AI at work: benefits for the labour market

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Contents

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Executive summary

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Finding a new job can be a tiring and frustrating process for many people. Equally, finding the right talent to hire can be expensive and time-consuming for a business. Improving this matching process in job markets has the potential to improve outcomes for society as a whole.

The lack of efficiency and transparency in labour markets costs employers time and money in finding the right candidate and leads to lower work satisfaction for employees, thereby negatively affecting economic productivity and growth. Economists call the time and costs involved 'search frictions', and refer to a situation in which one side of a negotiation does not have the same information as the other as 'asymmetry of information'.

These frictions, which manifest throughout the recruitment process, have recently been exacerbated by rapid changes in the nature of work, such as the rise of home-working, digitalisation, and specialisation.

The challenges in matching the right people with the right jobs are set to increase as demographic and technological shifts demand an ever faster evolution of qualifications and skills. For example, the skillsets required for jobs have changed by 25% since 2015. By 2027, this number is expected to double.

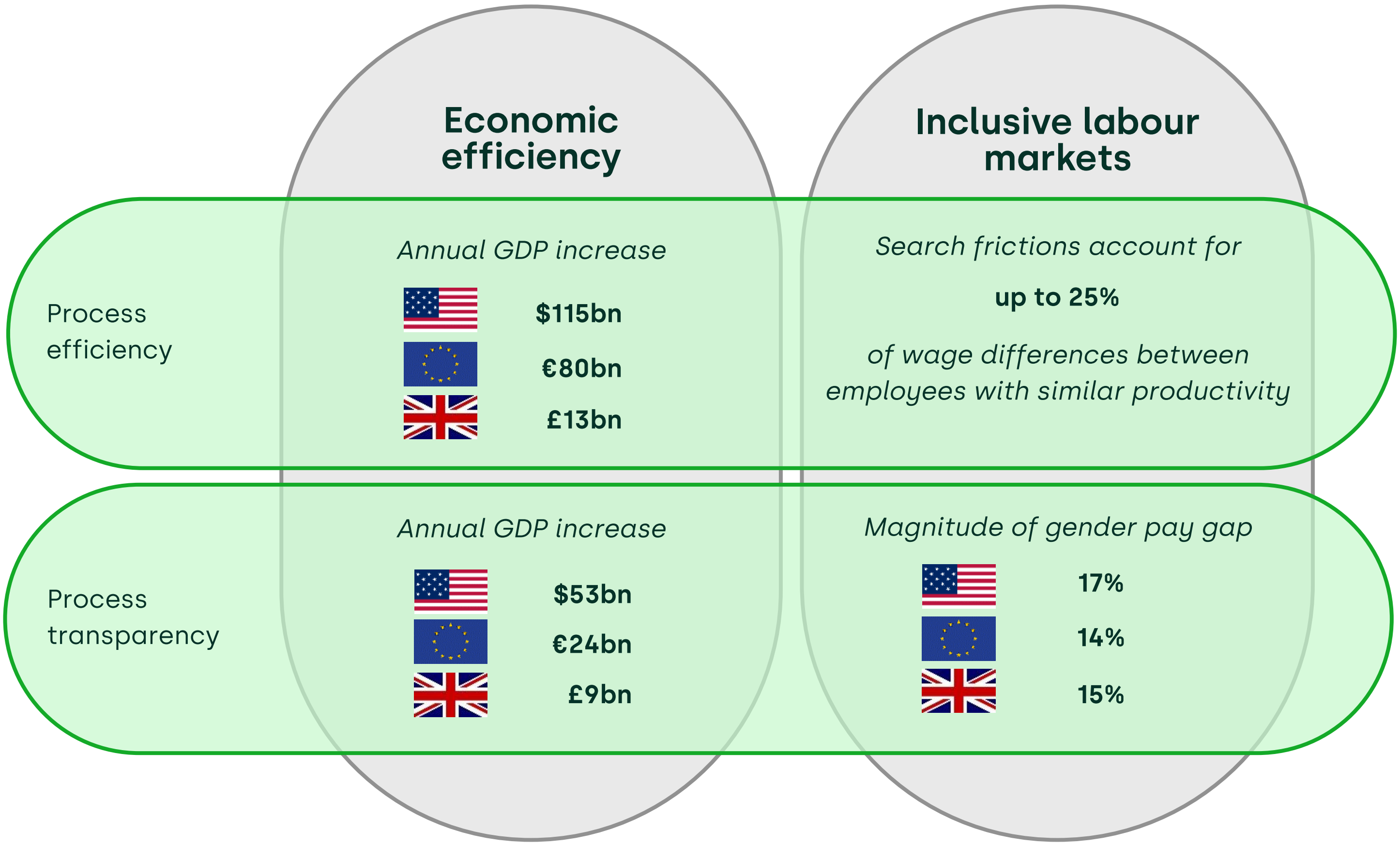
The benefits of AI in recruitment

The recent growth of AI tools in recruitment is addressing these challenges by helping labour markets to function more effectively and transparently. In this report, we look at the impact of using AI tools in recruitment on labour markets, with a focus on a selection of applications used in the candidate sourcing part of the recruitment process.

AI-powered search and recommendation tools help to drive the labour market's move towards more skills-based hiring, by alleviating some of the existing asymmetry of information. According to the OECD, 25% of workers are over- or under-skilled for their current position. By accessing more information about the skills profile and work experience of potential candidates, recruiters can increase the size of their talent pool to improve the quality of matches. AI tools also facilitate the cross-border recognition of skills, providing jobseekers with access to a wider range of employment opportunities.

Taking a conservative approach, using AI tools in recruitment is likely to have generated a value of at least \$168bn in the USA, €104bn in the EU, and £22bn in the UK in 2019, as illustrated in the figure below.

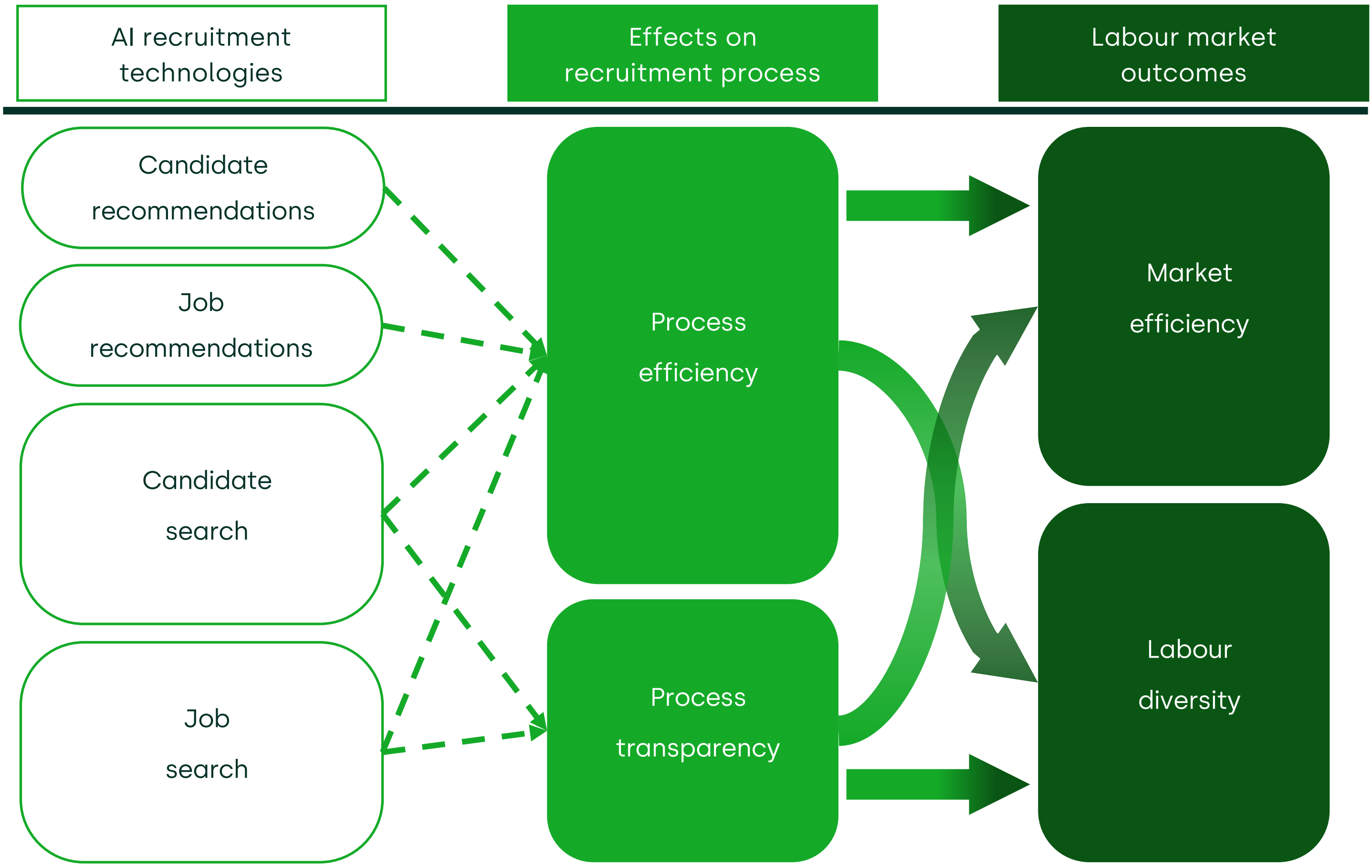
Summary of the benefits of AI in recruitment



Note: Estimates of annual GDP increase are based on 2019 figures. These estimates are expected to be representative, assuming a normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.
Source: Oxera analysis.

A recent survey by Aptitude Research shows that companies that leverage AI to identify potential qualified candidates are likely to fill vacancies more quickly and improve the quality of new hires. Search and recommendation tools in the sourcing stage make the job search simpler, faster, and more targeted. Through recommended vacancies or connections based on their skills or experience, jobseekers can be spared from sifting through large numbers of job advertisements. As shown in the figure below, this reduces search costs and facilitates the flow of information between recruiters and jobseekers.

Framework for assessing the benefits of AI in recruitment



Note: The sizes of the process efficiency and process transparency boxes provide an indication of the relative scale of the different effects. As labour diversity (measured in wage gaps) and market efficiency (measured in GDP) cannot be compared on a like-for-like basis, we assume these to be equal in size for the purposes of this illustration.
Source: Oxera.

One of the most important benefits of AI is that it helps recruitment to move away from traditional signals such as the school that a candidate attended, thereby creating opportunities for a broader and more diverse set of people, including those with less traditional career paths. The Aptitude Research survey shows that companies that leverage AI to identify potential qualified candidates are likely to improve diversity when sourcing candidates.

