

The Automation-Migration Interface and Migrants' Labour Market Integration

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Abstract

How is automation reshaping migrants' labour market integration? This article addresses that question by placing technological change at the centre of migration and integration research. Building on dual labour market theory, it develops the concept of the Automation-Migration Interface to explain how automation and artificial intelligence (AI) affect migrants through four linked mechanisms: task restructuring, occupational shifts, selection and matching, and institutional barriers. The analysis draws on a systematic review of academic research and selected grey literature. The review shows that the strongest evidence concerns how automation alters task demand and occupational structures, while direct evidence on migrant-specific outcomes remains more limited. Across the literature, migrants appear especially vulnerable where routine job ladders decrease, foreign credentials are weakly recognised, access to training is unequal, and algorithmic screening intensifies labour market gatekeeping. At the same time, technological change may support integration where migrants' skills complement automation and where institutions enable retraining, recognition, and mobility. The article argues that automation does not affect migrant integration uniformly; its consequences are mediated by labour market institutions, migration regimes, and forms of digital governance. It concludes that automation should be understood not as background context, but as an emerging condition of migrant labour market incorporation.

Introduction

Automation, artificial intelligence (AI), and related digital technologies are transforming labour markets in ways that are highly consequential for migration and integration. Research on technological change has shown that automation reshapes the task composition of work, contributes to occupational restructuring, and can intensify labour market polarization through the erosion of some routine middle-skill jobs alongside growth in both high-skill professional work and parts of the low-wage service economy (Autor et al., 2003; Goos et al., 2014; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). These developments are especially important for migrants, whose labour market incorporation is often shaped by occupational segmentation, uneven recognition of qualifications, legal status constraints, and unequal access to training and mobility opportunities (Piore, 1979; Reitz, 2001, 2007; Kanas et al., 2011; Piracha et al., 2012). Technological change needs to be therefore understood not only as an economic process that alters labour demand, but also as a social and institutional process that can reconfigure the conditions under which migrants enter, navigate, and advance within destination country labour markets.

Labour market outcomes are a central pillar of immigrant settlement and integration because they shape earnings, income security, social mobility, and broader participation in receiving societies (Chiswick, 1978; Borjas, 1985; Reitz, 2001; Bevelander & Pendakur, 2014). Migration scholarship has long demonstrated that integration is not exhausted by employment entry alone; job quality, skill utilisation, occupational matching, and opportunities for upward mobility are equally important dimensions of incorporation (Reitz, 2001, 2007; Fullin & Reyneri, 2011; Zwysen & Longhi, 2018). Yet these processes are increasingly unfolding in labour markets reorganised by automation and digitally mediated forms of

recruitment, evaluation, and management. AI does not simply affect the quantity of labour demanded. It also shapes how workers are screened, how skills are classified and valued, how credentials are interpreted, and how performance is monitored in the workplace (Kellogg et al., 2020; Raghavan et al., 2020; Ajunwa, 2020). For migrants, these developments may create opportunities in expanding sectors, but they may also deepen pre-existing inequalities where technological change intersects with labour market segmentation, weak transferability and portability of qualifications, or discriminatory forms of institutional gatekeeping (Pager & Shepherd, 2008; Reskin, 2003; Kalleberg, 2009).

This article revisits dual labour market theory to analyse how automation and AI reshape migrant labour market integration. In Piore's (1979) formulation, advanced economies are structured by a segmented labour market divided between a primary sector associated with stability, higher wages, and mobility prospects, and a secondary sector characterised by insecurity, lower pay, and limited progression. Migrants are often disproportionately incorporated into the latter, where they face greater exposure to instability and weaker returns to their skills (Piore, 1979; Reitz, 2001; Fullin & Reyneri, 2011). We argue that contemporary technological change can reinforce and rework these forms of segmentation. Automation may reduce demand for some routine occupations that have historically functioned as entry points or mobility ladders, while increasing demand in both highly skilled occupations and selected forms of difficult-to-automate service work (Autor et al., 2003; Goos et al., 2014; Acemoglu & Restrepo, 2020). At the same time, AI introduces new mechanisms of labour market filtering through automated screening, predictive assessment, and digitally mediated workplace control, all of which may shape migrants' access to jobs and conditions of work in ways that are not captured by aggregate employment trends alone (Kellogg et al., 2020; Raghavan et al., 2020).

To capture these dynamics, the article develops an Automation-Migration Interface Approach that treats technological change as mediated by labour market institutions, migration regimes, and social inequalities. Rather than asking only whether automation substitutes for or complements migrant labour, the article examines the mechanisms through which technological change shapes migrant incorporation. These mechanisms include changes in task composition, shifts in occupational demand, selecting and matching into sectors and regions, and barriers related to credential recognition, access to training, digital skills, and hiring practices. This perspective aligns with broader social science scholarship showing that labour market outcomes are mediated by institutions, networks, and gatekeeping processes rather than determined by market forces alone (Granovetter, 1973, 1995; Reskin, 2003; DiMaggio & Garip, 2012). For migrants in particular, the consequences of automation are likely to depend not only on exposure to technological change, but also on whether they can convert changing labour demand into stable employment, skill utilisation, and upward mobility.

