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SERVICE DELIVERY IN THE AGE OF ARTIFICIAL INTELLIGENCE

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A new dawn for public employment services: Service delivery in the age of artificial intelligence

Ailbhe Brioscú, Anne Lauringson, Anne Saint-Martin and Theodora Xenogiani

As part of broader digitalisation efforts, half of public employment services (PES) in OECD countries are employing Artificial Intelligence (AI) to enhance their services. AI is being adopted across all key tasks of PES, including most commonly to match jobseekers with vacancies. While several PES have been using such tools for a decade, adoption of AI has been increasing in recent years as these become more accessible. New AI use cases have emerged to assist employers in designing vacancy postings and jobseekers in their career management and job-search strategies. AI initiatives have significant impact on PES clients, changing how they interact with the PES and receive support, and PES staff, altering their day-to-day work. As PES seek to maximise the opportunities brought by AI, proactive steps should be taken to mitigate associated risks. Key considerations for PES include prioritising transparency of AI algorithms and explainability of results, establishing governance frameworks, ensuring end-users (staff and clients) are included and supported in the development and adoption process, and committing to rigorous monitoring and evaluation to increase the positive and manage any negative impact of AI solutions.

Keywords: Public employment services, unemployment, activation, artificial intelligence, job matching, profiling, digitalisation.

JEL Codes: J24, J63, J64, J68, O33.

Résumé

Dans le cadre d'efforts de numérisation plus larges, la moitié des services publics de l'emploi (SPE) des pays de l'OCDE utilisent l'intelligence artificielle (IA) pour améliorer leurs services. L'IA est adoptée dans toutes les tâches clés des SPE, plus généralement pour apparier les demandeurs d'emploi avec les offres d'emploi. Alors que plusieurs SPE utilisent ces outils depuis une dizaine d'années, l'adoption de l'IA s'est accrue ces dernières années, à mesure que ces outils devenaient plus accessibles. De nouveaux cas d'utilisation de l'IA sont apparus pour aider les employeurs à concevoir des offres d'emploi et les demandeurs d'emploi à gérer leur carrière et leurs stratégies de recherche d'emploi. Les initiatives en matière d'IA ont un impact significatif sur les clients des SPE, en modifiant la manière dont ils interagissent avec les SPE et reçoivent un soutien, et sur le personnel des SPE, en modifiant leur travail quotidien. Alors que les SPE cherchent à maximiser les opportunités offertes par l'IA, des mesures proactives devraient être prises pour atténuer les risques associés. Les SPE doivent notamment privilégier la transparence des algorithmes d'IA et la possibilité d'expliquer les résultats, établir des cadres de gouvernance, veiller à ce que les utilisateurs finaux (personnel et clients) soient inclus et soutenus dans le processus de développement et d'adoption, et s'engager dans un suivi et une évaluation rigoureuse afin d'accroître l'impact positif et de gérer tout impact négatif des solutions d'IA.

Abstract

Im Zuge allgemeiner Digitalisierungsbemühungen setzt die Hälfte der öffentlichen Arbeitsvermittlungen (öAV) in OECD-Ländern künstliche Intelligenz (KI) ein, um ihre Dienstleistungen zu verbessern. KI findet in allen wichtigen Aufgabenbereichen der öAV Anwendung, insbesondere um Stellensuchenden passende offene Stellen gezielt zu vermitteln. Während mehrere öAV solche Instrumente bereits seit Jahren einsetzen, hat die Nutzung von KI in den letzten Jahren zugenommen, da diese Tools nun leichter zugänglich sind. Es sind neue KI-Anwendungsfälle entstanden, die Arbeitgebern bei der Gestaltung von Stellenausschreibungen und Stellensuchenden bei ihrem Karrieremanagement und ihren Strategien zur Stellensuche helfen. KI-Initiativen haben sowohl auf die Kunden der öAV erhebliche Auswirkungen, da sie die Art und Weise verändern, wie sie mit den öAV interagieren und Unterstützung erhalten als auch auf die Mitarbeitenden der öAV, da KI ihre tägliche Arbeit verändert. Während die öAV versuchen, die mit der KI verbundenen Chancen zu maximieren, sollten proaktive Schritte unternommen werden, um die damit verbundenen Risiken zu minimieren. Zu den für die öAV wichtigsten Gesichtspunkten zählen die Transparenz der KI-Algorithmen und die Erklärbarkeit der Ergebnisse, die Schaffung eines Führungs- und Steuerungsrahmens, die Sicherstellung, dass die Endnutzer (Mitarbeitende und Kunden) in den Entwicklungs- und Einführungsprozess einbezogen und unterstützt werden, sowie ein enges Monitoring und eine rigorose Evaluation, um die positiven Auswirkungen von KI-Lösungen zu verstärken und etwaige negative Folgen zu reduzieren.

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Federal Ministry
of Labour and Social Affairs

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Executive summary

As part of intensified digitalisation and modernisation efforts in recent years, public employment services (PES) across the OECD are turning to Artificial Intelligence (AI) technologies to further enhance their activities and services to jobseekers, people at risk of job loss and employers.

In this journey, AI presents numerous opportunities for PES, including advantages arising from the self-learning nature of AI systems, the possibility for better targeting of PES services and more efficient use of resources (both human and financial). However, the use of AI poses several risks for PES, including ethical concerns, the risk of bias in AI systems, the need to foster transparency and explainability and potential resistance and lack of skills among staff. Any PES utilising AI or planning to develop such solutions should consider these holistically, in order to seize potential benefits while proactively mitigating any associated risks.

