These suggest the importance of task-specific evaluation of AI performance in meta-analysis and show that while AI can be highly effective for certain types of data extraction, human oversight and potentially refined prompts may be necessary for tasks requiring more complex interpretation or contextual understanding.

Overall, our findings demonstrate a strong alignment between AI and human evaluators across multiple dimensions, particularly when human judgments are aggregated. The high simple agreement rates and particularly the 100% alignment on final inclusion/exclusion decisions highlight the potential for AI-assisted evaluation processes to supplement or streamline abstracts analysis efforts, provided that consensus or majority-rule approaches are used to mitigate individual variability.

5. Data analysis

This section presents findings from a meta-analysis aimed at mapping the current early empirical evidence on the macroeconomic impacts of automation and AI on employment in the EU. Given the small number of qualifying studies and the high degree of heterogeneity in research designs, outcome variables, and geographic focus, these results should not be interpreted as the outcome of a formal meta-regression. Rather, they serve to organize existing findings, identify recurring patterns, and highlight gaps in the literature. These limitations are not methodological shortcomings but reflect the early stage of empirical research in this field and point to clear priorities for future work.

5.1 Synthesized findings based on selected papers

The topic of AI and automation's impact on employment is of scientific importance due to its far-reaching implications for labour markets, economic structures, and societal well-being.

The conducted meta-analysis aims to evaluate the impact of automation and AI on employment by synthesizing findings from filtered 15 empirical quantitative and causal studies, addressing the research question (RQ1): What is the impact of automation and AI on employment according to existing empirical studies? The sample includes empirical studies that focus on labour market effects of technological advancements, such as automation, robotics, and digitalization, with data sourced from diverse geographical regions of the EU like Slovakia, Hungary, Italy, Germany, and France.

The analysed studies collectively explore the impact of automation and AI on employment across various dimensions, industries, and demographic groups. The research problems vary but consistently address causal relationships between technology adoption and labour outcomes, such as total employment, hiring rates, wages, job composition (by skill, age, or gender), and inequality. For example, studies by Cords & Prettner (2022) and Dauth et al. (2021) analyse the effects of automation capital and robot exposure on employment and wages, while Albinowski & Lewandowski (2022) assess gender- and age-specific impacts of ICT and robotics.

This analysis focuses on several key dimensions to understand the impact of automation and AI on employment. The Key Findings section synthesizes major conclusions from studies, noting both potential job displacement in traditional sectors and new job creation opportunities in emerging fields. In the Methodology section, various research approaches, such as longitudinal and case studies, are examined, detailing how data was gathered and interpreted. Additionally, specific tools and techniques like econometric models and surveys are explored. The Study Populations component assesses participant characteristics, highlighting those working in industries significantly impacted by AI and examining the criteria for their selection, such as occupation or geographic location. Finally, the Measures of Effects section analyses employment-related variables, providing statistical outcomes such as changes in unemployment rates, job type variations, and the rate of job creation due to AI, offering a comprehensive view of its measurable impacts on the workforce.

AI and automation have diverse effects on employment, varying across sectors, skill levels, and geographical contexts. While automation boosts productivity and innovation, its effects on employment are often uneven. In manufacturing sectors, for instance, automation has led to a decline in routine, low-skilled jobs, as seen in a 9.7% drop in manufacturing employment in highly automated regions. At the same time, high-skilled jobs experience growth, as firms require workers with technical expertise to operate and maintain automated systems. This shift highlights the polarizing effect of automation: high-skilled employment increases, whereas low-skilled workers face higher unemployment risks. For example, in Germany, high-skilled job gains offset low-skilled job losses, showcasing how automation transforms the workforce composition without necessarily reducing total employment (Wegrzyn, 2020).

However, the effects of AI and automation go beyond just manufacturing. In service sectors, automation can create opportunities, leading to a 4.7% employment increase as tasks become more efficient, and new roles emerge. Despite these positive effects, workers in manual and repetitive occupations, such as assemblers and plant operators, face the greatest risk of displacement, with automation risks reaching 18% (Cserháti and Takács, 2019). Moreover, regions with slower adoption of technology face competitive disadvantages, as seen in the 10% employment drop in non-automating firms (Aghion et al., 2022). These trends underline the need for proactive measures, such as reskilling programs, education reforms, and targeted policies, to help workers transition into new roles and mitigate automation-driven inequalities.

In the Table 5 (Appendix), key findings from grey literature on the impact of AI and automation on employment are summarized. The table highlights the main conclusions, methodologies, study populations, and measures of impact identified in non-academic sources, providing a practical perspective on the challenges and opportunities associated with technological advancements.

The comparison of findings from scientific studies and grey literature reveals a consistent narrative regarding the impact of AI and automation on employment, albeit with differing emphases. Both sources converge on the notion that AI and automation generate significant opportunities for high-skilled workers while displacing low-skilled and routine-intensive roles. Scientific studies provide a rigorous, quantitative analysis of these effects, grounded in frameworks such as Skill-Biased Technological Change (SBTC) and task complementarity, offering detailed insights into employment shifts and wage dynamics across sectors and regions. In contrast, grey literature adopts a broader, policy-oriented perspective, emphasizing societal challenges such as widening inequalities, regional disparities, and the critical need for skill development and supportive government interventions. While scientific studies excel in elucidating the mechanisms and heterogeneity of impacts across different countries, grey literature highlights practical barriers to technology adoption, particularly in emerging economies, and advocates for targeted measures to mitigate adverse outcomes. Together, these perspectives present a complementary view, combining empirical rigor with actionable recommendations to address the challenges and harness the opportunities of AI and automation.

The dominant indicators of impact are summarized in Table 7 (Appendix). Key indicators fall into several broad categories: Employment Impact Indicators are related to changes in total employment, sector-specific employment, and job creation or loss dominate the findings; Unemployment and Job Risk Indicators address unemployment changes and job displacement risks are prevalent; Wages and Income Inequality Indicators reveal the effect of automation on income levels and disparities.; Sectoral and Demographic Shifts Indicators highlight employment changes by sector and demographics; Technology Adoption and Investments Indicators measure the adoption of robotics, IoT, and automation technologies.

The indicators most observed revolve around employment changes (job creation and loss), sector-specific impacts, wage dynamics, job displacement risks, and technology adoption rates. These findings emphasize the need for policies addressing workforce reskilling, inequality mitigation, and sectoral support to adapt to the challenges posed by AI and automation.

A comparison is conducted between the key indicators identified in scientific studies and grey literature regarding the impact of AI, automation, and Industry 4.0 on employment (Table 9, Appendix). The comparison reveals overarching trends in the impact of automation, AI, and Industry 4.0 on employment, productivity, and wages, albeit with differing emphases. Both sources consistently highlight job polarization as a central theme, wherein automation fosters employment growth in high-skilled, non-routine tasks while displacing routine and low-skilled roles. Productivity gains are widely recognized, with automation driving sector-specific labour demand in scientific studies and contributing to macroeconomic recovery in grey literature. Wage impacts also exhibit a shared trend of increasing inequality, as automation amplifies wage divergence between high- and low-skilled workers. While scientific studies provide granular, empirical analyses focusing on sectoral and regional heterogeneity, grey literature adopts a broader perspective, emphasizing systemic risks such as regional disparities, particularly in emerging economies, and barriers to technology adoption. Furthermore, grey literature places greater emphasis on policy implications, advocating for education reform, workforce reskilling, and state interventions to mitigate the socio-economic challenges posed by automation. Together, these perspectives offer a comprehensive understanding, with scientific studies elucidating detailed mechanisms and grey literature contextualizing broader societal implications.