Empirically, the article draws on a systematic review of academic research and selected grey literature, with a primary focus on the European Union (EU) and some comparative reference to the United States and China. The aim is not to produce a strict like-for-like comparison across contexts, but to identify recurring mechanisms and to assess how institutional settings condition the relationship between technological change and migrant labour market incorporation. The article asks: how do automation and

AI interact with migrant labour in the EU, and through which mechanisms do these interactions shape labour market integration, segmentation, and opportunities for mobility? Related questions address how technological change restructures tasks and occupations, how migrants are matched into evolving labour markets, and which barriers most strongly mediate outcomes such as wages, employment stability, occupational mobility, segregation, and skill utilisation.

Definitions and Scope

In this article, automation refers to the broad process through which machines, software, and redesigned workflows substitute for, complement, or reorganize specific work tasks (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2018). Robotics or industrial automation is a narrower category focused on physical equipment that replaces routine manual tasks in sectors such as manufacturing and warehousing, for example automated selecting systems or robotic picking (Acemoglu & Restrepo, 2020). Artificial intelligence, including machine learning, is treated as a distinct subset of digital technologies that automate or augment mainly cognitive functions such as prediction, classification, and language processing (Mitchell, 1997; Bishop, 2006), and it often affects hiring and workplace management through tools such as CV screening, predictive scheduling, and performance monitoring (Raghavan et al., 2020; Ajunwa, 2020; Kellogg, Valentine & Christin, 2020). Data science refers to the wider set of practices used to analyse data for forecasting and decision support, sometimes using machine learning and sometimes not (Provost & Fawcett, 2013; Donoho, 2017), while generative AI is a type of AI that produces new content such as text or code and can reshape tasks in customer service and professional work (Goodfellow et al., 2014; Vaswani et al., 2017; Bommasani et al., 2021). Keeping these concepts separate matters because they influence migrant workers' labour market integration through different channels, with robotics and industrial automation more directly altering demand for routine manual labour (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018), and AI also shaping access to jobs and job quality through screening, credential evaluation, and algorithmic management (Ajunwa, 2020; Raghavan et al., 2020; Kellogg, Valentine & Christin, 2020).

Theory: From Dual Labour Market Theory to the Automation-Migration Interface

Research on migrant labour market integration has long shown that migrants are incorporated unevenly into destination country labour markets, often through segmented jobs with lower wages, weaker protections, and limited mobility (Piore, 1979; Reitz, 2001, 2007; Bevelander, 2000). Dual labour market theory remains an important starting point because it explains migrant incorporation through the structural organization of labour demand rather than individual deficits. However, Piore's distinction between primary and secondary sectors is less suited to labour markets increasingly reshaped by automation, digitalisation, and algorithmic management. Today, segmentation is produced not only by sectoral location, but also by changing task structures, unequal access to mobility, and new forms of

digital gatekeeping in hiring and work organization (Autor et al., 2003; Goos et al., 2014; Kellogg et al., 2020).

To address these limits, this article proposes the Automation-Migration Interface Approach. The approach builds on Piore's insight that migrant incorporation is shaped by segmented labour demand, but treats segmentation as a dynamic outcome of technological change and institutional mediation rather than as a fixed property of sectors. Its core argument is that automation and AI affect migrant labour market integration through four linked mechanisms: task restructuring, occupational shifts, selecting and matching, and barriers that mediate outcomes. In this view, technological change reorganises the opportunity structure that migrants encounter and shapes whether they experience upgrading, exclusion, or persistent segmentation.

This approach also adopts a broader understanding of labour market integration. Integration is defined not only as employment entry, but as access to stable work, adequate pay, skill utilisation, and opportunities for mobility over time (Reitz, 2001; Bevelander & Pendakur, 2014). The same technology may therefore support integration where migrants can access retraining, credential recognition, and labour market protections, but weaken it where they are channelled into precarious, tightly monitored, or low-mobility work. Cross-national differences in training systems, welfare regimes, employment protection, and migration rules are therefore central to explaining why similar technological changes produce different outcomes across contexts (Reitz, 2007; Fasani et al., 2021).

Taken together, the Automation-Migration Interface Approach moves beyond the question of whether automation replaces or complements migrant labour. Instead, it identifies the mechanisms and institutional conditions through which technological change reshapes migrant incorporation, mobility, and segmentation.

Methods: LLM, human validation, geography and limitations

This literature review used in this paper employed a generative AI assisted methodology, leveraging the capabilities of large language models (LLM) to streamline and enhance the process. Specifically, we combined established systematic review techniques with capabilities of LLM to improve efficiency and comprehensiveness in literature search and screening. The final stage of both articles checking and analysing was done by humans.

Given the rapid expansion of scholarship on automation, AI, and employment, we used large language models (LLMs) to make evidence mapping feasible at scale. The LLMs supported two bounded tasks: (i) expanding and refining database search strings by generating synonyms and related terms, and (ii) triaging the large set of retrieved abstracts using explicit, rule-based prompts aligned to our inclusion criteria. Human reviewers then validated the LLM outputs, resolved borderline cases, and conducted full-text screening of shortlisted studies, ensuring that inclusion decisions ultimately rested with researchers. To support transparency and replication, we document the decision rules, report screening counts at each stage, and make the prompts and implementation notes available.