Wage gaps can be useful indicators to assess the degree of unfairness in labour markets. Currently the gender pay gap is 17% in the USA, 14% in the EU, and 15% in the UK; and differences in search frictions (such as in certain minority groups) account for up to 25% of the variation in wages across people who are equally productive. AI can help to close these pay gaps, thereby making labour markets—and societies more broadly—fairer and more trusting.

Policy implications

All new technologies, including emerging AI technologies, bring both benefits and potential harms to people and societies. A balanced regulatory approach is therefore required. Good regulation ensures predictability and legal certainty, while promoting the responsible development and application of new technology-enabled business models.

At the same time, it is important to avoid long-term regulatory constraints that inhibit the rapid pace of innovation and evolution of new technologies, such as AI. With this in mind, regulatory models for AI should be focused on core principles and outcomes, rather than inputs or specific solutions, which will allow them sufficient flexibility to adapt to new evidence and applications of AI technologies.

1 Introduction

1.1 Labour market issues

A long-standing fundamental challenge of labour markets is their tendency towards opacity (such as when it comes to the quality of a hire) and inefficiency (such as regarding the effort it takes to identify a relevant job opening). There are many causes of this, ranging from the fact that the job-finding process can be highly individualised to the information gap between jobseekers and employers.[1]

As a result, mismatches are often present in labour markets, which in turn affects the wider economy.[2] For the employer, a mismatch can result in lower productivity or a vacancy left unfilled; and for an employee, a mismatch can lead to unsatisfying work or compensation that does not accurately reflect their skills. Mismatches can have a tangible effect on real people, as in the case of Jacob's story (see Box 1.1).

Box 1.1 Jacob's story—part one: some dreams never die

Jacob had dreamed about working at Southwest Airlines for as long as he could remember. He applied and interviewed for internships and full-time jobs to no avail. But after each meeting, he connected with the Southwest employees and recruiters he had met on LinkedIn.

With a growing family to support, he eventually had to accept a job at a B2B IT company, but his dream of working for Southwest Airlines lived on…

(to be continued)

Source: CBS News (2013), 'LinkedIn: 5 job search success stories', MoneyWatch, accessed 8 September 2022.

Such tendencies in labour markets are in the spotlight more than ever now that the nature of work and the structure of the labour market are undergoing rapid changes.[3]

The skillset for jobs has changed by 25% since 2015. This shift is expected to increase to 50% by 2027

On the one hand, demographic and technological changes such as aging populations and automation of manufacturing are causing a decline in the working population in many countries, an increase in the demand for highly skilled labour, and rapid changes to the qualifications and skills that are in demand. Recent data shows that

[1] Carranza, E. and Pimkina, S. (2018), 'Overcoming information asymmetry in job search: the power of a reference letter', Policy Brief Issue 24, April, accessed 31 August 2022.
[2] An example of such a mismatch is underemployment, i.e. the underuse of a worker because a job does not use the worker's skills, is part-time, or leaves the worker idle. See Feldman, D.C. (1996), 'The nature, antecedents and consequences of underemployment', *Journal of Management*, **22**:3, pp. 385–407.
[3] ILO and OECD (2018), 'Global Skills Trends, Training Needs and Lifelong Learning Strategies for the Future of Work', accessed 29 August 2022.

the skills that employees need for a given position in 2022 have shifted 25% since 2015; by 2027, this is expected to be a 50% shift.[4]

On the other hand, the place of work is becoming a discussion point between jobseekers and businesses as remote working has become increasingly widespread, particularly following the COVID-19 pandemic. In the USA, remote job postings on LinkedIn shot up from less than 2% in January 2020, peaking at close to 20% of all job postings in spring 2020.[5]

These fundamental changes in the labour market mean that the efficiencies that AI generates in terms of matching and sorting skills and vacancies will become increasingly important as the nature of work becomes even more dynamic.

1.2 AI in recruitment

Over the last half a century, increasingly sophisticated AI applications have moved from the research lab into mainstream business usage, including in the recruitment sector. Unlike software that is programmed to perform a task, AI is programmed to *learn* how to perform a task. Take spam filters, for example. While regular spam filters can recognise predetermined patterns (e.g. an unusually frequent use of symbols or keywords), AI-based filters *learn* to recognise patterns of spam emails themselves by forming and updating their own rules for the characteristics that constitute spam. AI-based spam filters can therefore identify spam even when the patterns change.

There are various ways in which AI is used and how it can help to address the opacity and inefficiency of labour markets, depending on the stage of the recruitment process (see Figure 1.1). The use of AI in recruitment brings a unique set of risks, whose levels vary according to use cases, objectives, and the stage of the recruitment process.[6] When setting policies to regulate AI, both the risks and benefits need to be accounted for. In this report, we focus on assessing the benefits of AI used in the sourcing stage, i.e. where jobseekers are looking for and analysing open roles and where recruiters identify and engage with potential candidates.

[4] LinkedIn (2022), 'A Skills-First Blueprint for Better Job Outcomes', March, accessed 19 July 2022. Skill shifts are determined by comparing the most important skills that users reported on their LinkedIn profiles for a given kind of job in the past with the most important skills that are currently reported for the same type of job.
[5] See LinkedIn's Economic Graph (2022), 'Despite ongoing global uncertainty and high-profile layoffs, labor markets remain resilient', 8 December.
[6] Dattner, B., Chamorro-Premuzic, T., Buchband, R. and Schettler, L. (2019). 'The Legal and Ethical Implications of Using AI in Hiring', 25 April, accessed 7 December 2022.

Figure 1.1 Stages of the recruitment lifecycle

Note: The stages of the recruitment lifecycle are not always clearly separated and defined.
Source: Oxera.

Our findings indicate that in the sourcing stage there are several applications of AI that can generate substantial benefits for the labour market as a whole. This stage is well served by a growing number of recruitment platforms, and AI—if used well—can play a crucial role in helping labour markets to function more effectively. For example, AI can improve the search for open roles and the personalisation of job recommendations to jobseekers, allowing people like the fictional Ritu to find a better-suited vacancy (see Box 1.2).

Box 1.2 Ritu's story—part one: if only they knew

Ritu is a 36-year-old experienced marketing manager who wants to find a new job away from print-based and towards digital marketing due to the digital transformation. Although there is a lot of overlap between her previous employment and potential future jobs, she has trouble finding the right vacancies in her current network.

At the same time, many digital marketing firms are looking to employ people with Ritu's background. Unfortunately, they are not aware of Ritu's situation and eagerness to make a career change.

(to be continued)

Source: Oxera (fictional example).

AI tools can also assist in the identification of potential candidates by helping employers to find and engage with workers who may be 'underemployed' but are not actively seeking new opportunities (i.e. passive candidates), while at the same time providing new opportunities for progression to those workers.

At the same time, the benefits for jobseekers and employers can be substantial, as we unpack further in the remainder of this report.

- Section 2 explains and evidences how various types of AI tools in recruitment contribute to the efficiency and transparency of the recruitment process.
- Section 3 outlines the positive effects that are generated for jobseekers and employers by increasing labour diversity and labour market efficiency.
- Section 4 summarises our findings and outlines key implications for the regulatory debate.

2 How AI benefits the recruitment process

Recruiting a new hire can be a long and difficult process. The variety of jobs and potential candidates is simply too large for humans to effectively process, which can lead to undesirable outcomes, as we have seen in the examples of Jacob (Box 1.1) and Ritu (Box 1.2).

The key factors that bring about these undesirable outcomes—high search costs and the imperfect flow of information—are referred to as market failures by economists, as they prevent the market from delivering an efficient allocation of scarce resources.[7] AI-powered recruitment platforms are well positioned to support humans with search and matching challenges due to their ability to process, learn from and rationalise large amounts of data.

The remainder of this section elaborates on the underlying market failures of process inefficiency and opacity, before describing how the use of AI in the recruitment process can alleviate them and deliver a more efficient and transparent labour market.

2.1 How AI makes the job search simpler, faster and more targeted

There are many distinct applications of AI tools in the recruitment process that bring clear benefits to labour markets, such as personalised job or potential candidate recommendations. These applications are generally underpinned by multiple technologies (some of which are outlined in Box 2.1) working together.

Box 2.1 Selected AI technologies

Recommender systems[1]
can anticipate users' likely choices in order to offer them relevant suggestions based on their previous search behaviour, profile information, and engagement on a given platform.

Natural Language Processing (NLP)[2]
enables computers to process and analyse spoken and written language. Semantic analysis as a sub-field of NLP helps computers to interpret the *meaning* of words, phrases or systems.

Intelligent Automation[3]
combines automation, i.e. when algorithms perform standardised tasks, with AI, which helps to adapt the algorithm to a particular environment.

Source: [1] Zhang, Q., Lu, J. and Jin, Y. (2021), 'Artificial intelligence in recommender systems', *Complex and Intelligent Systems*, **7**, pp. 439–457. [2] IBM Cloud Education (2020), 'Natural Language Processing (NLP)', 2 July, accessed 25 August 2022. [3] IBM Cloud Education (2020), 'Intelligent Automation', 5 March, accessed 25 August 2022.