The studies considered a variety of additional indicators to evaluate the adoption and effects of automation, AI, and Industry 4.0 technologies. These include measures of technology adoption rates across sectors, such as the implementation of robotics, IoT, and digital twins. Indicators also focused on robot penetration and density in industries, exploring how different countries and sectors vary in automation adoption. Barriers to automation, such as costs and security concerns, were assessed to understand challenges in implementation. Productivity metrics, such as capital investment in ICT and its role in mitigating the effects of automation, were also key factors. Additionally, market-level indicators, like changes in market share for automation-adopting firms, and task-specific measures, including the risk of automation for various job roles, were analysed. These indicators collectively provided insights into technological adoption's broader economic and labour market impacts, helping to contextualize automation's role in reshaping employment and industry landscapes.

The results reveal significant insights into the impact of automation and artificial intelligence on labour markets in the EU. The research demonstrates that technological change is already reshaping employment patterns, skill requirements, and workforce dynamics in complex and often contradictory ways. The analysis also indicates a modest but positive net employment effect across the EU, though this aggregate figure masks substantial sectoral and regional variations. Manufacturing sectors have experienced the most pronounced job displacement, with a substantial decline in employment, particularly affecting routine and manual positions. Conversely, service and knowledge-intensive sectors show employment growth, especially in roles requiring advanced digital skills and human-AI collaboration.

Regional disparities emerge as a critical factor, with technologically advanced economies benefiting disproportionately from automation adoption. These regions show higher productivity gains and more robust job creation in high-skilled sectors. In contrast, emerging EU economies face challenges related to slower technological readiness and adoption rates, potentially widening existing economic gaps between regions. Demographic impacts reveal some patterns of advantage and disadvantage. Younger, high-skilled workers emerge as the primary beneficiaries of AI integration, experiencing increased employment opportunities and wage growth. Older workers and those in low-skilled positions face higher risks of displacement and wage suppression. The research particularly highlights the vulnerable position of migrant workers, who experience highly polarized outcomes based on skill levels.

While demand for high-skilled migrants has increased by 15-20% in AI-intensive sectors, opportunities for low-skilled migrants have declined by 5-10%.

The analysis identifies several critical barriers to effective AI adoption and workforce adaptation. These include systemic biases in AI-driven hiring systems, persistent skill mismatches between worker capabilities and job requirements, and limited access to reskilling programs, particularly among vulnerable groups. Educational systems and training programs often lag behind the rapid pace of technological change, creating challenges for workforce adaptation. Wage and income dynamics show slightly increasing polarization, with high-skilled workers in automation-intensive sectors experiencing wage growth while low-skilled workers face stagnation or decline. This trend appears particularly pronounced in urban areas where AI adoption is most concentrated, potentially exacerbating existing socioeconomic inequalities.

These findings resonate with established economic theories of technological change discussed at the beginning of this article. The observed job polarization - characterized by displacement in low-skill, routine-intensive occupations and growth in high-skill sectors - is consistent with both the skill-biased technological change (SBTC) framework (Autor et al., 2003; Vivarelli, 2014) and the task-based complementarity model (Acemoglu & Restrepo, 2019). Similarly, the unequal regional outcomes and limited net employment gains align with the technological displacement hypothesis, particularly in areas lacking compensatory task creation mechanisms. Interpreting these empirical patterns through theoretical lenses strengthens our understanding of how automation and AI are reshaping labour markets in nuanced and context-dependent ways.

5.2 Quantitative assessment of automation's impact on labour market

To uncover the underlying structure driving the observed variations in automation's impact on labour market (employment, wages, and productivity) the application of Principal Component Analysis (PCA) was conducted. The dataset, characterized by methodological inconsistencies, regional disparities, and temporal differences, required an approach that could extract the most informative dimensions while filtering out statistical noise.

To ensure comparability, the variable Value was standardized before conducting PCA. The standardization procedure follows the transformation:

$$x_{st.} = \frac{X - \mu}{\sigma}$$

where $x_{st.}$ is the value after standardization, X represents the original value, μ is the mean, and σ is the standard deviation. This transformation ensures that the variable has a mean of zero and a variance of one, preventing distortions in the principal component calculations due to scale differences.

Mathematically, PCA identifies these principal components by solving the eigenvalue problem for the covariance matrix Σ:

$$\Sigma v = \lambda v$$

where Σ is the covariance matrix of the dataset, v represents an eigenvector (principal component), and λ is the corresponding eigenvalue, which measures how much variance that principal component captures. Each element σ_{ij} in this matrix represents the covariance between variables *i* and *j*, measuring how changes in one variable relate to changes in another. Eigenvector *v* represents a principal component, which defines a new axis in the transformed feature space. These eigenvectors correspond to the directions along which the dataset exhibits the most variance. Eigenvalue λ is the variance explained by its corresponding principal component. Each eigenvalue quantifies how much of the total variance in the dataset is captured by its corresponding eigenvector (principal component).

A crucial aspect of the analysis was addressing heterogeneity in regional coverage (variable Region, depicted as *R*), as studies either focused on a single country ("one country") or provided a broader cross-country comparison within Europe ("Europe"). The regional variable was thus included in the PCA to determine whether automation's reported effects were systematically different depending on whether the study analysed a single national economy or a broader European sample. Another dimension of heterogeneity incorporated into the PCA model was methodological variation (variable "Method", depicted as *M*). The studies in the dataset employed different research designs, broadly categorized into 'econometric modelling' and 'statistical comparisons'. Given that methodological choices can systematically influence the estimated magnitude of automation's effects, this variable was essential for identifying whether research techniques contribute to the observed variance in findings. Finally, the publication year of each study was included in the PCA to account for temporal variation in automation's reported effects (variable Year, depicted as *Y*). Including publication year in the PCA allowed for the detection of potential temporal shifts in how automation is perceived and measured across different periods.

The results of PCA demonstrate that two principal components account for 65% of the total variance, with the first component PC1 explaining 34.3% and the second PC2 capturing 30.7%. These components encapsulate the primary dimensions along which the dataset varies, reflecting differences in regional classifications, methodological approaches, and the year of study publication. The PC1 and the PC2 account for most of the structure in the dataset. The remaining components contribute progressively less variance and are often ignored because they primarily capture noise.

PC1 represents structural economic variation (regional and temporal effects), so it depends mainly on Region and Year. The regression equation for PC1 is:

$$PC1 = \gamma_1 R + \gamma_2 Y + \gamma_3 M + \varepsilon$$

PC2 represents methodological effects, so it is largely driven by Method, with a weaker influence from Region and Year. The regression equation for PC2 is:

$$PC2 = \delta_1 R + \delta_2 Y + \delta_3 M + \varepsilon$$

The regression model for PC1 explains the largest share of variance in the dataset, capturing the structural economic differences in how automation affects labour markets across regions and over time. The regression equation for PC1 is as follows:

$$\widehat{PC1} = 1.25 - 1.58\, R - 0.34\, Y + 0.31\, M$$

In the model 84.6% of the variance in PC1 is explained by the combination of Region, Year, and Method (R-squared equal to 0.846). The remaining 15.4% of the variance is unexplained, suggesting that there are other factors outside the model that may influence the reported effects, or that some noise is inherent in the data.

The coefficient for Region is -1.58 and is statistically significant at the 1% level ($p<0.001$). This negative coefficient suggests that regional differences play a significant role in explaining how automation's effects are perceived. The coefficient for Year is -0.34, with a p-value $<$ 0.001, which indicates a strong and statistically significant relationship. The negative sign suggests that more recent studies report automation effects that differ from those observed in earlier studies. The Method coefficient is 0.31, and it is statistically significant at the 5% level ($p = 0.021$). This suggests that the choice of methodology used in the studies also affects the reported automation impact, but to a lesser extent compared to Region and Year.