LLMs were used only for bounded tasks that are transparent and replicable: (i) generating candidate synonyms to refine database search strings, and (ii) triaging abstracts and extracting predefined fields using rule-based prompts aligned with the inclusion criteria. We used GPT-4o for Level 1 abstract classification and GPT-4o mini for structured field extraction at Level 2, with deterministic settings (temperature = 0). Human reviewers validated the extracted fields, reviewed all borderline cases, and made all final inclusion decisions. Full-text screening was conducted independently by two reviewers, with disagreements resolved through discussion and adjudication. All prompts, schemas, screening rules, and stage counts are documented in Appendix A and summarised in a PRISMA flow diagram.

We employed a thorough, scoping, due to the novelty of the topic, systematic approach to identify studies examining the impact of automation and AI on employment. Furthermore, our search strategy was expanded to cover migration-related topics by incorporating keywords like 'migration', 'migrants', 'labour migration', 'Third-Country Nationals (TCNs)', and related terms alongside those for automation and AI. This approach ensured a comprehensive coverage of literature concerning the impact of automation and AI on both employment and labour migration.

An AI agent based on GPT4o specifically created for systematic review studies helped generate synonyms and related terms for key concepts and writing search strings for academic databases. Search was run entirely by researchers.

Following established recommendations for comprehensive literature reviews (DeSimone et al., 2021; Gusenbauer & Haddaway, 2020; Martín-Martín et al., 2021; Mongeon & Paul-Hus, 2016), our search spanned Scopus, EBSCOhost, and Web of Science. In addition to database queries, we conducted manual searches in Google Scholar, Semantic Scholar, and Google to capture additional publications and grey literature. We also examined the reference lists of identified studies and other key publications to ensure no relevant work was overlooked.

Large language models played a crucial role in streamlining the otherwise time-consuming screening process, impossible for a human mind in such a big volume. We implemented a hierarchical LLM-based screening method that prioritized criteria such as thematic fit and study design. For each criterion, highly specific prompts guided the LLM's classification of abstracts using Boolean decisions and data extraction techniques, such as identifying study location or time-period. These prompts were iteratively tested on a sample of abstracts, with the AI's classifications compared against those made by human reviewers to ensure accuracy. Given the substantial number of abstract of 9,717 papers initially identified, we leveraged API calls to OpenAI's GPT-4o and GPT-4o mini models to efficiently process the data and minimize costs.

A three-level screening process was employed, similar to the employment-focused meta-analysis (cf. Sowa et al. 2024), but tailored to the migration research context:

- Level 1 Screening: Abstracts were screened using OpenAI's GPT-4o model, focusing on thematic fit, causal study design, and quantitative methodology. Thematic fit was defined by studies discussing

automation and AI's impact on migrants, migration patterns, or labour migration within the EU or comparable contexts. This stage reduced the initial set to 35 papers.

- Level 2 Screening: LLM-based extraction of migration-specific criteria included location, inclusion of migration factors and economic indicators. Human reviewers validated the data and filtered studies further, resulting in 24 papers.
- Level 3 Screening: Two independent human reviewers conducted a rigorous assessment of full texts to ensure inclusion criteria were met. This stage emphasized studies examining automation and AI's impact on migrants at a macro level, causal inference, and econometric measures. The final set included 9 studies.

Manual searches identified migration-specific grey literature from relevant institutions and organizational reports. As with the employment-focused study, identical screening criteria were applied, resulting in the inclusion of additional sources.

Database reduction:

- Initial Dataset: 120 papers (manual search + migration-specific filter on 9,717 meta-analysis corpus) and 65 grey literature reports.
- Post-Level 1: 35 papers and 65 grey literature reports.
- Post-Level 2: 24 papers and 15 grey literature reports.
- Post-Level 3: 5 papers and 4 grey literature reports.

This tailored process ensured a focused and high-quality selection of studies examining the intersection of automation, AI, and migration dynamics.

In this article we apply the systematic literature review (SLR) to the set of academic articles and a set of grey literature considering 'the influence of automation, AI on labour migration and labour market integration which came out as a result of AI-assisted meta-analysis presented above. It follows a structured approach to synthesize and evaluate research findings on the interplay between artificial intelligence (AI), labour market dynamics, and migration and migrants. A systematic literature review is a structured, comprehensive, and methodical process for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners. It aims to provide a clear summary of the current evidence on a clearly defined research question.

To support the comparative synthesis, each included study was coded by primary geographic focus using information reported in the abstract/full text (study setting, sample, data source, and policy context). We used five mutually exclusive categories aligned with the review's comparative aim (EU/EEA vs major non-EU poles and multi-country evidence): (1) EU/EEA (studies focusing on the European Union, the European Economic Area, or specific EU/EEA member states); (2) United States (U.S.-only studies or analyses centred on U.S. labour markets and migration); (3) China (China-only studies, including internal migration where explicitly analysed as migration/mobility); (4) OECD/Global (multi-country studies

drawing on OECD datasets or broad cross-country/global evidence where no single country/region dominates); and (5) Other non-EU (single-country studies outside the EU/EEA, U.S., and China, e.g., UK-centred analyses).

When studies covered multiple settings, we applied the following decision rules: (i) if results were reported separately for one of the focal regions (EU/EEA, U.S., China), we coded to that region; (ii) if evidence was pooled across multiple countries without region-specific estimates, we coded as OECD/Global; (iii) where the empirical setting was ambiguous, we coded based on the data source and institutional context discussed most centrally in the paper. This coding was used for descriptive mapping and narrative comparison rather than for 'like-for-like' effect-size benchmarking across regions.