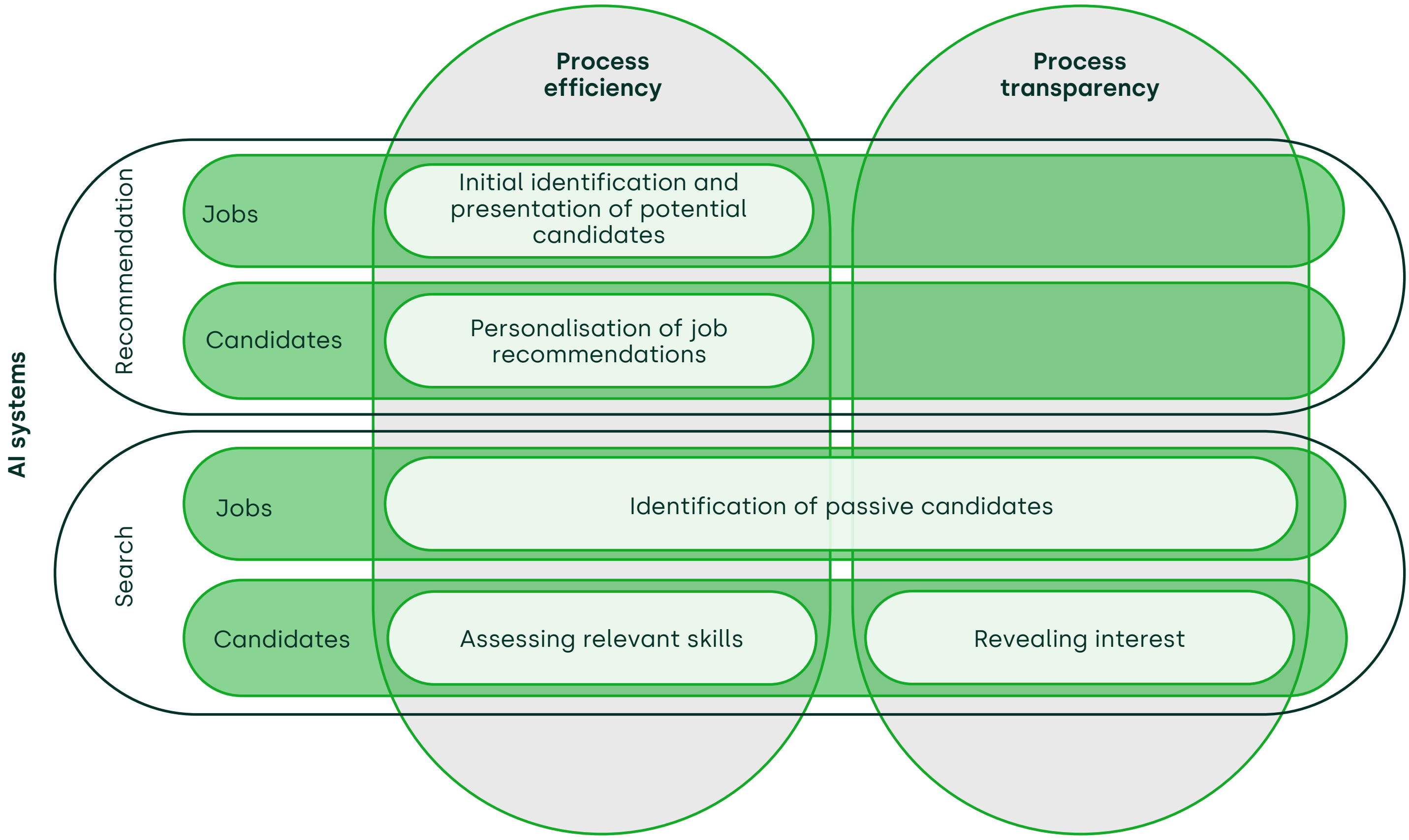
As these technologies can be used for a range of use cases, we do not assess the benefits of the underlying technologies as such. Instead,

[7] Bator, F.M. (1958), 'The Anatomy of Market Failure', *The Quarterly Journal of Economics*, **72**:3, pp. 351–379.

we focus on two particular applications in the recruitment sector that are each relevant to both hirers and jobseekers in the sourcing stage: search and recommendation tools.

These tools improve the efficiency and transparency of the recruitment process in various ways, as we outline in Figure 2.1 below. Both search and recommendation tools make the search process more efficient by reducing the cost of analysing a large amount of information to identify relevant job postings or potential candidates. In addition, search tools can make the search process more transparent as they facilitate the flow of information across labour market participants.

Figure 2.1 How AI tools enhance transparency and efficiency throughout the recruitment process



Source: Oxera.

In particular, AI-based search tools are designed to improve the search and matching process through the mechanisms outlined below.

- **Semantic search**—search engines using 'semantic search' have an understanding of the relationship between words and the contextual meaning behind them (i.e. their semantics), and are therefore more likely to provide relevant results to their users. This helps users to find results even if they did not search for exactly what was listed.
- **Passive search**—many job platforms allow users to create saved searches that automatically scan new job postings or candidate profiles. In doing so, the AI can account for the search criteria specified by the user as well as the user's behaviour and profile information. Users are then notified as soon as the algorithm identifies one or more relevant results. This helps candidates to

identify 'fresh' opportunities that they are more likely to have success with.

- **Identifying passive candidates**—based on user behaviour (e.g. the number of job listings viewed) and profile information (e.g. the duration of employment in their current position), AI-based search systems can also help recruiters by assessing when a user is likely to be open to a new position, even when they are not actively searching for a job. This helps to alleviate 'underemployment'.
- **Assessing relevant skills**—intelligent automation and NLP can be used for various types of pre-employment assessment that measure (technical) skills, even if these are not explicitly listed. This helps to facilitate cross-sectoral career changes.

Similarly, recommendation tools, such as those listed below, use AI technologies to learn from and anticipate likely user behaviour and provide users with appropriate recommendations.

- **Personalised recommendations**—AI-based recommendation systems can make personalised recommendations to jobseekers and hirers based on the stated and inferred likelihood of the candidate being a suitable match. This helps to improve the matching process, leading to better and faster matches.
- **Initial identification and presentation of potential qualified candidates**—AI systems are able to extract relevant information from potential candidates' profiles and rank them according to several criteria that are pre-set by recruiters. This helps to widen the pool of potential candidates that recruiters can assess.

2.2 Increased process efficiency

Inefficiencies in the recruitment process are reflected in the substantial cost in terms of time, money and effort put into the search process by both the jobseeker and the employer. Economists refer to circumstances impeding a match between two market participants as search frictions (see Box 2.2).

Box 2.2 Search frictions

In the labour market, search frictions refer to costs to a successful match between the employer and the jobseeker, making the search for a new job or a suitable job candidate more costly in terms of time, money or hassle.[1]

While AI may have limited influence on search frictions that arise from physical barriers to a match, such as moving costs, it is well placed to help reduce frictions where they relate to the access, processing and flow of information. For example, as illustrated in section 2.1, AI can optimise job search engines, making the search process easier and less time-consuming.

Source: [1] Petrosky-Nadeau, N. and Wasmer, E. (2017), *Labor, Credit, and Goods Markets: The Macroeconomics of Search and Unemployment*, The MIT Press.

It takes 36 days to fill an average company position

Research shows that there are substantial search frictions in labour markets. The application process can be long and difficult, taking between 17 and 26 days on average between 2010 and 2014.[8] On the hiring side, data from a random sample of 488 members of the largest HR-professional organisation in the world suggests that, on average,[9] it costs $4,425[10] and takes 36 days to fill an average company position.[11] As companies grow and the number of hires increases, hiring skilled workers tends to become more costly on average.[12]

Furthermore, a recent study finds that the time to fill a vacancy increases with the skills that the position requires when skilled workers are more scarce.[13] At a time when the working population in many countries is declining[14] and the demand for highly skilled labour is increasing, the efficient matching of jobseekers and employers is likely to become increasingly complex.[15]

Process inefficiencies may also delay or even prevent a successful match between an employer and an employee. If the cost of finding a new job outweighs the potential gains to be made, jobseekers may prefer not to switch to another job or may choose not to work at all, implying an inefficient use of talent.[16]

AI can help to improve process efficiency and simplify job transitions by making the search process more efficient for both jobseekers and hirers. For example, jobseekers can be spared from sifting through large numbers of job advertisements to find relevant positions if AI-powered recruitment platforms recommend relevant jobs or connections based on their skills, experience and stated and inferred preferences. This makes the job search simpler, faster and more

[8] The average length of the application process varies across geographies: Glassdoor finds that the average in this time period is 26 days in Germany and France, 18 days in the USA, and 23 days in the UK. This data is based on over 300,000 interviews submitted anonymously to Glassdoor during the six-year period from February 2009 to February 2015. The country averages are approximated based on Figure 2 of Glassdoor's research report—see Chamberlain, A. (2015), 'Why is Hiring Taking Longer?', June, accessed 14 October 2022.
[9] The median cost per hire is $1,633. The median time to fill a position is 30 days. See SHRM (2017), 'Talent Acquisition Benchmarking Report', accessed 10 October 2022.
[10] Cost per hire represents the costs involved in signing up a new hire. These costs include the sum of third-party agency fees, advertising agency fees, job fairs, online job board fees, employee referrals, the travel cost of applicants and staff, relocation costs, recruiter pay and benefits, and talent acquisition system costs, divided by the number of hires—see SHRM (2017), 'Talent Acquisition Benchmarking Report', accessed 10 October 2022. Hiring costs may vary depending on a number of factors such as geography and the skills required for a given position. For example, the American professional association NACE, which focuses on college-educated hiring, reports an average hiring cost of $6,110 for 218 of its members in 2018—see NACE (2019), 'Cost-per-hire varies by way employers calculate budget', 4 October, accessed 25 October 2022.
[11] SHRM (2017), 'Talent Acquisition Benchmarking Report', accessed 10 October 2022.
[12] Blatter, M., Muehlemann, S. and Schenker, S. (2012), 'The costs of hiring skilled workers', *European Economic Review*, **56**:1, pp. 20–35.
[13] These findings are based on Austrian administrative data—see Ziegler, L. (2021), 'Skill Demand and Wages. Evidence from Linked Vacancy Data', IZA Discussion Paper No. 14511.
[14] OECD (2022). 'Working age population', accessed 9 December 2022.
[15] Glassdoor and Indeed (2022), 'Indeed & Glassdoor's Hiring and Workplace Trends Report 2023', accessed 9 December 2022.
[16] Pissarides, C.A. (2011), 'Equilibrium in the Labor Market with Search Frictions', *American Economic Review*, **101**:4, pp. 1092–1105.

targeted, as illustrated in Box 2.3.

Box 2.3 Jacob's story—part two: AI makes a match

Remember Jacob from Box 1.1? Search frictions were part of the reason why he could not find a position that fulfilled his need and led to him being underemployed.

After connecting with various Southwest employees and recruiters on LinkedIn, he noticed that LinkedIn's 'People You May Know' feature suggested he connect with a Southwest recruiter he was linked to through another connection.

He sent the recruiter a connection request and she responded asking if he had time to chat about a job opening. Not long after, Jacob joined Southwest.

Source: CBS News (2013), 'LinkedIn: 5 job search success stories', MoneyWatch, accessed 8 September 2022.

AI can also optimise for candidate interest and likelihood of success in the hiring process to increase jobseeker efficiency. This can be based on explicit data (e.g. whether information from their profile matches information in the job description) and latent data (e.g. whether the user is browsing or applying to similar jobs or updating their skills, or based on their response rate to messages from recruiters) and rank jobs that might interest the candidate accordingly.

LinkedIn users with more complete profiles receive 50% more messages from recruiters, reflecting better AI matching

At the same time, search and recommendation tools can benefit recruiters by providing an initial identification and presentation of potential qualified candidates according to recruiters' criteria of likely fit for a given position. Candidates on LinkedIn with a more complete profile receive 50% more messages from recruiters on average than jobseekers with a less complete profile, as the AI can more precisely target its recommendations to recruiters when it has more information available to assess whether a candidate is a good match.[17] In providing these recommendations, the underlying algorithms can be explicitly set to omit variables that would allow one to infer aspects such as gender and race, and focus only on the stated and inferred skills and experience of a candidate.[18] This increases recruiters' ability to identify larger numbers of potential candidates, thereby broadening the available talent pool.