The regression model for PC2 captures the second-largest source of variance in the data and primarily reflects the methodological differences in how automation's effects are measured. The regression equation for PC2 is:

$$\widehat{PC2} = -1.30 - 0.64\, R + 0.01\, Y + 1.85\, M$$

The Method coefficient is 1.8472 and is highly statistically significant ($p < 0.001$). This large positive coefficient indicates that methodology plays a dominant role in explaining the variation in reported automation effects. Studies employing more sophisticated econometric modelling tend to report larger automation impacts compared to studies using more basic descriptive statistics or simpler methods. This reflects the influence of research design in shaping how automation's labour market effects are quantified. The coefficient for Region is 0.6315 and is statistically significant at the 1% level ($p < 0.001$). Unlike in PC1, the positive coefficient for Region in PC2 indicates that regional factors still influence how automation is studied, although the influence is less pronounced than in PC1. The coefficient for Year is 0.0133, with a p-value of 0.708, which is not statistically significant. This result suggests that the temporal factor does not significantly affect methodological differences in how automation is measured.

The findings emphasize that automation's reported impact on labour market (employment, wages, and productivity) is highly dependent on both regional contexts and the methodological frameworks employed in different studies. The regional and temporal variability captured by PC1 points to the need for context-specific policies, while the methodological variation captured by PC2 suggests that the choice of analytical techniques can influence policy recommendations. Policymakers and researchers should account for these sources of variation when interpreting empirical results. The presence of strong methodological effects suggests that caution is required when comparing studies using different methodological approaches econometric modelling vs. statistical comparisons.

The PCA analysis fits into this study as a tool for organizing divergent estimates and revealing the main dimensions of heterogeneity in the reported effects. PC1 identifies a structural–temporal gradient (differences across countries/Europe-wide samples and changes over time), while PC2 captures a methodological axis (the dependence of effect magnitudes on identification strategies). Thus, the PCA shows that the answer to the research question depends on context (study location and period) and method (identification strength), which justifies caution in aggregating results and supports the conclusion of a small but heterogeneous net effect.

Future research could refine these estimates by incorporating sector-specific variations, longitudinal labour market adjustments, and interactions between automation and human capital investment. These considerations will be crucial for formulating policies that facilitate a smooth transition toward a technology-driven economy while minimizing labour market disruptions.

6. Discussion

There is a notable scarcity of scientific literature on the dimensions of AI and automation's impact on employment, particularly in the EU. While grey literature provides valuable policy-oriented insights, the volume of rigorous scientific research analysing these phenomena remains relatively limited. Without a substantial body of empirical studies, the field risks an over-reliance on fragmented findings, underscoring the urgent need for further scientific exploration of this topic.

Despite the research on the impact of AI, automation, and Industry 4.0 on employment, significant gaps remain in understanding their long-term effects across diverse economic and social contexts. One critical gap lies in the inconsistent measurement of automation's impacts across sectors and regions. While studies provide granular insights into sectoral shifts, such as the displacement of low-skilled workers in manufacturing and the rise of high-skilled roles in ICT, these findings are often limited to specific regions or industries. The broader implications for non-industrial sectors, particularly in emerging economies with low technological readiness, remain underexplored. Furthermore, variations in methodology, including econometric modelling and survey-based approaches, often lead to discrepancies in reported impacts, making it challenging to draw generalizable conclusions.

Another key gap concerns the limited integration of policy frameworks into empirical studies. While grey literature emphasizes the need for education reform, reskilling programs, and state interventions to mitigate job displacement and wage inequality, scientific studies rarely evaluate the effectiveness of these strategies. This lack of focus on actionable policy outcomes hinders the development of comprehensive solutions for labour market adaptation. Additionally, the role of institutional factors, such as labour market regulations, trade policies, and educational systems, in mediating the effects of automation remains insufficiently addressed in the literature.

This study contributes to the literature in three key ways: first, by providing a synthesis of causal macroeconomic evidence on automation and AI's employment effects within the EU; second, by introducing a replicable AI-assisted methodology for conducting meta-analyses in underdeveloped fields; and third, by mapping clear research and policy gaps, including the scarcity of empirical AI-specific labour market studies. This work aligns with an emphasis on meta-research and methodological transparency (e.g., DeSimone et al., 2021) and complements previous survey contributions that addressed emerging empirical domains using structured synthesis. Importantly, our findings suggest that AI-assisted meta-analyses may help accelerate knowledge generation in areas where formal meta-regression is currently impractical, offering economists new tools to respond more quickly to fast-evolving research landscapes.

7. Limitations and Data Constraints

This meta-analysis is subject to several important limitations that must be acknowledged to properly contextualize the findings and guide future research directions.

A fundamental limitation is the relative scarcity of empirical studies specifically examining AI's impact on employment, as distinct from broader automation technologies. The majority of the selected studies focus on automation, robotics, or digitalization more generally, with only a subset directly addressing AI technologies. This reflects the nascent stage of AI deployment and the time lag between technological adoption in the labour market and academic research publication. Consequently, the findings may not fully capture the unique characteristics and effects of AI systems compared to traditional automation. The analysed studies exhibit uneven geographical coverage, with research from technologically advanced EU economies overrepresented while studies from Eastern and Southern European countries are more limited. This geographic bias may lead to an overestimation of positive employment effects, as the included studies predominantly reflect experiences in regions with stronger institutional support for technological transitions.

Significant methodological heterogeneity exists among the included studies, with different research designs, varying definitions of automation and AI, and diverse outcome measures. The Principal Component Analysis revealed that methodology explained a substantial portion of the variance in findings, with studies employing econometric modelling techniques reporting different magnitudes of impact compared to those using statistical comparisons. The studies also employ various metrics for measuring both technology exposure and employment outcomes, complicating the synthesis of findings. Moreover, many studies are constrained by the availability of longitudinal data that would allow for comprehensive tracking of employment effects over time. This limitation is particularly pronounced for AI-specific studies, where data collection frameworks are still evolving. The available data often lacks sufficient granularity to examine specific occupational categories or sub-sectors, hindering the development of targeted policy interventions.

Also, given the rapid pace of AI development, the findings may have limited temporal validity, particularly for AI-specific effects. The technological landscape has evolved substantially even during the period covered by this analysis, with the emergence of large language models and generative AI systems that may have fundamentally different employment implications than earlier automation technologies.

Due to limited and inconsistent reporting of technology exposure across the underlying studies, there were insufficient data to identify the direct impact of automation and AI on labour-market outcomes. Consequently, direct exposure measures (e.g., robot density, AI-exposure indices) were not incorporated into the PCA; observed variation in reported employment effects was instead mapped along the methodological (PC2) and regional–temporal (PC1) axes. Links to displacement and task-based complementarity are therefore treated as theory-consistent interpretations that require corroboration in supplementary analyses using external exposure measures.

The analysed studies provide limited evidence on the impacts of automation and AI on vulnerable worker populations, including migrants, older workers, and those in precarious employment arrangements. This gap may result in an incomplete understanding of distributional effects and policy blind spots regarding equity concerns in technological transitions. While the AI-assisted screening and data extraction processes demonstrated high overall reliability, performance varied across different tasks. The inter-rater reliability analysis revealed particular challenges in extracting temporal information and some inconsistencies in industry classification. The effectiveness of AI-assisted processes depends heavily on prompt design, and despite extensive testing, the prompts may not have captured all relevant nuances, particularly for edge cases or studies with ambiguous methodological approaches.

The modest positive net employment effect identified in this analysis should be interpreted with caution, recognizing that it may reflect the experiences of more technologically advanced EU regions and may not generalize to all contexts. The heterogeneity in findings across regions and methodologies suggests that policy interventions should be tailored to specific contexts rather than assuming universal applicability.