In order to make this literature review possible we created an extra ChatGPT agent disconnected from the Internet and Dalle with internal knowledge base. It is an advanced assistant designed to support systematic literature reviews (SLRs) by streamlining the process and enhancing its quality. It helps organize and screen studies based on inclusion and exclusion criteria, extract key findings, and synthesize themes or trends to highlight insights and research gaps. It also aids in assessing the quality and credibility of sources, creating visual tools like PRISMA diagrams or conceptual maps, and structuring the review in alignment with standard guidelines like PRISMA or Cochrane. By facilitating analysis, synthesis, and iterative refinement, it aims to save time while ensuring methodological rigor and clarity throughout the review process.

We have encountered also limitations. LLM-assisted screening can introduce systematic classification bias (e.g., missing migration-relevant studies that use atypical terminology, or overweighting keyword cues), which may yield false exclusions despite structured prompting. Coverage is also constrained by database and search-engine scope and by the dominance of English-language indexing, potentially underrepresenting non-English or regionally published evidence. We mitigated these risks through multi-database searching, manual and grey-literature searches, iterative prompt testing against human judgements, and final human full-text screening; nevertheless, replications using additional databases, languages, or alternative models could identify somewhat different eligible studies.

The dataset draws on three linked sets of material. First, we identified a core set of ten academic studies used to trace the mechanism pathway between automation, AI, and labour market change. These studies cover a range of mechanisms rather than a single outcome: Wang et al. (2024) examines AI and intergenerational mobility in China; Chen et al. (2024) analyses worker mobility and machine-learning adoption; Niu et al. (2024) studies workplace automation and energy poverty; Ross et al. (2024) models system-wide labour market effects of technological change; Zhao (2020) considers long-term unemployment prediction; Medici et al. (2023) examines technological self-efficacy and mobility intentions; del Rio-Chanona et al. (2021) analyses occupational mobility under automation; Alabdulkareem et al. (2018) studies skill polarization and mobility; Rajkumar et al. (2022) focuses on weak ties and job mobility; and Mandelman and Zlate (2022) examine offshoring, immigration, and labour market polarization. Several of these studies operationalise mobility as an occupational,

geographic, or network mechanism rather than measuring migrant status directly; they are therefore used primarily to illuminate stages of the mechanism pathway.

Second, for the comparative migration-focused analysis, we retained the subset of academic studies that explicitly engage migration or mobility across identifiable geographic contexts. This subset includes evidence from the United States, Germany, the United Kingdom, and China. Mandelman and Zlate (2022) address low-skilled immigration in the United States; Ross et al. (2024) provides Germany-based evidence relevant to the EU; del Rio-Chanona et al. (2021) contributes UK-centred evidence on labour reallocation under automation; Alabdulkareem et al. (2018) examines urban mobility and skill polarization in the United States; and Niu et al. (2024) analyses rural-to-urban migration in China. This smaller set is used for the cross-context comparison between EU/EEA and non-EU evidence.

Third, we included a limited set of grey literature to capture policy-oriented and institutional evidence not yet fully represented in the academic literature. Borgonovi et al. (2023) examines cross-country trends in AI skill demand in OECD countries; Lane et al. (2023) analyses employer and worker perceptions of AI adoption across several OECD economies; Seiger et al. (2024) focuses on the role of Third-Country Nationals in the EU's digital and green transitions; and the Federal Reserve working paper version of Mandelman and Zlate provides additional background on offshoring, automation, and low-skilled immigration. These reports are used selectively to contextualise the academic findings, especially in relation to the EU policy environment and emerging skills demand.

Results

We synthesise the evidence through the Automation-Migration Interface pathway shown in Table 1. The pathway links automation and AI adoption to task restructuring, occupational change, migrant selecting and matching, and the barriers that mediate outcomes such as wages, stability, mobility, segregation, and skill utilisation. It also highlights where institutions intervene most strongly across the process.

Table 1

Mechanism pathway of Automation-Migration Interface: Automation/AI adoption → task restructuring → occupational shifts → migrant selecting → barriers → outcomes (wages, mobility, segmentation)

Stage (ordered)	Core mechanism	Typical indicators / operationalisation (examples)	Where institutions intervene most
1	Automation/AI adoption	Robot density; AI/software diffusion; firm tech adoption; routine-task intensity; capital-labour substitution	Innovation policy; sectoral structure; regulation of tech deployment
2	Task restructuring	Changes in task content (routine ↓, non-routine/cognitive ↑); augmentation vs substitution; digital task growth	Training systems; employer incentives; workplace standards
3	Occupational shifts	Job polarization; sectoral reallocation; upgrading/downgrading; job quality changes	Employment protection; collective bargaining; wage-setting; ALMPs
4	Migrant selecting & matching	Entry into specific occupations/regions; recruitment channels; network-based matching; occupational segregation	Migration regime rules; recognition of credentials; anti-discrimination enforcement
5	Barriers & mediators	Credential recognition; training access; language/digital skills; algorithmic screening bias; legal status; welfare/work protections	Welfare eligibility; status-linked rights; enforcement capacity; platform/AI governance
6	Outcomes	Wages; employment stability; occupational mobility; geographic mobility; segregation; skill utilisation	Redistribution; social protection; integration policy; labour standards

This structure allows us to compare studies that measure migrant outcomes directly with studies that illuminate key mechanisms, such as occupational mobility, matching, or geographic reallocation. The evidence is strongest for the earlier stages of the pathway, especially task restructuring and occupational change, while direct evidence on migrant-specific outcomes and institutional mediators remains more limited. We therefore present the results sequentially, moving from technological adoption and task change to selecting, barriers, and labour market outcomes, and interpret cross-regional differences through institutional context rather than as like-for-like comparisons.