An area where this can be especially impactful is cross-border recruitment, where there is significant scope to reduce the cost of recruitment and simplify the recognition of foreign skills—and thereby increase labour mobility, which is currently increasing at a lower rate in the EU than in previous years[19] and declining in both the USA and the

[17] Data provided by LinkedIn suggests that this figure is generally consistent over time.
[18] See, for example, Ahammad, P. (2021), 'An update for responsible AI at LinkedIn', 24 May, accessed 31 August 2022.
[19] European Commission (2022), 'Annual Report on Intra-EU Labour Mobility 2021', May, accessed 14 October 2022.

UK.[20] For example, NLP can help with the automatic translation of important documents and foreign diplomas; and AI-assisted skills assessments may replace the signalling relevance of diplomas, which has traditionally been an obstacle to cross-border labour migration.[21]

This is likely to be particularly relevant for key industrial hubs within the EU single market, as well as in the USA and UK, where—in the face of current demographic and technological developments—migrant workers are likely to play a key role in filling labour shortages.[22] While evidence suggests a positive but small impact on global economic growth,[23] international labour migration often represents considerable net gains to public finances.[24]

For jobseekers, improvements in the recognition of skills would mean access to a wider range of employment opportunities, and AI-based recommendation tools can help to increase jobseekers' awareness of relevant vacancies abroad. The benefits are even more likely to occur when employers offer remote-working jobs, as this eliminates physical relocation barriers to generating a match.

A survey shows that firms using AI matching are likely to fill vacancies more quickly and improve the quality of new hires

The above examples illustrate how AI can support the growing trend towards more skills-based hiring.[25] It can facilitate the cross-border recognition of skills—expanding the pool of potential candidates and employment opportunities alike. This makes it easier for recruiters to fill positions, especially where labour markets are tight. It also improves workers' ability to put their skills to use, which has been found to be associated with greater job satisfaction, as discussed further in section 2.3.1.[26]

[20] USA: Azzopardi, D., Fareed, F., Hermansen, M., Lenain, P. and Sutherland, D. (2020), 'The decline in labour mobility in the United States: Insights from new administrative data', OECD Economics Department Working Papers No. 1644. UK: Sumption, M., Forde, C., Alberti, G. and Walsh, P.W. (2022), 'How is the End of Free Movement Affecting the Low-wage Labour Force in the UK?', 15 August, accessed 9 December 2022.
[21] ILO, OECD and World Bank (2015), 'The contribution of Labour Mobility to Economic Growth'.
[22] Labour shortages, especially with respect to skilled workers, have been reported in the EU, the UK, and the USA alike—see Allenbach-Amman, J. (2022), 'Labour shortages felt all over Europe', 13 October, for the EU; Giles, C. (2022), 'Brexit intensifies labour shortages as companies struggle to hire', 15 August, for the UK; and U.S. Chamber of Commerce (2022), 'Understanding America's Labor Shortage', 19 August, for the USA, all accessed 14 October 2022.
[23] Brunow, S., Nijkamp, P. and Poot, J. (2015), 'Chapter 19 - The Impact of International Migration on Economic Growth in the Global Economy', in B.R. Chiswick and P.W. Miller (eds), *Handbook of the Economics of International Migration*, **1**, pp. 1027–1075, North-Holland.
[24] OECD (2013), 'The fiscal impact of immigration in OECD countries', in OECD, *International Migration Outlook*, pp. 125–189; Hennessey G. and Hagen-Zanker, J. (2020), 'The fiscal impact of immigration. A review of the evidence', Working paper 573, Swiss Agency for Development Cooperation.
[25] Fuller, J., Langer, C. and Sigelman, M. (2022), 'Skills-Based Hiring Is on the Rise', 11 February, accessed 19 October 2022.
[26] Allen, J. and van der Velden, R. (2001), 'Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction, and On-the-Job Search', *Oxford Economic Papers*, **53**:3, pp. 434–452; and Badillo Amador, L., López Nicolás, A. and Vila, L.E. (2012), 'The consequences on job satisfaction of job–worker educational and skill mismatches in the Spanish labour market: a panel analysis', *Applied Economics Letters*, **19**:4, pp. 319–324.

All of these applications save recruiters and jobseekers time and make the hiring process more skills-focused, more efficient and cheaper. A recent survey (including responses from over 400 talent acquisition leaders of firms with 1,000 employees and above across all industries) confirms these benefits: companies that leverage AI matching are found to be three times more likely to improve the time to fill a vacancy, and three times more likely to improve the quality of a hire.[27]

2.3 Increased process transparency

The lack of process transparency in recruitment arises mainly from the imperfect flow of information between jobseeker and recruiter, and across labour market participants more generally. Just as it is difficult for an employer to get an accurate idea of how skilled, motivated or interested a candidate really is, candidates may not find it easy to deduce what their abilities are worth on the labour market. This can make it difficult for both parties to correctly assess the value of a potential match. Economists explain such circumstances through the lens of asymmetric information (see Box 2.4).

Box 2.4 Asymmetric information

Asymmetric information refers to a state in which one side of the market has more or better information than the other. This can result in a 'market for lemons' problem, i.e. a situation in which—due to information asymmetry—good and bad options cannot be differentiated by a buyer.[1]

Applied to the labour market, the fact that the quality of a prospective employee is unclear to the employer leads a rational employer to assume that the potential employee is of an average quality. As a result, candidates with above-average skills will not receive offers in line with their level of qualification, which makes it less likely that the offer will be accepted. This is an outcome that is undesirable for businesses and jobseekers alike.

Source: [1] Akerlof, G.A. (1970), 'The market for "lemons": Quality uncertainty and the market mechanism', *Quarterly Journal of Economics*, **84**:3, pp. 488–500.

While there have been regulatory efforts to promote transparency in a number of jurisdictions, this is not enough to resolve the issues around asymmetric information.[28]

[27] Laurano, M. (2022), 'Talent acquisition technology and the modern recruiter', Aptitude Research.
[28] For example, the European Commission has adopted directive 2019/1152 on transparent and predictable working conditions. This directive requires employers to provide workers with more complete information concerning the employment relationship, specifying which information workers have the right to receive from the employer. In the UK the Good Work Plan aimed to overhaul the labour market, requiring that more information is shared with workers, such as normal hours of work, paid leave, probationary periods and training. Similar legislation has been implemented in some states in the USA, such as the Workplace Transparency Act in Illinois in 2020, the California Fair Pay Act in 2016, or the Colorado Equal Pay Transparency Rules in 2021.

In fact, asymmetric information is increasingly relevant for labour markets due to their rapid evolution. For example, trends such as the digital transformation, globalisation, and demographic changes are already affecting the labour market.[29] The sectors with the fastest-growing labour demand tend to require higher skills, and skills that are required now are likely to be different to those needed in the future.[30]

Correctly assessing whether the skills of the (potential) candidates match the (future) requirements of the vacancy is thus becoming increasingly difficult for humans to do—both from the perspective of the candidate and from the perspective of the employer. This means that AI has a larger role to play in assessing the skills of the candidate (section 2.3.1), and AI can help by ensuring that increasingly unpredictable hiring decisions are not driven by inherent human biases (section 2.3.2).

2.3.1 Skills mismatches

25% of workers in the OECD are over- or under-skilled for their current position

Informational asymmetry is one of the causes of skills mismatches (meaning a discrepancy between the skills sought by employers and the skills possessed by individuals).[31] Evidence shows that skills mismatches are a key determinant of lower work satisfaction[32] and, ultimately, lower labour productivity.[33]

A study based on the first European Skills and Jobs Survey in 2014[34] suggests that 'about 39% of adult EU employees are over-skilled and trapped in low quality jobs'.[35] For the USA, 52% of the jobs in 2018 require skills training beyond high school, but not a four-year degree, whereas only 43% have access to the skills training necessary to fill these jobs.[36] Looking at the UK, data suggests that, in 2015, 31% of workers are over- or under-skilled.[37] Similar data collected between 2008 and 2013 for 22 OECD countries[38] suggests that 25% of workers are over- or under-skilled for their current position.[39] This proportion

[29] ILO and OECD (2018), 'Global Skills Trends, Training Needs and Lifelong Learning Strategies for the Future of Work', accessed 29 August 2022.
[30] ILO (2022), 'World Employment and Social Outlook: Trends 2022', Geneva: International Labour Office.
[31] Nikolov, A., Nikolova, D., Ganev, P. and Aleksiev, Y. (2018), 'Skills Mismatches–An Impediment to the Competitiveness of EU Businesses', p. 65.
[32] Badillo Amador, L., López Nicolás, A. and Vila, L.E. (2012), 'The consequences on job satisfaction of job–worker educational and skill mismatches in the Spanish labour market: a panel analysis', *Applied Economics Letters*, **19**:4, pp. 319–324.
[33] McGowan, M.A. and Andrews, D. (2017), 'Labor Market Mismatch and Labor Productivity: Evidence from PIAAC Data', *Research in Labor Economics*, **45**, pp. 199–241; Adalet, M. and Andrews, D. (2017), 'Labour Market Mismatch and Labour Productivity: Evidence from PIAAC Data', *OECD Economics Department Working Papers*, No. 1209.
[34] The first European Skills and Jobs Survey was carried out in 2014 in all EU27 member states and the UK, and surveyed about 49,000 adult employees.
[35] Cedefop (2018), 'Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey', Luxembourg: Publications Office, Cedefop reference series, **106**, p. 85.
[36] National Skills Coalition (2018), 'The Skills Mismatch', accessed 12 December 2022.
[37] Office for National Statistics (2016), 'Analysis of the UK labour market - estimates of skills mismatch using measures of over and under education: 2015', accessed 12 December 2022.
[38] Namely, Austria, Belgium, Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Italy, Ireland, Japan, the Netherlands, Norway, Poland, Russia, Slovak Republic, South Korea, Spain, Sweden, the UK and the USA.
[39] Pellizzari, M. and Fichen, A. (2017), 'A new measure of skill mismatch: theory and evidence from PIAAC', *IZA Journal of Labor Economics*, **6**:1, pp. 1–30.

varies greatly across the individual countries, ranging from less than 10% in Estonia, 11% in France, and 18% in the UK to 27% in Ireland and 34% in Germany, and up to around 40% in the USA and Spain.