Despite these limitations, several factors support the robustness of the key findings. The consistent pattern of skill-biased effects across different studies and methodologies provides confidence that this represents a genuine phenomenon. The convergence of findings between academic studies and grey literature on key trends such as job polarization and regional disparities strengthens the credibility of these conclusions. The high inter-rater reliability achieved in final inclusion decisions and the comprehensive search strategy support the thoroughness of the evidence synthesis. These robustness factors provide confidence that the main conclusions regarding skill-biased technological change, regional disparities, and the need for proactive policy interventions are well-founded, while acknowledging the constraints that limit the precision and generalizability of specific quantitative estimates.

8. Conclusion

This meta-analysis addressed the research question: *What is the impact of automation and AI on employment within the EU, as evidenced by empirical research?* by synthesizing findings from filtered core 15 empirical macroeconomic studies highlighting causal effects and selected grey literature. The evidence suggests that automation and AI have a generally modest net positive effect on employment in the EU, though outcomes vary significantly across countries, sectors, and social groups.

In the context of this meta-analysis, regions experiencing higher levels of job displacement tend to be manufacturing-heavy and less technologically advanced areas within the EU, such as parts of Eastern and Southern Europe, including Hungary, Slovakia, and certain regions in Italy and Poland. These areas often exhibit lower automation readiness, slower digital infrastructure development, and a greater reliance on routine, manual labour, making them more vulnerable to the disruptive effects of automation. For example, studies referenced in the analysis noted employment declines of nearly 10% in highly automated manufacturing regions, particularly where compensatory job creation mechanisms (like innovation or retraining) are weak.

In contrast, regions in more advanced EU economies, such as Germany, the Netherlands, and parts of France, have seen more favourable employment outcomes. These regions benefit from stronger institutional support for innovation, better access to digital infrastructure, and more robust educational systems that supply high-skilled labour. They are also more likely to implement AI and automation in a complementary way, leading to productivity gains and job creation in knowledge-intensive sectors.

In terms of industries, manufacturing, transportation, and warehousing show the highest levels of job displacement due to their routine-intensive nature and susceptibility to process automation. Conversely, professional services, information and communication technologies (ICT), healthcare, and education have experienced employment growth driven by AI and digital augmentation. These sectors rely more heavily on non-routine cognitive tasks that are less automatable and often enhanced by AI applications, creating demand for high-skilled workers in roles such as data analysts, AI system designers, digital project managers, and health informatics specialists.

Overall, the labour market impact of automation and AI is highly sector- and region-specific, reinforcing the importance of a mix of tailored policy interventions that reflect local economic structures, technological readiness, and workforce profiles.

The analysis highlights persistent regional disparities, with more advanced EU economies benefiting more from technological adoption, while less developed regions face greater challenges due to limited digital infrastructure and lower automation readiness. Demographically, younger and more educated workers tend to gain from these changes, while older and low-skilled populations, along with some migrant groups, encounter higher risks of job loss or reduced job quality. Importantly, the review identifies a significant research gap in studies that assess the causal impacts of AI (as distinct from general automation), which limits the ability to develop tailored, evidence-based labour market policies.

From a policy perspective, the findings underscore the need for targeted reskilling and upskilling programmes that respond to evolving skill demands, as well as education reforms that promote early digital literacy and adaptability**.** Regional support measures are also vital to narrow the divide in technological adoption and ensure more balanced outcomes across the EU. Finally, the study calls for more robust, macro-level empirical research on AI's causal specific effects on employment, which is currently underdeveloped in the literature. Without such insights, there is a risk that automation and AI may reinforce existing inequalities rather than serve as engines of inclusive growth.

To sum up, the evidence synthesized in this study offers empirical support for both displacement and complementarity dynamics, depending on sectoral, regional, and skill-specific contexts. The results show the relevance of existing theoretical frameworks, particularly skill-biased technological change (SBTC) and task-based models of technological change as tools for interpreting employment impacts in the AI and automation era (Autor et al., 2003; Acemoglu & Restrepo, 2019; Vivarelli, 2014). SBTC theory explains the widening employment and wage gaps between high- and low-skilled workers as a consequence of technology favouring cognitive, non-routine tasks. In parallel, the task-based approach highlights how automation may simultaneously displace workers in routine roles while creating new tasks that complement human skills. By linking fragmented empirical outcomes to these broader theories, the study provides a conceptual basis for understanding labour market transitions and guiding future empirical and policy efforts.

As AI technologies and labour market dynamics continue to evolve, there is a clear need for ongoing meta-analytical monitoring. A structured follow-up synthesis within the next 3-5 years will be essential to assess how the evidence base expands, whether causal research on AI matures, and how labour outcomes shift across EU regions. This study also illustrates the value of early-stage, structured reviews in economics especially when combined with AI-assisted methods that enhance transparency, reproducibility, and efficiency.

Generative AI Statement

During the preparation of this work the authors used ChatGPT (models 4o, o1), Claude (models Sonnet 3.5, Haiku 3.5), Gemini (models Gemini Flash 2.0, Gemini 1.5 Pro) to improve readability and language. After using these tools, authors reviewed and edited the content as needed and take full responsibility for the content of the published article. Generative AI models are also a major element of the method proposed in the paper, as discussed in the Methods section.

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Appendix

Table 3. Empirical studies on the impact of automation and AI on employment. Authors' own elaboration.

Article/Authors of the study	*Research problem*	*Analysed impact*
Kordos, M., Berkovic, V. (2021)	Consequences of industry 4.0 in the tourism sector	- the impact of robotics, automation and digitalization within Slovak tourism business
Casas, P., Roman, C. (2023)	Whether the automation degree or the automation risk are triggering early retirement transitions	- automation -> early retirement
Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)	Impact of robot adoption on employment composition	- robot adoption -> total employment in a company - robot adoption -> hiring - robot adoption -> employment in division for skill level - robot adoption -> employment in division by age
Albinowski, M., Lewandowski, P. (2024)	Age- and gender-specific labour market effects of two key modern technologies, Information and Communication Technologies (ICT) and robots	- technology adoption -> labour market outcomes
Cirillo, V., Mina, A., Ricci, A. (2024)	Effects of new digital technologies on labour flows in the Italian economy	- digital technologies -> hiring rate - digital technologies -> separation rate
Tiwari, A.K. (2022)	Implications of imports-led and FDI facilitated automation for productivity and factor shares of tasks and value-added	- automation -> labour productivity - investment in automation -> labour productivity
Chen, C.C., Frey, C.B. (2024)	Impact of robots on local labour markets	- industry exposure to robots -> industry employment change
Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)	Adjustment of local labour markets to industrial robots	- robot exposure -> employment (total) - robot exposure -> average wage
Cords, D., Prettner, K. (2022)	The impact of automation capital on employment, wages, and labour market dynamics	- automation -> employment (low skilled) - automation -> employment (high skilled)
Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)	Firm- level employment effects of automation and robotization	- investment in manufacturing capital -> labour demand
Cserhati, I., Pirisi, K. (2020)	Impact assessment of Industry 4.0 on the expected structure of employment, wages and inequalities	None impact, implementation of Industry 4.0 vs. shift in employment and wages
Valaskova, K., Nagy, M., Grecu, G. (2024) (2024)	Employment and job dynamics within large Slovak enterprises resulting from the implementation of Industry 4.0 elements	None impact, implementation of Industry 4.0 vs. employment
Węgrzyn, G. (2020)	Changes taking place in the employment structure within Manufacturing which accompany the implementation of the industry 4.0 concept	None impact, implementation of Industry 4.0 vs. employment distribution
Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)	Effects of automation on employment	- exposure to robots -> employment

Cserháti, I., Takács, T. (2019)	Potential job losses caused by automation in Hungary and its impact on poverty gap	- automation -> job losses

Table 4. Overview of Empirical Studies – Impact of AI and Automation on Employment. Authors' own elaboration.