Evidence on adoption, task restructuring, and occupational shifts (Stages 1 to 3)

Across the included studies, the strongest and most consistent evidence concerns the upstream part of the mechanism pathway, namely how automation and AI adoption changes task demand and reshapes occupational structures. At this stage, studies typically operationalise exposure through measures of technological change or adoption at the sector, firm, or macro level, and then trace implications for labour demand across skill groups. For example, system-wide modelling for Germany links labour

augmenting technological change to shifts in labour demand that increase the importance of higher-skill profiles in technology intensive sectors (Ross et al., 2024). Complementary evidence from firm and labour market settings connects adoption conditions to workforce reallocation pressures, highlighting that technology diffusion is not simply a technical process but one that is shaped by labour market frictions and mobility (Chen et al., 2024; del Rio-Chanona et al., 2021).

A central finding at Stage 3 is that occupational change under automation tends to be asymmetric across the skill distribution. Several studies describe this as occupational polarization, with contraction in routinised middle-skill work and expansion in high-skill roles alongside persistent demand for low-skill service work (Mandelman and Zlate, 2022; Alabdulkareem et al., 2018). In the U.S., modelling of offshoring and automation shows reduced demand for middle-skill jobs and a rise in high-skill and low-skill service demand, with downstream implications for who fills those service roles (Mandelman and Zlate, 2022). Evidence on skill structures and urban labour markets similarly highlights how occupational systems can polarise around skill profiles, reinforcing uneven access to upgrading pathways (Alabdulkareem et al., 2018). Network and mobility-oriented studies add that these shifts restructure feasible transition pathways between occupations, which matters for later stages of selecting and barriers even when migrant status is not the primary unit of analysis (del Rio-Chanona et al., 2021; Rajkumar et al., 2022) .

Taken together, the Stage 1 to Stage 3 evidence provides the enabling conditions for the migration-focused links later in the pathway. Automation and AI adoption changes what tasks are valued, and those task changes aggregate into occupational and sectoral shifts that expand some job ladders while narrowing others (Ross et al., 2024; Mandelman and Zlate, 2022). The next subsections therefore move from these upstream changes to the downstream mechanisms, focusing on how migrants select into the evolving opportunity structure and how barriers such as credential recognition, training access, and algorithmic screening shape observed outcomes (Zhao, 2020; Medici et al., 2023).

Migrant selecting and matching (Stage 4)

At Stage 4, the reviewed literature highlights that migrants do not enter a neutral labour market. They are selected into jobs and places shaped by prior task and occupational restructuring, and matching is mediated by recruitment channels, networks, and mobility constraints. In the U.S., Mandelman and Zlate (2022) show how automation and offshoring contribute to a dual structure in which rising demand for local services is met largely by low-skilled immigrants, while limited mobility and oversupply keep these workers concentrated in low-wage, low-mobility occupations.

Several studies contribute mechanism evidence on how selecting and matching occurs even when migrant status is not the primary outcome. del Rio-Chanona et al. (2021) model occupational mobility under automation as a network of feasible job-to-job transitions, showing that displacement risk depends not only on which jobs decline but also on whether workers can realistically move into expanding occupations. Alabdulkareem et al. (2018) similarly emphasise that skill structures and urban

labour markets can reinforce polarized opportunity sets and constrain transitions from low- to high-skill roles, which helps explain why migrant concentration can persist in certain sectors and cities. Rajkumar et al. (2022) adds complementary evidence from job-matching networks, showing that access to weak-tie connections can causally increase job mobility, which is directly relevant to understanding how migrants may gain or lose access to better matches as labour markets restructure.

Finally, the evidence suggests that individual adaptability can influence selecting outcomes, but that it interacts with opportunity structures rather than replacing them. Medici et al. (2023) finds that technological self-efficacy is associated with stronger mobility intentions in the face of technological advancement, indicating one micro-level channel through which workers may pursue better matches when tasks change. Taken together, Stage 4 findings support the interpretation that technology shocks shape migrant outcomes partly through selecting and matching processes that depend on mobility pathways, network access, and the structure of local labour demand, setting up the next stage on barriers and mediators that can block or enable these transitions.

Barriers and mediators (Stage 5)

Across the reviewed literature, Stage 5 on barriers and mediators explain why similar technology shocks can produce very different outcomes for migrants. A recurring barrier is restricted access to mobility and upgrading pathways, including limited opportunities to retrain, weak portability of skills across sectors, and constraints on geographic or occupational movement. For example, migrant concentration in low wage service work is reinforced by limited mobility and thin progression ladders in sectors that expand under polarization dynamics (Mandelman and Zlate, 2022). Related evidence on occupational transition structures shows that adjustment depends on whether workers can realistically move into expanding occupations, not only on whether those occupations exist (del Rio-Chanona et al., 2021) .