AI tools can help to alleviate the problem of asymmetric information by providing more information to employers and employees, while also reducing the impact of human biases linked to traditional proxies such as educational background. If the employee is more aware of their skills, their worth, and the employer's needs, they can make a more informed decision, including whether to seek better-matching job opportunities. This is also the case for employers: if the employer knows more about the skills profile, work experience and interest of (potential) candidates (e.g. through assessments or demonstrations of relevant skills), they can identify non-traditional applicants, even for hard-to-fill roles, and increase the size of their talent pool to improve the quality of matches, as in the case of Ritu (see Box 2.5).

Box 2.5 Ritu's story—part two: AI helps information flow

Remember Ritu from Box 1.2? She is looking for a job in digital marketing to move away from the shrinking area of print marketing, but is unsure which specific positions have the greatest overlap with her skillset. Ritu has therefore set her LinkedIn profile to 'open-to-work' and described her situation and ambitions in the 'About' section of her profile.

Because AI can assess the likelihood that a person has a certain skill even if it is not explicitly listed, recruiters are able to find her for vacancies that she did not know she was suitable for.

Within a week, she has several interviews scheduled.

Source: Oxera (fictional example).

On LinkedIn, 45% of companies currently rely on skills data—including skills listed on profiles, demonstrated through an assessment and/or endorsed by others, and skills inferred by AI systems—to search for and identify candidates.[40]

2.3.2 Towards more diversity in the workplace

Where information is scarce or hard to come by, or quick decisions need to be made, humans tend to subconsciously rely on mental shortcuts called heuristics.[41] While heuristics are useful to simplify complex decisions and judgements, they are sometimes flawed and can result in cognitive biases (see Box 2.6).[42]

[40] Ghayad, R. (2022), 'What puzzling effect did COVID-19 have on the US labour market? An expert explains', World Economic Forum – Opinion, accessed 31 August 2022.
[41] Kahneman, D. (2011), *Thinking, fast and slow*, Farrar, Straus and Giroux.
[42] Whysall, Z. (2018), 'Cognitive Biases in Recruitment, Selection, and Promotion: The Risk of Subconscious Discrimination', in V. Caven and S. Nachmias (eds), *Hidden inequalities in the workplace*, Springer, pp. 215–243.

Box 2.6 Heuristics and cognitive biases

Heuristics are mental shortcuts that allow people to make judgments and solve problems quickly and efficiently. However, heuristics are often flawed and can introduce subconscious yet systematic biases in the human decision-making process.[1] The list below shows some examples of cognitive biases[2] that may affect the recruitment process:

- halo effect—the tendency to extend a person's positive traits to other (unrelated) areas of their personality;
- in-group bias—the tendency for people to give preferential treatment to others whom they perceive to be members of their own group;
- mere exposure effect—the tendency for people to develop a preference for things merely because they are familiar with them.

Source: [1] Tversky, A. and Kahneman, D. (1982), 'Judgment under uncertainty: Heuristics and biases', in D. Kahneman, P. Slovic and A. Tversky (eds), *Judgment under uncertainty: Heuristics and biases*, pp. 3–20. Cambridge University Press. [2] Wilke, A. and Mata, R. (2012), 'Cognitive bias', in V.S. Ramachandran (ed.), *Encyclopedia of Human Behavior* (second edition), Academic Press, pp. 531–535.

This means that the lack of transparency caused by information asymmetries in labour markets can be further aggravated by human biases. For example, when recruiters review candidate profiles, they have to make a quick decision on whether to further consider that candidate. These instances are likely to be influenced by cognitive biases such as the 'halo effect'.

Another way of reducing cognitive load in light of the myriad of job opportunities or potential candidates is to rely on one's personal network, which may reflect in-group bias.

For example, employers may be inclined to hire candidates who went to the same school, as they have a better idea of their quality of education than they do for other schools. Jobseekers, on the other hand, may look to employers for which their peers already work, rather than going to the trouble of searching for other employers, even if they may be a better fit.

Research confirms that many jobseekers do, in fact, rely on their social contacts to find a job. In 2001 the share of the workforce that first heard about their current position through their personal network was 31% in Great Britain, 44% in the USA, and 51% in Italy.[43]

However, these implicit cognitive biases can be problematic with respect to the recruitment process, as they obscure the decision-making process and may lead to discriminatory outcomes.[44] This can

[43] Franzen, A. and Hangartner, D. (2006), 'Social Networks and Labour Market Outcomes: The Non-Monetary Benefits of Social Capital', *European Sociological Review*, **22**:4, pp. 353–368.
[44] Whysall, Z. (2018), 'Cognitive Biases in Recruitment, Selection, and Promotion: The Risk of Subconscious Discrimination', in V. Caven and S. Nachmias (eds), *Hidden inequalities in the workplace*, Springer, pp. 215–243.

hamper diversity in the workplace, depriving companies of the ability to leverage the potential benefits of a diverse workforce.[45]

It can be difficult to eliminate cognitive biases at the individual and organisational level, especially because they are not reduced if someone becomes aware of their existence.[46] This means that well-defined AI-based search and recommendation tools are uniquely positioned to help mitigate cognitive biases.

First, AI-assisted search reduces the user's cognitive load. Since AI can consider a broader range of jobseekers and a more inclusive pool of candidates, it can increase users' awareness of open positions and suitable hires beyond interpersonal networks, and thereby promote greater diversity in the workplace. Applications such as the assessing of skills in combination with automatically anonymised resumes are also able to diversify the candidate pool as they create opportunities for a broader set of populations, such as individuals with less traditional career paths.[47]

Second, developers can build tools in ways that account for potential biases in hiring and avoid perpetuating them. For example, selection criteria of algorithms can be explicitly set to omit aspects such as gender and race and focus on pre-specified features such as the skills of the candidate (as reported or indirectly inferred from their profile). The application of AI in the recruitment process thus enables employers to move to more diverse and more merit-based recruitment.

A survey shows that companies that leverage AI matching are more likely to improve diverse sources

However, while AI can go a long way in helping to mitigate cognitive biases, there may also be a risk of it picking up unconscious stereotypes in the developer or patterns of bias that are present in the data. This means that these algorithms need to be carefully constructed and appropriately assessed to avoid building in human biases.[48] It is important to note, however, that overly restricting the use of AI would not lead to a disappearance of risk—but would instead ensure that the relatively bad status quo of labour markets is perpetuated. A recent survey confirms that a careful implementation of AI in the recruitment process yields promising results: companies that leverage AI matching are found to be twice as likely to improve diverse sources.[49]

[45] Empirical studies show a positive relationship between workplace diversity and a company's performance with respect to exports, innovation and profits. See Parrotta, P., Pozzoli, D. and Sala, D. (2016), 'Ethnic diversity and firms' export behavior', *European Economic Review*, **89**, pp. 248–263; Ozgen, C., Nijkamp, P. and Poot, J. (2017), 'The elusive effects of workplace diversity on innovation', *Regional Science*, **96**:S1, pp. S29–S49; Herring C. (2009), 'Does Diversity Pay?: Race, Gender, and the Business Case for Diversity', *American Sociological Review*, **74**:2, pp. 208–224.
[46] Kahneman, D. (2011), *Thinking, fast and slow*, Farrar, Straus and Giroux.
[47] The literature shows that, due to its ability to carry out the hiring process free of 'unconscious bias' at a massive scale, AI can partially overtake the recruitment and selection process. See Raveendra, P.V., Satish, Y. and Singh, P. (2020), 'Changing Landscape of Recruitment Industry: A Study on the Impact of Artificial Intelligence on Eliminating Hiring Bias from Recruitment and Selection Process', *Journal of Computational and Theoretical Nanoscience*, **17**:9, pp. 4404–4407.
[48] Soleimani, M. and Pauleen, D.J. (2022), 'Mitigating Cognitive Biases in Developing AI-Assisted Recruitment Systems: A Knowledge-Sharing Approach', *International Journal of Knowledge Management*, **18**:1, pp. 1–18.
[49] Laurano, M. (2022), 'Talent acquisition technology and the modern recruiter', Aptitude Research.

3 Positive effects of well-functioning labour markets

As explained in the previous section, applications used in the sourcing part of the recruitment process can help to mitigate two key labour market failures—search frictions and asymmetric information.

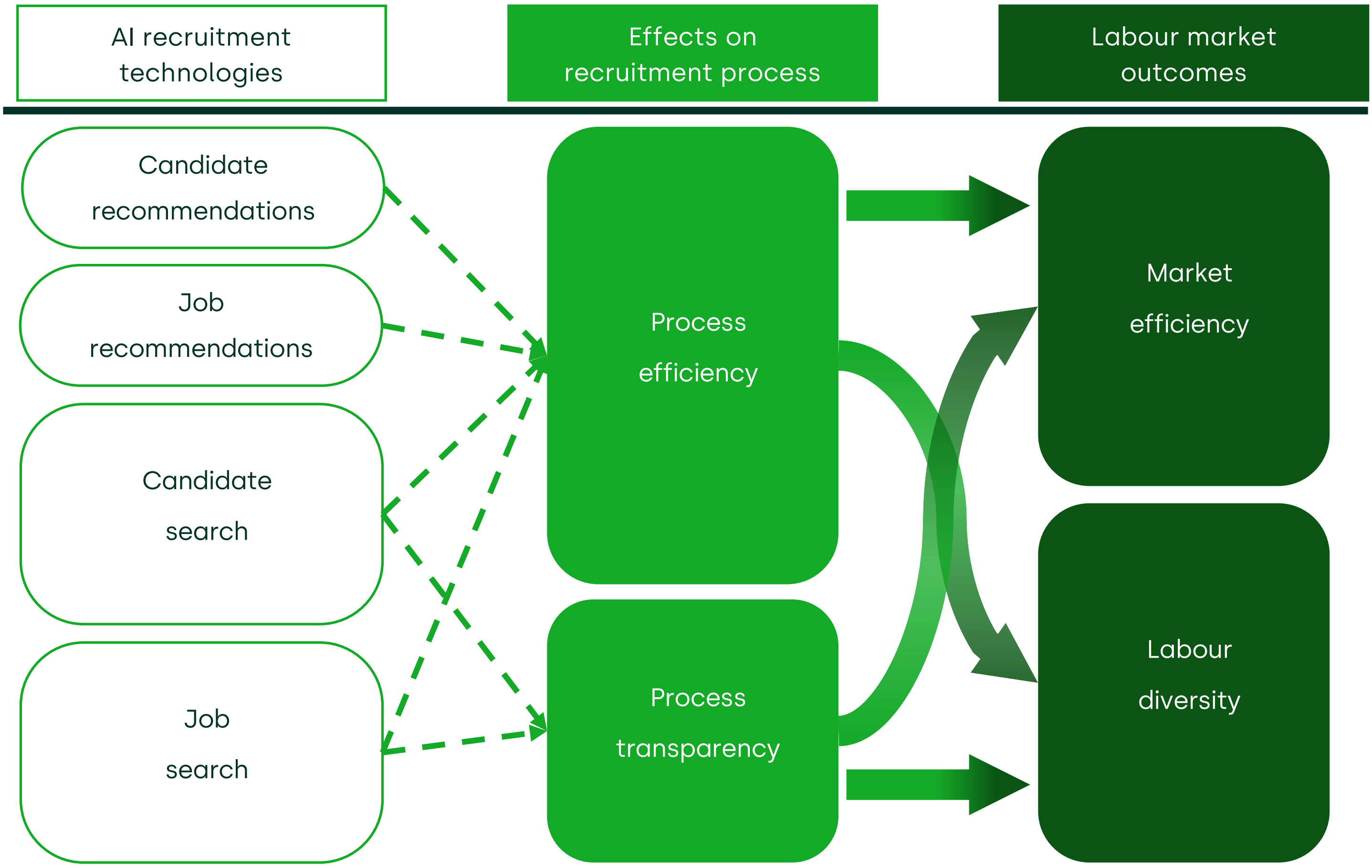
Alleviating these market failures can then lead to improved outcomes for businesses, jobseekers and society more generally as a result of greater efficiency and transparency in the recruitment process. This, in turn, makes it easier for jobseekers to find the right job and for businesses to find the right candidate.