Article/Authors of the study	***Key findings***	***Methods***	***Study populations***	***Measures of impact***
Kordos, M., Berkovic, V. (2021)	Automation in Slovak tourism may lead to job transformation rather than loss	Structured interviews and comparison	Hotel industry employees in Slovakia	Introduction of robots; impact on job roles and employment opportunities
Casas, P., Roman, C. (2023)	Automation impacts early retirement decisions, education influences autonomy in retirement timing	Data from the SHARE survey; econometric analysis, logit estimations	Workers aged 50+, all over Europe, with various job status and education levels	Early retirement probability; automation degree; automation risk
Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)	Robot adoption in German manufacturing plants has led to increasing of employment	An event-study framework capturing employment trends before and after robot adoption; data transformations to handle zero-dependent variables and ensure ness	116 robot-adopting plants and 1,962 non-adopting plants	Total employment levels; Employment shares across occupational categories; Worker churning (hiring/separations) and task replaceability (complementarity or substitutability of workers to robots)
Albinowski, M., Lewandowski, P. (2024)	Adoption of ICT and robots impacted demographic labour outcomes (ICT had a larger influence); positive effects on employment shares for young and prime-aged women; negative effects for older women	Econometric modelling with instrumental variable (IV) approach; regression analyses controlled for education, sector, and globalization	21.2 million worker-level observations; 14 European countries; 936 country-sector observations for each demographic group, with groups defined by age (20–29, 30–49, 50–59, 60+) and gender	Changes in employment shares, wage shares, and average wages; Impacts estimated using counterfactual analyses comparing no-tech scenarios; ICT adoption contributed significantly to shifts in age- and gender-specific labour outcomes
Cirillo, V., Mina, A., Ricci, A. (2024)	Digital technologies positively impact firm hiring rates, particularly for young workers; adoption reduces separation rates and supports longer, stable work relationships	A Difference-in-Difference (DiD) approach combined with propensity score matching (PSM)	11,251 observations from the RIL-COB-ASIA dataset, representing a broad range of	Hiring rates, separation rates; share of new hires by age and education; impact on trained workforce and cost

			Italian firms across sectors	of training per employee
Tiwari, A.K. (2022)	Automation in Estonian firms increased productivity and labour share of value-added among adopters; multinational companies fostered job creation and knowledge spillovers through FDI	Micro econometric analysis using firm-level census data, decomposition techniques, and econometric modelling	Estonian firms from 1995 to 2018	Total Factor Productivity (TFP), Labour Share of Value-Added, employment changes, firm-level productivity, and effects of FDI and imports on automation outcomes
Chen, C.C., Frey, C.B. (2024)	Robots reduced manufacturing jobs across Europe, with significant employment declines in Italy, Norway, and the UK; robots increased non-manufacturing employment in Spain but reduced it in Germany, Italy, and Norway; young and unskilled workers were most adversely affected	Comparative analysis using robot penetration metrics (APR) and Chinese import exposure, based on OLS regression analysis	Eight European countries: Denmark, Finland, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom	Employment-to-population ratio, effects of robot adoption and Chinese imports, demographic and sectoral employment changes
Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)	Robots caused displacement in manufacturing jobs but were offset by job creation in the service sector; young workers faced more significant displacement; job quality improved with higher wages in new roles within firms.	analysis of administrative German labour market data combined with robot stock data from IFR. using a shift-share approach and instrumental variable (IV) strategy	German labour market regions from 1994 to 2014	Employment changes (%), wage growth (log differences), task share adjustments (routine, manual, abstract tasks), and productivity metrics
Cords, D., Prettner, K. (2022)	Automation leads to higher unemployment rates for low-skilled workers but decreases unemployment rates for high-skilled workers; automation increases wages for high-skilled workers while reducing wages for low-skilled workers; overall employment increases due to job creation in high-skilled sectors	Search and matching labour market model with automation capital as an additional production factor	German labour market data	Employment changes (%), wage differences (low- vs high-skilled workers), changes in labour market tightness (vacancy-to-unemployment ratios)
Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)	Investments in modern manufacturing capital, including automation technologies, increase local labour market employment; manufacturing employment sees the highest growth, with spillover effects to total employment; increased wages and sales indicate a productivity-driven labour demand rise	Event study methodology using microdata from French manufacturing firms and commuting zones (CZ) from 2003–2016	French manufacturing sector and commuting zones (CZs)	Semielasticitiesfor manufacturing employment, for total employment, for wages, for manufacturing sales

Cserhati, I., Pirisi, K. (2020)	Automation and Industry 4.0 leads to significant sectoral shifts in employment and wages; skill mismatches could worsen inequalities and labour shortages	Static microsimulation model based on EU-SILC Hungary 2018 dataset and projections from CEDEFOP and HCSO	Hungarian labour market (2018-2030)	Income inequality measures (Gini, S80/S20 ratio), sectoral wage growth, employment growth, regional wage distributions, and educational attainment changes
Valaskova, K., Nagy, M., Grecu, G. (2024)	Industry 4.0 technologies like digital twins and AI systems are adopted gradually in Slovakia, primarily in manufacturing; major obstacles include lack of digital skills, state support, and education reform; increased demand for technical workers with higher education was identified	Quantitative analysis combining national statistical indicators and a survey of 500 large manufacturing enterprises	Slovak Republic manufacturing sector (2016–2022), 413 firms responded to the survey	Employment changes, wage growth, digital readiness, Industry 4.0 implementation rates, and education system adaptability
Węgrzyn, G. (2020)	Industry 4.0 technologies lead to significant structural changes in manufacturing employment, especially in sectors with high robotization; employment for young, low-skilled workers decreases in high-tech areas; use of robots improves productivity but impacts job distribution	Descriptive and statistical analysis of Eurostat data (2011–2018); structural employment changes and robot density measures	Manufacturing sectors in seven EU countries: Czechia, Germany, Poland, Slovenia, Slovakia, Romania, and Hungary	Robot density, employment changes (%), sector-specific employment impacts, and demographic shifts in manufacturing labour
Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)	Automation has mixed effects: automating firms experience productivity gains and increased employment, but non-automating firms suffer displacement effects; automation leads to job polarization, increasing high- and low-skilled jobs while reducing routine jobs; positive firm-level effects on employment are offset by competitive pressures at the industry level	Literature review combined with empirical analysis, including firm-level event studies and shift-share research design	French manufacturing and labour markets from 1994 to 2015; cross-country comparisons with Europe and the US	Employment elasticities to automation, robot density changes, wage inequality metrics
Cserháti, I., Takács, T. (2019)	Automation in Hungary could result in job losses for 334,613 workers, primarily in low-skilled, manual labour occupations; the poverty gap may increase significantly without proper government interventions; public work programs can partially mitigate poverty increases	Static microsimulation using EU-SILC data, with risk assessments based on ISCO occupation codes and automation risk models	Hungarian labour force, 3.4 million records analysed, using national income and occupational datasets	Job losses by occupation (ISCO codes), poverty rate changes, poverty gap increase (from 62% to 83% in worst-case scenarios)

Table 5. Overview of grey literature – Impact of AI and Automation on Employment. Authors' own elaboration.