A second cluster of mediators concerns human capital translation and access to training, especially credential recognition and digital preparedness. Grey literature and EU focused evidence underline that many migrants, including Third Country Nationals, face persistent barriers due to unrecognised qualifications and limited access to upskilling, even as digital and green transitions raise demand for higher skill profiles (Seiger et al., 2024; Lane et al., 2023). Micro-level evidence further suggests that technological self-efficacy is associated with stronger mobility intentions under technological change, indicating that digital confidence and perceived ability to adapt can shape whether individuals pursue transitions when tasks shift (Medici et al., 2023).

A third mediator is institutional and algorithmic filtering in labour market access. The literature highlights risks that AI-enabled decision tools in employment services or hiring can disadvantage low-skilled migrants through biased classification and screening, which can compound existing segmentation (Zhao, 2020). More broadly, institutional context shapes the strength of these barriers through welfare eligibility, employment protections, and the availability of transition supports. For example, discussions of policy responses in both EU and non-EU contexts emphasise that displaced workers, including

migrants, often require unemployment support, retraining assistance, and mobility or housing support to translate labour demand shifts into stable employment, particularly under rapid structural change (Ross et al., 2024; Niu et al., 2024).

Together, findings of Stage 5 indicate that migrant outcomes are not determined by automation exposure alone. They are mediated by whether migrants can convert skills into recognised credentials, access training and digital capability building, navigate algorithmic gatekeeping, and rely on institutional protections that reduce the costs of occupational and geographic transitions (Seiger et al., 2024; Zhao, 2020; Medici et al., 2023).

Outcomes for migrants and mobility (Stage 6)

At Stage 6, the reviewed literature links technology-driven restructuring to outcomes for migrants across wages, employment stability, mobility, segregation, and skill utilisation. Where migrant outcomes are measured directly, the most consistent pattern is that polarization dynamics can widen gaps between higher- and lower-skilled migrants, particularly through occupational concentration in lower-wage service work and limited upward mobility. In the U.S., Mandelman and Zlate (2022) show that automation and offshoring contribute to labour-market polarization in ways that increase demand for local services and draw low-skilled immigrants into those sectors, with implications for wage dispersion and persistent concentration in low-wage jobs (Mandelman and Zlate, 2022).

Evidence from China highlights mobility outcomes that are closely tied to stability and vulnerability. Niu et al. (2024) links automation-related shocks to intensified rural-to-urban migration pressures, suggesting that labour demand shifts can translate into mobility but not necessarily into secure, upward transitions for lower-skilled movers, especially when shocks are regionally uneven (Niu et al., 2024). This complements the broader mechanism evidence that occupational and geographic transitions are constrained by the structure of feasible pathways, which shapes who can move into expanding jobs and who remains exposed to instability (del Rio-Chanona et al., 2021).

Several studies also point to outcomes that operate through access and gatekeeping. Zhao (2020) highlights that AI-enabled classification and screening tools can disadvantage low-skilled and migrant groups through biased risk prediction or decision rules, which can reduce access to opportunities and reinforce segregation effects even when labour demand exists (Zhao, 2020). In contrast, evidence on mobility and matching mechanisms indicates potential channels for improving outcomes. Rajkumar et al. (2022) shows that expanding weak-tie connections can causally increase job mobility, which is relevant for understanding how migrants may access better matches in restructuring labour markets (Rajkumar et al., 2022). Medici et al. (2023) similarly finds that technological self-efficacy is associated with stronger mobility intentions, pointing to a channel through which digital confidence and perceived adaptability can shape whether workers pursue occupational or geographic moves under technological change (Medici et al., 2023).

Taken together, Stage 6 outcomes are best understood as the product of the full pathway. Task and occupational change create new opportunity structures, but realised outcomes for migrants depend on whether selecting leads to good matches and whether barriers, including training access, credential recognition, legal status constraints, and algorithmic gatekeeping, allow migrants to convert mobility into stable and well-matched employment (Mandelman and Zlate, 2022; Zhao, 2020; Medici et al., 2023)

Conclusion and scope limits

This article asked how automation and artificial intelligence (AI) interact with migrant labour in the European Union, and through which mechanisms these interactions shape labour market integration, segmentation, and opportunities for upward mobility. The review suggests that automation does not affect migrants through a single, uniform pathway. Rather, its effects are mediated through a sequence of linked processes: the restructuring of tasks, shifts in occupational demand, the selecting and matching of migrants into changing labour market opportunities, and the institutional barriers that shape whether technological change leads to upgrading, exclusion, or persistent segmentation. In this sense, the main contribution of the article is to show that automation should be understood not simply as a labour-saving technology, but as a structuring condition of migrant incorporation.

With regard to the first supporting question, the review shows that automation and AI reshape tasks and occupations in ways broadly consistent with labour market polarization. Across the literature, the most robust evidence concerns upstream changes in labour demand: routine middle-skill work tends to be most exposed to restructuring, while demand grows in both highly skilled occupations and selected forms of low-wage service work that remain difficult to automate (Ross et al., 2024; Mandelman & Zlate, 2022; Alabdulkareem et al., 2018). For migrants, this matters because many are concentrated in segments of the labour market where entry jobs are vulnerable to reorganisation, progression ladders are thin, and technological change may intensify rather than reduce precarity. At the same time, migrants with recognised qualifications and technological skills may benefit from growing demand in more automation-resilient or technology-complementary sectors. The answer to whether automation substitutes for or complements migrant labour is therefore conditional: it depends on migrants' location within the occupational structure and on the institutional context in which technological change unfolds.