We now make an assessment of the potential benefits that are generated by the use of AI tools in recruitment. To do so, we evaluate the links in the academic literature between each of the effects on the recruitment process (i.e. a reduction in search frictions and asymmetric information) and two categories of labour market outcome:

- market efficiency, leading to quantifiable benefits in terms of gross domestic product (GDP);
- labour diversity, leading to fairer labour market outcomes (which, for the purposes of this report, we quantify in terms of wage gaps).

We then quantify the negative impacts that search frictions and asymmetric information have each year on the economies of the USA, the EU and the UK, which AI can help to mitigate. This framework is summarised in Figure 3.1 below.

Figure 3.1 Framework for assessing the benefits of AI in recruitment



Note: The sizes of the process efficiency and process transparency boxes provide an indication of the relative scale of the different effects. As labour diversity (measured in wage gaps) and market efficiency (measured in GDP) cannot be compared on a like-for-like basis, we assume these to be equal in size for the purposes of this illustration.
Source: Oxera.

3.1 Economic measures

3.1.1 Process efficiency

The question of how search frictions affect unemployment and economic growth has been considered extensively in the economics literature.[50] As search frictions decline, the quality of the match between employees and firms increases, leading to an increase in economic growth.[51]

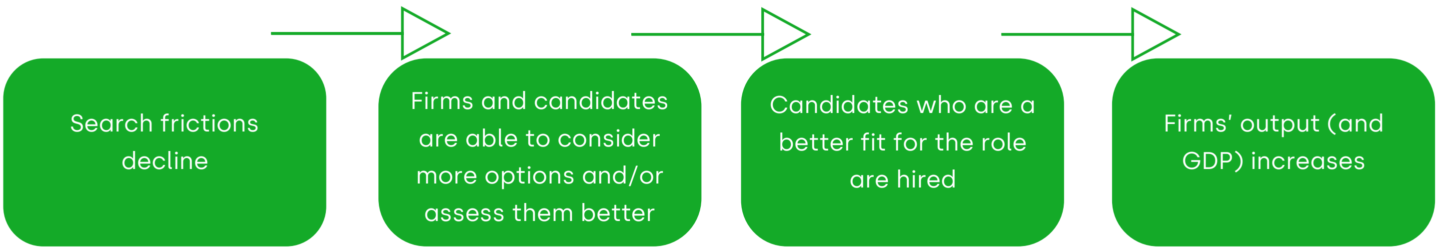
The fundamental idea behind this mechanism is that the productivity of a firm depends not only on the productivity of the firm's technology and the productivity of its employees, but also on how well the

[50] See Stigler, G. (1961), 'The Economics of Information', *Journal of Political Economy*, **69**, pp. 213–25; Stigler, G. (1962), 'Information in the Labor Market', *Journal of Political Economy*, **70**, pp. 94–105; Diamond, P. (1982), 'Wage Determination and Efficiency in Search Equilibrium', *The Review of Economic Studies*, **49**, pp. 217–27; Mortensen, D. (1982), 'Property Rights and Efficiency in Mating, Racing and Related Games', *American Economic Review*, **72**, pp. 968–79; and Pissarides, C.A. (1985), 'Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages', *American Economic Review*, **75**, pp. 676–90.
[51] Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437.

requirements of the employer and the skillset of the employee match each other.[52]

Helping to decrease search frictions (thereby aiding productivity) has become increasingly relevant, as annual labour productivity growth has been decreasing across the world. In the UK, it dropped from 2.3% between 1974 and 2008 to 0.5% between 2008 and 2020.[53] Similarly, for the USA the average annual labour productivity growth between 2010 and 2018 was 0.8%, compared with average annual growth of 2.1% between 1947 and 2018.[54] For the EU, it dropped from 1.1% between 1998 and 2007 to 0.5% between 2008 and 2016.[55] A better match between a particular firm and a particular employee can lead to increased labour productivity, leading to the firm being able to produce more, as illustrated in Figure 3.2.

Figure 3.2 The relationship between search frictions and GDP



Source: Oxera, based on Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437.

Research by Martellini and Menzio (2020) has developed a strategy to measure the rate of decline of search frictions and their contribution to economic growth for an economy that is on a balanced growth path.[56] This implies making a number of assumptions, which we consider plausible.[57] A balanced growth path means that, even though the efficiency of the search technology keeps increasing over time, the following economic variables do not have an overriding secular trend that is persistent across business cycles (even if there are natural fluctuations in these variables in line with the business cycle).

[52] See Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12.
[53] National Institute of Economic and Social Research (2022), 'Why is UK Productivity Low and How Can It Improve?', accessed 12 December 2022.
[54] U.S. Bureau of Labor Statistics (2021), 'The U.S. productivity slowdown: an economy-wide and industry-level analysis', accessed 12 December 2022.
[55] This is based on a three-year moving average. European Central Bank (2017), 'The slowdown in euro area productivity in a global context', *Economic Bulletin*, Issue 3, p. 48.
[56] See Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, p. 4389. While Martellini and Menzio (2020) provide evidence that the US economy is indeed on a balanced growth path, there is some discussion about this in the academic literature. See Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437; and Birinci, S., See, K. and Wee, S.L. (2020), 'Job applications and labor market flows', FRB St. Louis Working Paper.
[57] While we acknowledge that during the COVID-19 period many labour markets are likely to have deviated from a balanced growth path, for the purposes of this report we are assessing the benefits that AI has had in the time period predating COVID-19.

- Unemployment—i.e. the share of the working population that is out of work at a given time.
- Vacancies—i.e. the number of unoccupied jobs.
- Labour market tightness—i.e. the ratio of vacancies to the number of unemployed workers. The job market is said to be 'tight' if there are many open vacancies and available workers are scarce, and it is said to be 'loose' if the opposite is true.
- Job finding rate—i.e. the share of unemployed workers who find a job and become employed in a given period.
- Job separation rate—i.e. the share of employed workers who lose or quit their job and become unemployed in a given period.

Using Martellini and Menzio's novel identification strategy, there are two broad steps to assessing the impact of search frictions. First, the authors identify a proxy for the rate at which search frictions have historically declined—the year-on-year growth in the average number of applications per vacancy.[58] The number of applications per vacancy has increased from 24 in 1982 to 31–59 in 2011 in the USA.[59] Taking the midpoint of 31 and 59, this translates to a yearly growth rate of 2.2%, which is calculated as the annual average GDP impact, smoothing out any year-on-year variance, over the period 1982 to 2011.[60]

However, this measure captures two aspects that evolve over time: the improvement in search technology—our main variable of interest—and the growth of the labour force. The authors isolate the effect of the improvement in search technology by compensating for the effect of the growth of the labour force, which we do separately for the USA, the EU and the UK.[61]

This results in a 1.93% to 2.07% decline in search frictions due to the improvement in search technology caused by AI. This process is illustrated in Table 3.1.

[58] See Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4415–4418.
[59] See Faberman, J. and Menzio, G. (2018), 'Evidence on the Relationship between Recruiting and Starting Wage', *Labour Economics*, **50**, pp. 67–79; Marinescu, I; and Wolthoff, R. (2016), 'Opening the Black Box of the Matching Function: The Power of Words', Working Manuscript, Univ. Toronto; and Faberman, J. and Kudlyak, M. (2016), 'The Intensity of Job Search and Search Duration', Working Paper no. 2016-13, Fed. Reserve Bank San Francisco.
[60] Using the compound annual growth rate. We apply the yearly growth rate of 2.2% derived based on statistics in the USA to the USA, EU and UK due to a lack of data availability for the EU and UK. However, we correct for any differences related to variation in the growth of the labour force between these regions.
[61] We do so by multiplying the growth in the labour force by a parameter that measures the returns to scale of the labour force (beta). Martellini and Menzio (2020) estimate the value of beta to be equal to 0.32. Growth of the labour force based on World Bank data. Compound annual growth rate from 1990 to 2019 was computed for each jurisdiction. See World Development Indicators, World Bank (2022), 'Labor force, total', 8 February, accessed 2 September 2022.

Table 3.1 Quantifying the decline in search frictions

		USA	EU	UK
Growth in applications per vacancy	[A]	2.2%	2.2%	2.2%
Growth in labour force	[B]	0.85%	0.42%	0.56%
Beta	[C]	0.32	0.32	0.32
Decrease in search frictions due to technology	**[D] = [A] – [C] x [B]**	**1.93%**	**2.07%**	**2.02%**

Source: Oxera, based on Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437.

Next, we estimate how this decrease in search frictions translates to an improvement in productivity. This relationship depends on the quality of firm–worker matches, because a given decrease in search frictions is more effective at raising productivity if the quality of the newly made matches is higher. We thus divide the decline in search frictions by a parameter describing the quality of the match, estimated by the academic literature to be 3.6 (with lower values implying better matches).[62] This yields the resulting productivity increase, as illustrated in Table 3.2.[63]

Table 3.2 Quantifying the improvement in labour productivity

		USA	EU	UK
Decrease in search frictions due to technology (1982–2011)	[A]	1.93%	2.07%	2.02%
Quality of match	[B]	3.6	3.6	3.6
Improvement in labour productivity	**[C] = [A] / [B]**	**0.54%**	**0.57%**	**0.56%**

Source: Oxera analysis based on Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437.