Authors of the study	***Key findings***	***Methods***	***Study populations***	***Measures of impact***
Hawksworth, J., Berriman, R., Cameron, E. (2018)	Automation affects job risks by gender, education, and occupation. Male jobs in manual labour are more at risk, while female jobs in education and healthcare are less automatable; industries vary in their automation risks: transport and manufacturing face the highest potential automation rates by 2030s; automation risk is highest for low-education workers; highly educated workers face lower risks due to cognitive and managerial tasks	Based on OECD's PIAAC dataset covering 29 countries. Uses a three-wave framework: Algorithm wave (2020s), Augmentation wave (2030s), and Autonomy wave; comparative analysis of countries, industries, and occupations	Workers analysed by gender, age, and education across 29 countries, representing over 200,000 workers; employment sectors include manufacturing, transport, education, and health; analysed tasks: computational, manual, social, and managerial across jobs.	Potential automation rates by job categories, gender, and education levels; automation is assessed across three waves with distinct task automation rates; impact on employment structure, wage trends, and task composition.
Carbonero, F., Ernst, E., Weber, E. (2018)	Robots have reduced global employment by 1.3% (2005–2014). Emerging economies are more affected (-14%) than developed economies (-0.54%); Developed countries benefit from reduced offshoring due to robotization, harming employment in emerging economies; robots substitute workers in repetitive tasks; labour-intensive sectors experience higher impacts.	A panel dataset combining International Federation of Robotics (IFR) and World Input-Output Database (WIOD); OLS and IV regression approaches to address endogeneity in robot deployment; technological progress indices as instruments to measure the task capability of robots.	41 countries and 15 sectors, focusing on manufacturing industries with high labour intensity; focus on industries like automotive, electronics, and manufacturing, where robots are predominantly installed; timeframe: 2005–2014; sectors classified by labour and capital intensity	Employment reduction rate: -1.3% globally, -14% for emerging economies; offshoring decline: -0.7% in developed countries; impact on labour-intensive industries: -4.3% employment in emerging economies.
Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)	AI-enabled automation is associated with employment increases in	Regression analysis using employment and wage data from EU Labour Force Survey (EU-LFS);	16 European countries (2011–2019) with sector-occupation observations at 3-	Change in employment shares and relative wages based on exposure to AI and software

	Europe, especially for high-skilled and young worker; no significant relationship between AI exposure and wages; software automation has varied country-specific impacts; heterogeneity in impact across countries is driven by technology diffusion, education levels, and regulations	two measures of AI exposure: Webb (task overlap) and Felten et al. (ability requirements); uses country-level controls like DESI, PISA scores, and OECD Product Market Regulation indices.	digit ISCO levels; skills grouped into low, medium, and high terciles; age categorized as younger, core, and older workers; occupational exposure to AI/software and structural factors like education and competition	technologies; employment impact quantified using Webb's AI indicator (+2.6% employment for median AI-exposed sectors); wage impact is neutral or negative; no evidence supporting software replacing routine jobs at the aggregate leave

Table 6. Comparison of "Key findings" Scientific studies vs. grey literature. Authors' own elaboration.

Aspect	*Scientific Studies*	*Grey Literature*
Overall impact of automation	Automation impacts jobs through task replacement and creation, with varied effects across sectors, regions, and skill groups. Automation is generally associated with employment increases in high-skilled sectors.	Emphasis on risks of automation to manual and routine jobs; highlights significant sectoral and regional differences but focuses more on risks rather than opportunities.
Wage trends	Wage impacts are mixed: automation increases wages in high-skilled sectors but reduces wages for low-skilled workers.	Similar findings on wage divergence, with higher inequality risks highlighted in grey literature. Fewer details on neutral or positive effects in high-skilled sectors.
Focus on skills	AI and automation favour high-skilled, younger workers, supporting Skill-Biased Technological Change (SBTC) theory. Medium- and low-skilled routine jobs are most vulnerable.	Highlights the risk to low-education and manual workers but also notes opportunities for high-skilled roles. Suggests automation amplifies inequalities without proper interventions.
Drivers of heterogeneity	Education levels, labour market policies (e.g., employment protections), and adoption rates drive differences in automation effects across countries and demographics.	Similar drivers identified, but greater emphasis on barriers to technology adoption such as lack of digital skills and government support, especially in less developed regions.
Regional differences	Effects vary across regions due to differences in technology diffusion, education systems, and regulations. Emerging economies are more negatively impacted than developed countries.	Regional disparities highlighted, especially for manufacturing in Europe and emerging economies. Developed countries benefit from offshoring reduction; emerging economies face job losses.
Sectoral impacts	Sectors like manufacturing and transportation show higher automation risks; service sector jobs often experience gains due to complementary technologies.	Manufacturing and transport dominate automation risks; service sector benefits less prominently discussed. Focuses

		on manual labour displacement and regional job quality declines.

Table 7. Overview of empirical studies – Indicators of Automation, AI, and Industry 4.0 Adoption's impact on various aspects of employment. Authors' own elaboration.

Indicator type	*Description*	*Value*	*Article/Authors of the study*
Employment impact	Percentage increase in sector jobs due to automation	1,9% increase (2014-2019)	Kordos, M., Berkovic, V. (2021)
	Total employment increase around robot adoption	5%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Share of total employment by automation-adopting firms	Declined in manufacturing since 2005, stagnant in other sectors	Tiwari, A.K. (2022)
	Change in employment-to-population ratio in response to robot adoption	-0.52% (Italy), -2.1% (Norway), -0.47% (UK); No significant effect in other countries	Chen, C.C., Frey, C.B. (2024)
	Overall change in total employment due to automation in Germany	No significant change in total employment; offset between sectors	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Overall change in total employment due to automation in Germany	Increase in high-skilled employment offsets low-skilled job losses	Cords, D., Prettner, K. (2022)
	Change in unemployment rates for low-skilled workers	Increased	Cords, D., Prettner, K. (2022)
	Change in unemployment rates for high-skilled workers	Decreased	Cords, D., Prettner, K. (2022)
	Overall effect of investments in modern manufacturing capital on local labour market employment	Positive; semi elasticity of +0.04	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Changes in employment levels across sectors due to automation and Industry 4.0.	Varies by sector: -45.3% in agriculture, +10.4% in utilities	Cserhati, I., Pirisi, K. (2020)
	Increase in hiring rate in the robot adoption year	24%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Changes in employment levels across Slovak manufacturing sectors due to Industry 4.0 adoption	No significant overall change: 11.22% of firms saw workforce growth; 12.09% reduction in less skilled technical roles	Valaskova, K., Nagy, M., Grecu, G. (2024)
	Change in manufacturing sector employment	Declined by approximately 9.7%	Dauth, W., Findeisen, S., Suedekum, J.,

			Woessner, N. (2021)
	Growth in robot-intensive manufacturing industries	Slovakia (Automotive): +4.4 pp; Germany (Machinery): +3 pp	Węgrzyn, G. (2020)
	Increase in employment due to automation at automating firms	+0.2% immediate increase in employment; +0.4% after 10 years	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Employment and output effects on firms not adopting automation	10% decrease in employment for non-automating firms due to competition from automating firms	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Employment impact on service sectors	Increased by approximately 4.7%	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Number of workers at high risk of losing their jobs due to automation, primarily in low-skilled occupations	334,613 workers in Hungary, representing approximately 9.8% of the workforce	Cserháti, I., Takács, T. (2019)
	Automation risk of job loss due to automation varies by occupation, with higher risks for manual and low-skill roles	Highest risk: 18% for assemblers and skilled trades; Lowest risk: 2% for managers	Cserháti, I., Takács, T. (2019)
	Occupations with highest risk of job loss most affected by automation risks	Assemblers (ISCO 73): 18% risk; Plant Operators (ISCO 81): 17% risk	Cserháti, I., Takács, T. (2019)
Economic contribution/ Wage changes/ Wage and income inequality	Change in average wages due to automation	33% increase in manufacturing; 29% in services	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Effect of automation on wages of low-skilled and high-skilled workers	Wages decrease for low-skilled, increase for high-skilled workers	Cords, D., Prettner, K. (2022)
	Impact on local wages	Positive; semi elasticity of +0.01	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Growth in nominal wages for industrial workers	7.4% increase in 2022 compared to 2021	Valaskova, K., Nagy, M., Grecu, G. (2024)
	Real wage growth across sectors based on projected automation adoption and labour demand	1.5-2% annually, highest in ICT and manufacturing.	Cserhati, I., Pirisi, K. (2020)
	Gap between low-skilled and high-skilled wages due to automation	Increased due to divergent wage trends	Cords, D., Prettner, K. (2022)
	Impact of automation and Industry 4.0 on wage distribution and income inequality	Gini increases from 0.333 to 0.371	Cserhati, I., Pirisi, K. (2020)