With regard to the second supporting question, the review finds that migrants are selected and matched into evolving labour markets through socially and institutionally structured pathways rather than through neutral market adjustment alone. Automation changes the opportunity structure, but migrants' labour market incorporation depends on the recruitment systems, networks, legal statuses, and regional labour market conditions through which they access work. Evidence on occupational mobility, matching, and network effects suggests that technological change shapes not only which jobs decline or expand, but also who can realistically move into emerging opportunities (del Rio-Chanona et al., 2021; Rajkumar et al., 2022). This is especially important for migrants, whose transitions are often constrained by weaker access to bridging ties, employer recognition, and secure mobility pathways. In this respect, the review supports a relational understanding of labour market integration: migrants' outcomes are shaped not

only by their skills, but also by how they are channelled into, or excluded from, particular labour market niches.

With regard to the third supporting question, the review shows that institutional mediators are central to explaining variation in outcomes. Access to training, recognition of foreign qualifications, host-country language and digital skills, employment protections, and welfare support all influence whether migrants can adapt to task restructuring and translate labour market change into upward mobility. At the same time, the increasing use of AI-enabled screening, matching, scheduling, and monitoring introduces new forms of gatekeeping that may reproduce existing forms of disadvantage under the appearance of technical neutrality (Zhao, 2020; Medici et al., 2023). The review therefore suggests that migrants face a double exposure under technological change: they are often concentrated in labour market segments where automation can weaken mobility ladders and degrade job quality, while also confronting digitally mediated filtering that may limit access to better jobs before labour market outcomes are observed. Labour market integration under automation is thus shaped less by exposure alone than by the institutional conditions that govern recognition, retraining, mobility, and contestation.

Taken together, the findings support the Automation-Migration Interface Approach developed in this article. The approach extends dual labour market theory by treating segmentation not as a fixed characteristic of sectors, but as a dynamic outcome of task restructuring, occupational change, and institutional mediation. Read in this way, Piore's core insight remains valuable: migrant incorporation continues to be shaped by segmented labour demand. However, the review also shows that the contemporary form of segmentation is increasingly reorganised through digital technologies, automated decision-making, and the changing governance of labour markets. Migrant integration is therefore best understood as a process shaped jointly by labour demand, mobility pathways, and institutional gatekeeping.

The findings also have implications for the EU context. The reviewed evidence suggests that migrants, including Third-Country Nationals, can contribute significantly to digital and green transitions, but that this potential is unlikely to be realised where skills remain under-recognised, access to upskilling is unequal, and labour market institutions do not support occupational mobility. Inclusive integration under technological change requires more than access to employment; it depends on whether migrants can obtain stable work, use their skills effectively, and move into jobs with longer-term prospects. In that sense, the question for policy is not only how to manage automation, but how to govern its distributional and integration consequences.

Several limitations remain. The evidence base is still modest and uneven, many studies do not measure migrant status directly, cross-regional comparisons are only indicative, and the review is constrained by coverage limits and possible screening error. As a mechanism-based review, it also does not provide pooled effect sizes.

These limitations point to a clear agenda for future research. More evidence is needed that measures migrants directly, compares institutional contexts systematically, and examines how automation, digital

labour market intermediation, and migrant incorporation interact over time.

Declarations

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Author Contribution

A. conceptualised the study and drafted the manuscript. B. contributed to the analysis and interpretation of the findings. C. and D. developed the methodology. All authors reviewed, revised, and approved the final manuscript.

References

1. Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. *The economics of artificial intelligence: An agenda* (pp. 197–236). University of Chicago Press.
2. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy*, 128(6), 2188–2244.
3. Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018). Unpacking the polarization of workplace skills. *Science advances*, 4(7), eaao6030.
4. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4), 1279–1333.
5. Bevelander, P. (2000). *Immigrant employment integration and structural change in Sweden, 1970–1995* (Vol. 15). Lund University.
6. Bevelander, P., & Pendakur, R. (2014). The labour market integration of refugee and family reunion immigrants: A comparison of outcomes in Canada and Sweden. *Journal of Ethnic and Migration Studies*, 40(5), 689–709.
7. Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern recognition and machine learning* (Vol. 4, p. 738). springer. 4.
8. Borjas, G. J. (1985). Assimilation, changes in cohort quality, and the earnings of immigrants. *Journal of labor Economics*, 3(4), 463–489.
9. Borgonovi, F., Calvino, F., Criscuolo, C., Samek, L., Seitz, H., Nania, J., & O’Kane, L. (2023). Emerging trends in AI skill demand across 14 OECD countries. *OECD Artificial Intelligence Papers*.
10. Chen, R., Balasubramanian, N., & Forman, C. (2024). How does worker mobility affect business adoption of a new technology? The case of machine learning. *Strategic Management Journal*, 45(8), 1510–1538.