Based on the decrease in search frictions observed over 1982–2011, the GDP impact of search frictions ranges from 0.54% to 0.58% per year, depending on the geography. Table 3.3 quantifies the current impact of search frictions for the USA, the EU and the UK by applying the average annual impact to the current level of GDP. Applying this approach to the GDP of 2019, we find an annual GDP impact—i.e. a benefit accruing to these economies every year—of decreasing search frictions of $115bn for the USA, €80bn for the EU and £13bn for the

[62] The relationship depends on the distribution of the quality of firm–worker matches, and in particular the tail coefficient of the Pareto distribution, with lower values of the tail coefficient describing better matches. See Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, p. 4418; and Martellini, P. (2019), 'The City-Size Wage Premium: Origins and Aggregate Implications', Manuscript, University of Pennsylvania.
[63] See proposition 4 in Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, December, p. 4422.

UK.[64] These estimates are expected to be representative assuming a normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.

Table 3.3 Search frictions in labour markets—annual welfare impact

		USA	EU	UK
Annual impact of search frictions	[A]	0.54%	0.57%	0.56%
GDP (2019)	[B]	\$21,381bn[2]	€14,018bn[1]	£2,238bn[3]
Annual GDP impact of decreasing search frictions	**[C] = [A] x [B]**	**\$115bn**	**€80bn**	**£13bn**

Note: Estimates of annual GDP increase are based on 2019 figures. These estimates are expected to be representative assuming a normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.
Source: Oxera analysis based on Martellini, P. and Menzio, G. (2020), 'Declining Search Frictions, Unemployment, and Growth', *Journal of Political Economy*, **128**:12, pp. 4387–4437. [1] Eurostat (2022), 'GDP and main components (output, expenditure and income)', 20 October, accessed 27 October 2022. [2] Bureau of Economic Analysis, U.S. Department of Commerce (2022), 'Gross Domestic Product', 18 October, accessed 27 October 2022. [3] Office for National Statistics (2022), 'UK Economic Accounts: main aggregates', 30 September, accessed 27 October 2022.

3.1.2 Process transparency

The other path through which AI can improve market efficiency is by enhancing process transparency. Economic research has established that the information in labour markets tends to be asymmetric, with different sides of the market seeking information from the other side that is initially not available to them.[65]

To estimate the negative impact of asymmetric information in labour markets, we build on research by Conlon, Pilossoph, Wiswall and Zafar (2018).[66] The authors construct a model to investigate the role of information asymmetries in the labour market.[67] In particular, they use novel data on workers' expectations about the number and value of future job offers, along with actual employment outcomes from a representative survey of US households.

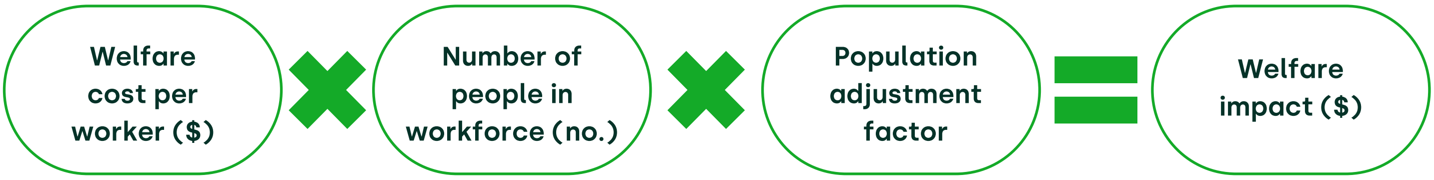
From this framework they quantify the cost of asymmetric information to society per worker for different levels of education (college-educated and non-college-educated). They calculate the costs under two different model assumptions, yielding \$817 per year for college-

[64] The COVID-19 pandemic has caused unprecedented disruption to labour markets around the world. While this has the potential to lead to significant changes to the way people find jobs and undertake work, the types of benefit that we discuss (i.e. search frictions) are likely to be just as valid in post-COVID labour markets.
[65] Wadensjö, E. (2013), 'Labor Market Transparency', *IZA Discussion Papers*, No. 7658.
[66] Conlon J.J., Pilossoph, L., Wiswall, M. and Zafar, B. (2018), 'Labor Market Search With Imperfect Information and Learning', *NBER Working Paper Series*, No. 24988.
[67] The authors build a model of search on and off the job, augmented to allow for heterogeneous worker beliefs and learning.

educated workers and $175 per year per non-college-educated workers for the most conservative scenario.[68]

While the authors indicate that their estimates are arguably a lower bound on the importance of incomplete information,[69] we take a cautious approach and apply the welfare cost only to the share of the workforce for which AI tools were used as part of their recruitment.[70] For this, we use the ratio of LinkedIn users as a share of the population that is between 15 and 64 years old as a proxy for each of the jurisdictions.[71] This process is illustrated in Figure 3.3.

Figure 3.3 Asymmetric information—stylised calculation of welfare impact



Source: Oxera.

Using figures for 2019, our modelling results indicate that asymmetric information may generate a negative impact of approximately $53bn per year in the USA, €24bn per year in the EU and £9bn per year in the UK.[72] Table 3.4 breaks down these results by geography and education level. These estimates are expected to be representative assuming a

[68] The baseline model (the most conservative) assumes that individuals are able to learn, whereas the other model is constructed without the possibility of learning. The presence of learning in the model mitigates the welfare costs per worker. In addition, the authors argue that these estimates provide a lower bound on the importance of incomplete information, because they assume that workers are not fully informed about only one aspect of the labour market (i.e. the mean of the distribution).
[69] They indicate this because they made the assumption in their research that workers are not fully informed about only one aspect of the labour market (i.e. the mean of the distribution). See Conlon, J.J., Pilossoph, L., Wiswall, M. and Zafar, B. (2018), 'Labor Market Search With Imperfect Information and Learning', *NBER Working Paper Series*, No. 24988.
[70] The article on which our estimates for process transparency are based calculates a per-worker cost. As the paper that our methodology for process efficiency is based on provides a methodology to estimate the *overall* increase in labour productivity triggered by improvements in search technology, such an adjustment is required only for process transparency.
[71] The workforce size by education level is retrieved from different data sources. Data for the EU: Eurostat (2022), 'Full-time and part-time employment by sex, age and educational attainment level', 4 July, accessed 2 September 2022. Data for the USA: U.S. Bureau of Labor Statistics (2022), 'Employment status of the civilian noninstitutional population 25 years and over by educational attainment, sex, race, and Hispanic or Latino ethnicity', 20 January, accessed 2 September 2022. For the UK, the workforce size by education level was constructed based on data about employment by education level and population by education level, based on OECD Statistics (2021), 'Educational attainment and labour-force status', 16 September, accessed 2 September 2022. Shares of LinkedIn users among the population older than 15 years old were computed using data on the number of LinkedIn users in December 2019 provided by LinkedIn, and population data for 2019 from World Development Indicators, World Bank (2022), 'Population ages 15-64, total', 20 July 2022, accessed 2 September 2022. This approach also makes the estimates more conservative because it does not account for the fact that LinkedIn users may be more highly educated on average, implying that the welfare benefits may be larger in reality than estimated.
[72] The reported values represent conservative estimates of the total welfare cost. Where the original paper reports different values for the welfare cost per worker, we adopt the most conservative (smallest) estimates, acting to reduce the estimated benefits.

normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.

Table 3.4 Asymmetric information in labour markets—annual welfare impact

		USA	EU	UK
Welfare cost—college-educated workforce	[A]	$48bn	€48bn	£10bn
Welfare cost—non-college-educated workforce	[B]	$15bn	€20bn	£2bn
Share of working age population that uses LinkedIn[1,2]	[C]	84%	35%	70%
Total welfare cost after adjustment	**[D] = ([A] + [B]) * [C]**	**$53bn**	**€24bn**	**£9bn**

Note: [1] Data on the number of LinkedIn users for December 2019 was provided by LinkedIn. [2] Data on population size in 2019 from World Development Indicators, World Bank (2022), 'Population ages 15-64, total', 20 July 2022, accessed 2 September 2022. Estimates of annual GDP increase are based on 2019 figures. These estimates are expected to be representative assuming a normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.
Source: Oxera analysis based on Conlon, J.J., Pilossoph, L., Wiswall, M. and Zafar, B. (2018), 'Labor Market Search With Imperfect Information and Learning', *NBER Working Paper Series*, No. 24988.

3.2 Non-economic measures

The positive effects of AI cannot be captured solely through assessing the impact on GDP. Another important dimension of the possible effects is the distributional aspect of labour market outcomes.

In this context, the goal of analysing diversity in the labour market is to investigate whether the hiring process leads to unfair outcomes. In addition to fair outcomes being important for their own sake, fairness ensures that the right incentives exist for people and engenders trust in society more broadly.

The current level of diversity in the labour market is broadly considered insufficient.[73] For the purposes of this report we measure labour market diversity through wage gaps, which is a common approach in the economics literature. This is because wage gaps are often seen to be a result of a lack in diversity: less diverse work places can result in (unconsciously) biased searches for employees, making it harder for minorities to secure well-paying jobs.[74] While the most-discussed pay gap relates to gender, the empirical literature has also investigated and found pay gaps among different ethnicities.[75]

[73] European Commission - Competence Centre on Foresight (2022), 'Growing disparities in labour markets', accessed 2 September 2022; Giupponi, G. and Machin, S. (2022), 'Labour market inequality', *IFS Deaton Review of Inequalities*.
[74] Lippens, L., Baert, S., Ghekiere, A., Verhaeghe, P. and Derous, E. (2022), 'Is labour market discrimination against ethnic minorities better explained by taste or statistics? A systematic review of the empirical evidence', *Journal of Ethnic and Migration Studies*. Wage gaps are generally measured while statistically correcting for other factors (e.g. differences in education), which might affect wages.
[75] Adamson, D. and Fausti, S. (2000), 'Asymmetric Information and Wage Differences Across Groups: Labor Market Discrimination or Nondiscriminatory Market Outcome', *Economics Staff Paper Series*, 144.

The current gender pay gap is:

17% in the USA

14% in the EU

15% in the UK

25% of variation in wages can be attributed to search frictions

3.2.1 Wage gaps

Wage gaps refer to differences between the wages that two groups of a population are paid to do the same job. Where differences in worker remuneration do not reflect differences in workers' suitability and willingness to do the job, they are typically considered to be unfair.