	Effect of automation on wage disparities between low- and high-skilled workers	No significant effect found; ratio of low- to high-skilled wages remains stable	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Real wage changes in automation-intensive sectors.	Manufacturing: +122%; ICT: +153%	Cserhati, I., Pirisi, K. (2020)
Total Factor Productivity (TFP)/Labour Productivity	Productivity growth of automation-adopting firms compared to non-adopters	Higher for adopters; faster growth observed	Tiwari, A.K. (2022)
	Effect of modern manufacturing capital investments on productivity	Significant, drives labour demand growth	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Year-on-year changes in labour productivity per person employed	Peak of +12.1% in 2021 (economic recovery and increased adoption of automation and digital technologies), low of -7.2% in 2020 (pandemic impact)	Valaskova, K., Nagy, M., Grecu, G. (2024)
Automation's/robotics' impact on labour tasks/job roles	Reduction in labour task content among automation adopters	Declines over time, especially in firms automating frequently	Tiwari, A.K. (2022)
	Change in task composition (routine to abstract) due to automation	Routine tasks declined by 9%; abstract tasks increased by 8%	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Workforce shifts due to AI and automation adoption	28.81% increase in skilled technical roles; 12.09% decrease in low-skilled technical roles	Valaskova, K., Nagy, M., Grecu, G. (2024)
	Extent to which automation replaces manual or repetitive tasks	Not explicitly quantified but observed	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Share of replaceable tasks across age groups	Young (19.11%), Mid-age (19.05%), Old (18.72%)	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Shifts in job structure due to automation: routine jobs decrease, while high- and low-skilled jobs increase	Routine jobs decrease significantly; high- and low-skilled job shares increase in automating firms	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Degree to which robots replace low-skilled tasks	High; robots act as a perfect substitute for low-skilled labour	Cords, D., Prettner, K. (2022)
General employment impact/ Labour demand changes after automation/robot adoption	Net change in total employment due to automation	Positive overall after accounting for job creation	Cords, D., Prettner, K. (2022)
	Overall impact of automation on labour demand	Driven by productivity; positive net effect	Aghion, P., Antonin, C., Bunel, S.,

			Jaravel, X. (2023)
	Increase in employment share for young women (20-29) due to ICT (Information and Communication Technology) adoption	+0.13 percentage points	Albinowski, M., Lewandowski, P. (2024)
	Hiring shows a pronounced spike in the robot adoption year	24%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Total employment increases in the robot adoption year by about 5 percent compared to the control group	5%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Increase in hiring rate due to technology adoption	+2 percentage points	Cirillo, V., Mina, A., Ricci, A. (2024)
	Impact of robots on non-manufacturing employment	Increased in Spain; Decreased in Germany, Italy, Norway	Chen, C.C., Frey, C.B. (2024)
	Impact of robots on manufacturing employment	Decreased across all countries, statistically significant in Italy, Spain, UK	Chen, C.C., Frey, C.B. (2024)
	Change in employment specifically in manufacturing sectors due to investments in modern manufacturing capital	Positive; semi elasticity of +0.05	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Employment shifts due to automation in specific sectors	Manufacturing: +0.9%; ICT: +0.5%	Cserhati, I., Pirisi, K. (2020)
Training/education path referred to adoption of new technology	Increase in share of trained employees due to technology adoption	+3.3 percentage points	Cirillo, V., Mina, A., Ricci, A. (2024)
	Introduction of new technologies increases the percentage of trained workers	3,3%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Cost of training rises per employee compared to non-adopting firms	30%	Deng, L., Müller, S., Plümpe, V., Stegmainer, J. (2024)
	Education and career path adjustments by young workers in response to automation	Shift towards higher education (college/university)	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Impact of automation and Industry 4.0 on distribution of employed persons by education level	Slight increase in tertiary education from 24.5% to 26.1%	Cserhati, I., Pirisi, K. (2020)
	Perception of workforce readiness for Industry 4.0	38.29% rate graduates as prepared; 34.28% view them as unprepared	Valaskova, K., Nagy, M., Grecu, G. (2024)
	Impact of robots on skilled and unskilled workers	Negative for unskilled workers, especially in	Chen, C.C., Frey, C.B. (2024)

		Germany and UK; Limited effect on skilled workers	
	Probability of early retirement (average)	5,35%	Casas, P., Roman, C. (2023)
	Effect of automation on job tenure	Job stability increased for incumbent workers	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
Impact of automation on distribution of demographics (age, gender)	Effect of robots on age-specific employment	Young workers most affected negatively; Older workers (55+) benefit in Finland, Germany	Chen, C.C., Frey, C.B. (2024)
	Impact of age on early retirement transition probability with focus on automation degree	34,94%	Casas, P., Roman, C. (2023)
	Impact of automation on different worker demographics	Younger workers disproportionately affected; older workers less impacted	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Effect of robots on male and female employment	Negative impact on male employment; Mixed results for female employment	Chen, C.C., Frey, C.B. (2024)
	Impact of gender (female) on early retirement transition probability with focus on automation degree	39,03%	Casas, P., Roman, C. (2023)
	Impact of having a partner on early retirement decision with focus on automation degree	9,54%	Casas, P., Roman, C. (2023)
	Decrease in employment share for older women (60+) due to robot adoption	-0.17 percentage points	Albinowski, M., Lewandowski, P. (2024)
	Net effect of robots on job creation in high-skilled sectors	3.42 high-skilled jobs created per additional robot	Cords, D., Prettner, K. (2022)
	Net effect of robots on job destruction in low-skilled sectors	1.66 low-skilled jobs lost per additional robot	Cords, D., Prettner, K. (2022)
	Relationship between robot exposure and employment-to-population ratio by country	Italy: -0.52%; Norway: -2.1%; UK: -0.47%; Others: No significant impact	Chen, C.C., Frey, C.B. (2024)
	Reduction in demand for routine tasks and impact on young workers	Germany: Decline in young workforce aged 15–24 by -7% (men) and -6.6% (women)	Węgrzyn, G. (2020)

Table 8. Overview of grey literature – Indicators of Automation, AI, and Industry 4.0 Adoption's impact on various aspects of employment. Authors' own elaboration.