11. del Rio-Chanona, R. M., Mealy, P., Beguerisse-Díaz, M., Lafond, F., & Farmer, J. D. (2021). Occupational mobility and automation: a data-driven network model. *Journal of The Royal Society Interface*, 18(174).
12. DiMaggio, P., & Garip, F. (2012). Network effects and social inequality. *Annual review of sociology*, 38(1), 93–118.
13. Donoho, D. (2017). 50 years of data science. *Journal of computational and graphical statistics*, 26(4), 745–766.
14. Fasani, F., Frattini, T., & Minale, L. (2021). Lift the ban? Initial employment restrictions and refugee labour market outcomes. *Journal of the European Economic Association*, 19(5), 2803–2854.
15. Fullin, G., & Reyneri, E. (2011). Low unemployment and bad jobs for new immigrants in Italy. *International Migration*, 49(1), 118–147.
16. Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, 27.
17. Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review*, 104(8), 2509–2526.
18. Graetz, G., & Michaels, G. (2018). Online Appendix for Robots at Work.
19. Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 78(6), 1360–1380.
20. Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research synthesis methods*, 11(2), 181–217.
21. Kalleberg, A. L. (2009). Precarious work, insecure workers: Employment relations in transition. *American sociological review*, 74(1), 1–22.
22. Kanas, A., Van Tubergen, F., & Van der Lippe, T. (2011). The role of social contacts in the employment status of immigrants: A panel study of immigrants in Germany. *International Sociology*, 26(1), 95–122.
23. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of management annals*, 14(1), 366–410.
24. Lane, M., Williams, M., & Broecke, S. (2023). OECD Social, Employment and Migration Working Papers: The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. Paris: OECD Publications.
25. Mandelman, F. S., & Zlate, A. (2022). Offshoring, automation, low-skilled immigration, and labor market polarization. *American Economic Journal: Macroeconomics*, 14(1), 355–389.
26. Martín-Martín, A., Thelwall, M., Orduna-Malea, E., & Delgado López-Cózar, E. (2021). Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations. *Scientometrics*, 126(1), 871–906.

27. Medici, G., Grote, G., Igic, I., & Hirschi, A. (2023). Technological self-efficacy and occupational mobility intentions in the face of technological advancement: a moderated mediation model. *European Journal of Work and Organizational Psychology*, 32(4), 538–548.
28. Mitchell, T. M. (1997). Does machine learning really work? *AI magazine*, 18(3), 11–11.
29. Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: a comparative analysis. *Scientometrics*, 106(1), 213–228.
30. Niu, X., Li, C., Li, X., & Zhang, Y. (2024). Impacts of workplace automation on energy poverty: The new challenge of achieving SDG 7 in the context of technological revolution. *Heliyon*, 10(3).
31. Pager, D., & Shepherd, H. (2008). The sociology of discrimination: Racial discrimination in employment, housing, credit, and consumer markets. *Annu. Rev. Sociol.*, 34(1), 181–209.
32. Piore, M. J. (1979). *Birds of passage: Migrant labor and industrial societies*. Cambridge University Press.
33. Piracha, M., Tani, M., & Vadean, F. (2012). Immigrant over-and under-education: The role of home country labour market experience. *IZA Journal of Migration*, 1(1), 3.
34. Provost, F., & Fawcett, T. (2013). *Data science for business*. O'Reilly.
35. Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency* (pp. 469–481).
36. Rajkumar, K., Saint-Jacques, G., Bojinov, I., Brynjolfsson, E., & Aral, S. (2022). A causal test of the strength of weak ties. *Science*, 377(6612), 1304–1310.
37. Reitz, J. G. (2001). Immigrant skill utilization in the Canadian labour market: Implications of human capital research. *Journal of International Migration and Integration/Revue de l'integration et de la migration internationale*, 2(3), 347–378.
38. Reitz, J. G. (2007a). Immigrant employment success in Canada, Part I: Individual and contextual causes. *Journal of International Migration and Integration/Revue de l'integration et de la migration internationale*, 8(1), 11–36.
39. Reitz, J. G. (2007b). Immigrant employment success in Canada, part II: Understanding the decline. *Journal of International Migration and Integration*, 8(1), 37–62.
40. Reskin, B. F. (2003). Including mechanisms in our models of ascriptive inequality. *American sociological review*, 68(1), 1–21.
41. Ross, A. G., McGregor, P. G., & Swales, J. K. (2024). Labour market dynamics in the era of technological advancements: The system-wide impacts of labour augmenting technological change. *Technology in Society*, 77, 102539.
42. Seiger, F., Majorano, S. F., Kalantaryan, S., Biagi, F., & Ortolani, M., G (2024). *The contribution of third-country nationals to the twin transition in the EU* (Vol. 137170JRC). European Commission, Joint Research Centre.

42. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.
43. Wang, J., Luo, C., Dong, Y., & Guo, C. Y. (2024). Does intergenerational mobility affect corporate innovation? Evidence from Chinese manufacturing enterprises. *International Review of Economics & Finance*, 91, 526–538.
44. Zhao, L. F. (2020). Data-driven approach for predicting and explaining the risk of long-term unemployment. In *E3S Web of Conferences* (Vol. 214, p. 01023). EDP Sciences.
45. Zwysen, W., & Longhi, S. (2018). Employment and earning differences in the early career of ethnic minority British graduates: The importance of university career, parental background and area characteristics. *Journal of Ethnic and Migration Studies*, 44(1), 154–172.