The most well-known type of wage gap is the gender pay gap. Gender pay gaps are sizeable in labour markets across the world. In the USA, the gender pay gap is currently estimated to be 17% of median earnings,[76] in the EU it is estimated to be 14%,[77] and in the UK it is estimated to be 15%.[78]

Academic research has identified a robust link between the existence of wage gaps and various factors causing them. Next to factors such as industry productivity,[79] time spent in the workforce[80] or discriminatory practices,[81] academic research identifies a robust link between typical labour market failures and the existence of wage gaps.[82]

As detailed in section 2, search frictions and asymmetric information are key drivers of process inefficiency and opacity in the recruitment process, which—as some groups may be more affected than others—can result in biased recruitment decisions and pay gaps. Research shows that up to 25% of variation in wages between workers who are similar can be attributed to differences in search frictions, as opposed to differences in worker productivity.[83]

The gender pay gap is not the only problematic wage gap. For example, research in Germany has found that foreigners face more severe frictions in finding a job than Germans, due to, among other reasons, a less extensive search network, or more limited knowledge of the country's language, search channels and application routines.[84]

[76] U.S. Census Bureau (2021), 'Current Population Reports - Income and Poverty in the United States: 2020', September, pp. 60–273.
[77] European Commission – Competence Centre on Foresight (2021), 'The gender pay gap situation in the EU', 2021 Factsheet on the gender pay gap, accessed 2 September 2022.
[78] House of Common Library – UK Parliament (2022), 'The gender pay gap', 7 April, accessed 2 September 2022.
[79] Dickens, W.T. and Katz, L.F. (1987), 'Inter-Industry Wage Differences and Industry Characteristics', pp. 48–89 in K. Lang and J.S. Leonard (eds), *Unemployment and the Structure of Labor Markets*, Basil Blackwell.
[80] Lundberg, S. and Rose, E. (2000). 'Parenthood and the earnings of married men and women', *Labour Economics*, **7**:6, pp. 689–710.
[81] Goldin, C. and Rouse, C. (2000). 'Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians', *American Economic Review*, **90**:4, pp. 715–741.
[82] Gayle, G.L. and Golan, L. (2012), 'Estimating a Dynamic Adverse-Selection Model: Labour-Force Experience and the Changing Gender Earnings Gap 1968-1997', *The Review of Economic Studies*, **79**:1, pp. 227–267; and Abe, M. (2006), 'Does Asymmetric Information Influence the Wage Differential between Men and Women?', *Japan Labor Review*, **3**:4, Autumn, pp. 23–56.
[83] Van den Berg, G.J. and Ridder, G. (1998), 'An Empirical Equilibrium Search Model of the Labor Market', *Econometrica*, **66**:5, pp. 1183–1221.
[84] See Hirsch, B., Schank, T. and Schnabel, C. (2010), 'Differences in labor supply to monopsonistic firms and the gender pay gap: An empirical analysis using linked employer-employee data from Germany', *Journal of Labor Economics*, **28**:2, pp. 291–330; and Hirsch, B. and Jahn, E.J. (2012), 'Is There Monopsonistic Discrimination against Immigrants? First Evidence from Linked Employer-Employee Data,' *IZA Discussion Papers*, No. 6472.

It was estimated that those frictions in Germany cause 4.7% lower wages for immigrants than for native workers.[85]

While labour market frictions are not the only drivers of wage gaps, AI is likely to be able to play a role in helping to reduce them by increasing both process efficiency and transparency. For example, AI can improve labour diversity by reducing the structural costs that certain groups of people face, and allowing people to enter and participate in the market on a more level playing field. In addition, by decreasing information asymmetry through AI, recruiters are able to take a more merit-based approach to hiring, as opposed to having to rely on traditional signals such as the schools a potential candidate attended.

[85] A study on immigrant search assimilation in Canada finds substantial differences in job offer arrival rates, which is the initial offer of wage, and job destruction rates, the decline in employment, between natives and immigrants. These differences account for three quarters of the observed earnings gap between natives and immigrants. The estimates imply that it takes immigrants on average 13 years to acquire the same search opportunities as natives. See Bowlus, A.J., Miyairi, M. and Robinson, C. (2016), 'Immigrant job search assimilation in Canada', *The Canadian Journal of Economics / Revue Canadienne d'Economique*, **49**:1, pp. 5–51, http://www.jstor.org/stable/43974472.

4 Policy implications

All new technologies—including emerging AI technologies—bring both benefits and potential harms to people and societies, which requires a balanced approach to regulation.[86] Good regulation promotes the responsible development and application of new technology-enabled business models while providing predictability and legal certainty.

It is also important to avoid long-term regulatory constraints that may inhibit the rapid innovation and evolution of new technologies, such as AI. With this in mind, regulatory models for AI should be focused on core principles and outcomes, rather than inputs or specific solutions, allowing them sufficient flexibility to adapt to new knowledge, evidence and applications of AI technologies.

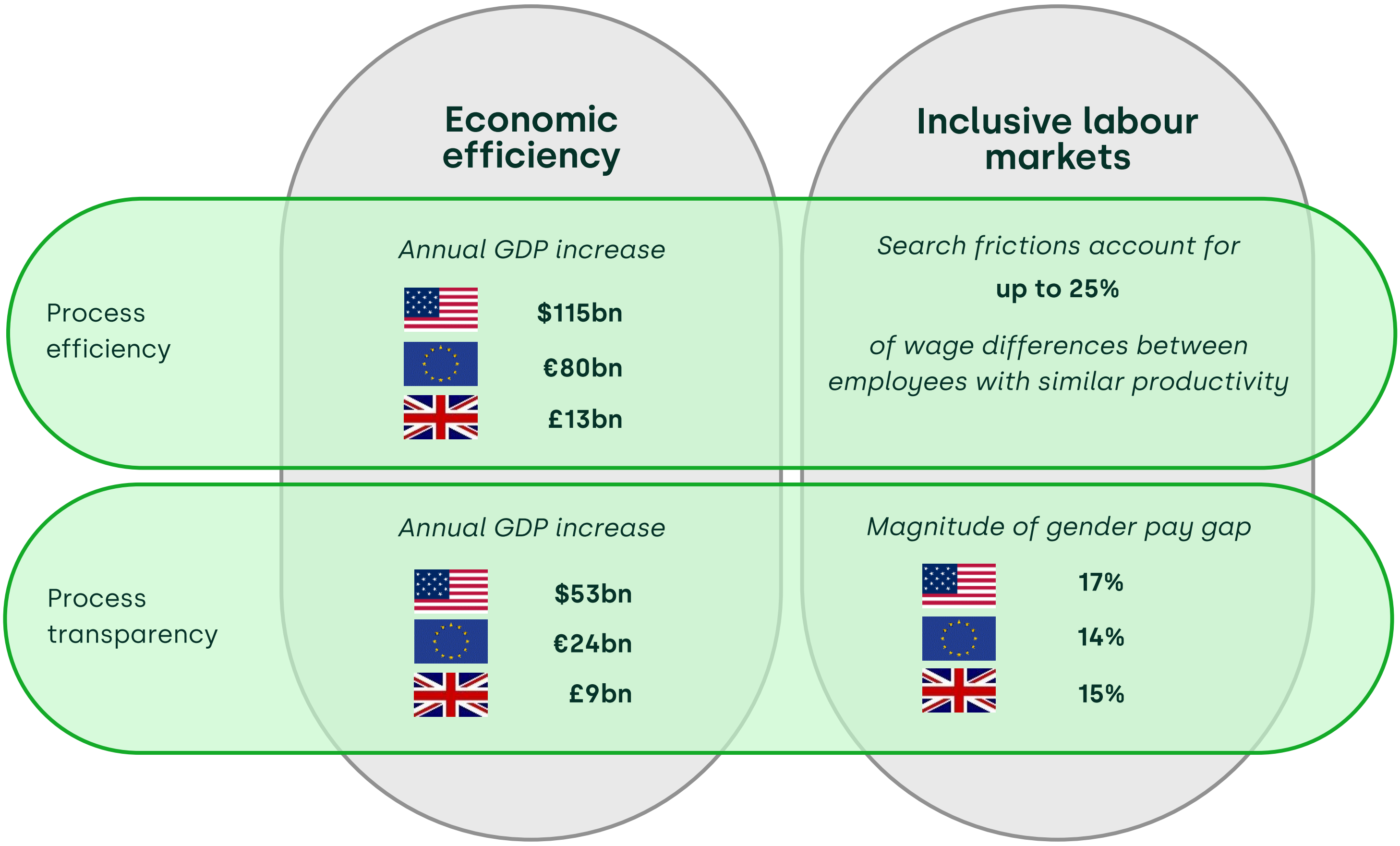
In particular, these regulatory models should also take into account the various benefits that AI offers in different contexts and allow for targeting specific problematic uses of AI as opposed to taking an overly broad approach. This approach would foster innovation and investment while remaining cognisant of the potential harms that may result from the inappropriate use of AI technologies.

AI applications may create disproportionately large benefits relating to labour efficiency and diversity—especially because the job-finding process is highly individualised and characterised by a large information gap between jobseekers and employers. Recent usage of AI in the sourcing stage of the recruitment lifecycle has helped labour markets to function more efficiently and transparently. These AI tools are uniquely positioned to help labour markets to adapt to the evolving 'future of work' in rapidly changing conditions.

Our research indicates that four key AI systems—search and recommendation systems, for both jobseekers and employers—are well placed to enable large potential benefits to labour market efficiency and diversity by alleviating market failures that are present in labour markets. This yields sizeable benefits, as outlined in Figure 4.1 below.

[86] HLEG (2019), 'Ethics Guidelines', 8 April, accessed 28 July 2022.

Figure 4.1 Summary of the benefits of AI in recruitment



Note: Estimates of annual GDP increase are based on 2019 figures. These estimates are expected to be representative, assuming a normalisation of countries' economic growth paths with the end of the COVID-19 pandemic.
Source: Oxera analysis.

It is crucial for policymakers to thoroughly consider how these benefits can best be maintained and incentivised while regulating AI.

A principles-based regulatory model—as opposed to a narrower technology-centric regulatory model—is likely to be better able to accommodate the rapid pace of innovation in AI while providing a baseline for the following key regulatory objectives.

- **Objective-oriented**: to ensure an optimal principles-based regulatory model, it is important to clearly define the objectives and desired outcomes of the regulation and how the regulation will contribute to meeting those objectives.
- **Flexible and pro-innovation**: flexible and pro-innovation regulations allow policymakers and regulators to assess stakeholders' compliance on the basis of whether they are meeting those objectives, as opposed to specifically detailing the process and method by which those objectives should be met. This allows vital innovation to happen while providing reporting on outcomes to evidence compliance. This approach creates incentives for stakeholders to achieve the structural goals of the regulation in the most efficient way possible.
- **Predictable**: to ensure that such regulation remains accessible and proportionate for SMEs and start-ups, AI regulation could allow for regulatory 'safe harbours'. Safe harbours allow those firms that

consider regular reporting on outcomes to be too costly or uncertain to follow standardised rules to guarantee that they are not deterred from participating and innovating in the market.

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