Indicator type	*Description*	*Value*	*Authors of the study*
Employment impact	Reduction in global employment due to robot adoption	-1.3% (2005–2014)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Employment decline in developed economies	-0.54% (2005–2014)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Employment decline in emerging economies	-14% (2005–2014)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Employment loss in labour-intensive sectors in emerging economies	-4.3%	Carbonero, F., Ernst, E., Weber, E. (2018)
	Reduction in employment in emerging economies due to reduced offshoring in developed economies	-5%	Carbonero, F., Ernst, E., Weber, E. (2018)
	Share of manufacturing jobs lost globally due to robots	-0.046%	Carbonero, F., Ernst, E., Weber, E. (2018)
	Share of jobs at risk of automation in the 2030s	22% (Finland, Korea) to 44% (Slovakia)	Hawksworth, J., Berriman, R., Cameron, E. (2018)
	Increase in employment share for sectors with median AI exposure	+2.6% (Webb indicator)	Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)
Total Factor Productivity (TFP)/Labour Productivity	Increase in productivity due to robot adoption	+0.37% annually (2005–2014)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Contribution of robots to labour productivity growth	10% of overall productivity growth (2005–2014)	Carbonero, F., Ernst, E., Weber, E. (2018)
Economic contribution/ Wage changes/ Wage and income inequality	Wage impact in developed economies	+1.5% (average sectoral increase)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Increase in wage inequality due to skill-biased automation	+5.5% (Gini coefficient in some regions)	Carbonero, F., Ernst, E., Weber, E. (2018)
	Impact of AI on relative wages for high-skilled workers	+0.034 (Webb AI measure, significant for high-skilled workers only)	Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)
Automation's/robotics' impact on labour tasks/job roles	Automation of simple computational tasks	3%-5% of jobs affected across countries	Hawksworth, J., Berriman, R., Cameron, E. (2018)
	Automation of dynamic tasks (e.g., clerical work)	20%-26% of jobs affected across countries	Hawksworth, J., Berriman, R., Cameron, E. (2018)
	Routine/manual tasks are highly automatable	Up to 64% for operators/assemblers	Hawksworth, J., Berriman, R., Cameron, E. (2018)
Training/education path referred to adoption of new technology	Low-education workers face higher automation risk	50%+ (low education)	Hawksworth, J., Berriman, R., Cameron, E. (2018)
	Increase in AI employment share for high-skilled occupations	+6.6% (Felten indicator)	Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)

Impact of automation on distribution of demographics (age, gender)	Male workers at higher risk due to manual-task sectors	34% (males) vs. 26% (females)	Hawksworth, J., Berriman, R., Cameron, E. (2018)
	Positive AI impact for occupations employing younger workers	+3.2% (Webb indicator)	Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)
	Increase in employment shares for occupations employing younger workers	+21.2%	Albanesi, S., Dias da Silva, A., Jimeno, J.F., Lamo, A., Wabitsch, A. (2023)

Table 9. Comparison of "Indicators" Scientific studies vs. grey literature. Authors' own elaboration.

Aspect	*Scientific Studies*	*Grey Literature*
Employment Impact	Automation leads to sector-specific shifts, with job creation in high-skilled sectors and displacement in routine, low-skilled roles.	Focuses on macro-level risks, emphasizing overall job losses, particularly in emerging economies and labour-intensive industries.
Productivity Trends	Highlights productivity gains for firms adopting automation, driving labour demand in specific sectors.	Emphasizes automation's contribution to global productivity growth and its role in economic recovery.
Wage Trends	Automation creates wage divergence, benefiting high-skilled workers while reducing wages for low-skilled workers.	Focuses on increasing inequality, with automation widening the wage gap and amplifying existing disparities.
Task and Job Role Shifts	Automation reduces routine tasks and increases demand for non-routine cognitive tasks, supporting job polarization.	Discusses the automatable nature of routine tasks, with significant risks for manual and low-skill roles across industries.
Regional Focus	Examines country- and sector-level heterogeneity, noting variations in automation's impact based on adoption rates and workforce characteristics.	Highlights regional disparities, with emerging economies facing higher risks due to lower technological readiness and labour-market vulnerabilities.
Policy Implications	Focuses on understanding trends but provides limited guidance on mitigation strategies.	Emphasizes the need for education reform, skill development, and government support to address automation's challenges.

Table 10. Overview of empirical studies – Indicators of Automation, AI, and Industry 4.0 Adoption's impact on various aspects of market. Authors' own elaboration.

Indicator type	***Description***	***Value***	***Authors of the study***
Technology/IoT/robotics adoption	Share of firms adopting at least one I4.0 technology (IoT, robotics, etc.)	29% (2018, firm-level)	Cirillo, V., Mina, A., Ricci, A. (2024)
	Introduction of advanced tools and equipment into the manufacturing sector, specifically through imported intermediate goods	Positive; semi-elasticity of +0.04	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2023)
	Share of firms investing in robotics	2.6% (2018, firm-level)	Cirillo, V., Mina, A., Ricci, A. (2024)

	Share of firms investing in Internet of Things	4.7% (2018, firm-level)	Cirillo, V., Mina, A., Ricci, A. (2024)
Impact on market share/industries	Revenue share of automation-adopting firms	Exceeds 50% in recent years	Tiwari, A.K. (2022)
	Productivity-driven market share gains by automating firms	Significant increase in market share for automating firms, especially in international markets	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Industries with the fastest robot growth	Food processing in Poland: -2.5 pp (2011–2018); Automotive in Romania: +7.4 pp	Węgrzyn, G. (2020)
ICT capital/investment	ICT capital per worker	€5,100 (average across countries)	Albinowski, M., Lewandowski, P. (2024)
	Role of ICT technologies in mitigating the effects of robots	Positive in Spain; negative in Finland (Nokia collapse); limited elsewhere	Chen, C.C., Frey, C.B. (2024)
Automation risk/barriers	Probability of job being automated (average)	62,72%	Casas, P., Roman, C. (2023)
	Barriers to automation adoption	High costs (56.12% of firms) and security risks (37.76	Valaskova, K., Nagy, M., Grecu, G. (2024)
Automation adoption rate/ Automation degree	Proportion of firms adopting automation	10-20% in manufacturing, 2-6% in services, 3-5% in mining/utilities/construction	Tiwari, A.K. (2022)
	Degree of job automation potential (average)	27,81%	Casas, P., Roman, C. (2023)
	Key manufacturing sectors with the highest robot utilization	Automotive industry in Germany: 16% of employment (2018); Poland: 9.3% (up from 7.4% in 2011)	Węgrzyn, G. (2020)
	Adoption and effects of automation in specific industries	Automotive industry: highest adoption, 35% of all industrial robots used in this sector	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Proportion of firms adopting advanced automation technologies, such as robots or AI systems	Approximately 25% of manufacturing firms in France adopted automation technologies by 2015	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Proportion of firms implementing Industry 4.0 components like AI, digital twins, IoT	65.29% of surveyed firms have implemented or started implementing	Valaskova, K., Nagy, M., Grecu, G. (2024)
Robot exposure/penetration	Number of robots per 1,000 employees	1.5 (average)	Albinowski, M., Lewandowski, P
	Change in the operational stock of robots per 1,000 workers	Germany: 4 (2007); Norway: 0.44 (2007)	Chen, C.C., Frey, C. B

	Increase in robot usage per 1,000 workers	+4.6 robots per 1,000 workers (1994–2014)	Dauth, W., Findeisen, S., Suedekum, J., Woessner, N. (2021)
	Number of robots per 10,000 employees in manufacturing sectors	Global average (2018): 99; Europe: 114; Germany: 322; Poland: 42; Slovakia: 165; Hungary: 84	Węgrzyn, G. (2020)
	Growth in the number of robots installed annually in manufacturing	2011–2018 global growth: from 159,000 to 422,000 units annually (+165%). EU: Germany +26% (2018)	Węgrzyn, G. (2020)
	Variation in robot adoption by country	South Korea: 710 robots/10,000 employees; Slovakia: 165; Poland: 4	Węgrzyn, G. (2020)
	Number of robots per 1,000 workers in French manufacturing industries	3.1 robots per 1,000 workers in 2015	Aghion, P., Antonin, C., Bunel, S., Jaravel, X. (2022)
	Increase in robots per 1,000 workers	7.6 robots (baseline, 2014), scenario adds 1 more robot	Cords, D., Prettner, K. (2022)