Based on responses to an OECD survey, this paper provides a comprehensive mapping of AI use cases across OECD PES. The results of this mapping indicate that half of OECD PES are enhancing the performance and user-friendliness of their digital tools and services with AI technologies. Key trends in AI use include the following:

- AI is being used by PES to support jobseekers throughout the customer journey: from chatbots to provide information on how to register with the PES and available services, measures and benefits (17% of PES), jobseeker profiling tools to better understand their needs (17% of PES), tools to guide career management and job-search strategies of jobseekers (15% of PES), tools to target active labour market policies (ALMPs) to jobseeker needs (in one PES) and job matching systems to recommend suitable job opportunities (20% of PES). Furthermore, the same (or part of the same) AI algorithm is sometimes used for the different functions of these comprehensive solutions, such as to recommend job search strategies, training possibilities, as well as specific job vacancies. These developments are likely to increase across OECD countries, as more PES aim to develop comprehensive digital ecosystems to provide personalised support to jobseekers with AI helping at each step of the labour market integration pathway.
- To date, AI technologies are most commonly adopted by PES to match jobseekers with vacancies, seen in almost one-in-five OECD PES. AI-driven matching enables PES to take into account wider data sources, keep the matching algorithm up-to-date and personalise job recommendations, thus increasing the performance of the matching algorithm and user-friendliness of the job matching platforms. In particular, AI technologies are used by PES to facilitate competency-based matching, including through a smoother integration of occupation and skills taxonomies (e.g. the European Skills, Competences, and Occupations classification, *ESCO*). Advancements in natural language processing techniques have proven particularly useful in aiding PES job matching, by enabling better identification of the competencies held by jobseekers and those needed by employers; enhancing the matching between the two. As such technologies advance further and become increasingly accessible for PES, upgrading matching tools with AI is likely to remain one of the most prevalent AI use cases among PES.
- AI has been increasingly taken up by PES in recent years to develop additional tools to better support employers in job matching process. For example, some PES are using AI to aid employers

in creating vacancy postings (20% of PES), including to correctly classify occupations and help with the drafting of vacancy descriptions based on historical postings. Furthermore, a few PES are using AI to detect illegalities in vacancies posted by employers (in 7% of PES), diagnose vacancies that will be difficult to fill to help redesign those job offers (in one PES), and proactively identify employers with high recruitment likelihood (in one PES).

- AI-based tools also have the potential to support PES with their administrative tasks such as detecting fraud in benefit administration. Nevertheless, the use of AI to assist benefit administration is limited across OECD PES, seeing only two PES use cases, and is likely to remain so due to ethical concerns, legal barriers (including in the EU under the General Data Protection Regulation) and high-profile cases of poorly implemented systems.
- An emerging use case of AI in PES is that of knowledge generation, both to produce and forecast labour market information (in 10% of PES), such as skills needs, and to monitor and evaluate ALMPs (in 5% of PES). While still largely in its infancy across OECD countries, significant potential for the future exists due to limited risks for individual people and the ability to produce more systematic and advanced analysis. This includes better understanding of sub-group impacts of ALMPs through the use of machine learning in counterfactual impact evaluations and enabling text analysis which has various applications including, for example, in analysing job posting data and text-based data held by the PES, such as jobseeker individual action plans.
- Although not widespread, a few OECD PES are using click data in their AI tools. Such click data from a jobseeker's interactions with the digital services of the PES can be used as a proxy for a jobseeker's motivation in jobseeker profiling tools. Similarly, in the case of matching tools, a jobseeker's browsing patterns on the PES vacancy portal can be used to understand their interests and preferences regarding their future employment.
- Although comparatively newer technologies, the first few applications of Generative AI and large language models (LLMs) by PES have already been implemented or are under development. These technologies have various potential use cases for PES, particularly in developing interactive solutions such as enhanced chatbots and virtual assistants for both PES clients and staff.

The adoption of AI tools by PES changes their operation models and processes, and therefore has significant implications for PES staff; most commonly through changes to the task composition of their jobs. A secondary impact is driven by the changes to PES workforce demands, including in terms of potential changes to the staff numbers and skills required. The net impact of AI adoption on PES staff needs remains to be seen until countries are further along their AI integration journey. As with wider organisational change, the adoption of AI by PES may be met by resistance and lack of trust by PES staff, including due to fears relating to the potential impacts of these technologies on their jobs. PES must be proactive in addressing such potential challenges, including by providing adequate support and training to both staff and clients in this transition.

For a successful and sustainable AI adoption, PES need to establish frameworks and structures to clearly guide and govern AI use within PES. Such frameworks should foster transparency and explainability of AI tools and involve end-users (both PES staff and clients) in the development of AI solutions, in order to both ensure these solutions meet the needs of end users and to foster trust and transparency in these new technologies. In addition, AI initiatives in PES should be monitored and evaluated continuously, along all stages of their lifecycle to both avoid any bias development and to understand the efficiency and effectiveness of such solutions.

As AI adoption is still largely recent in the world of PES and with many more countries likely to embark on this journey soon, the benefit of peer learning opportunities is clear. The OECD can play an important role in fostering this process and in identifying good practices, including through future work on this topic both across countries and within specific PES and contexts.

Synthèse

Dans le cadre de l'intensification des efforts de numérisation et de modernisation déployés ces dernières années, les services publics de l'emploi (SPE) de l'OCDE se tournent vers les technologies de l'intelligence artificielle (IA) pour améliorer davantage leurs activités et leurs services fournis aux demandeurs d'emploi, aux personnes exposées au risque de perte d'emploi et aux employeurs.

Dans cette démarche, l'IA présente de nombreuses opportunités pour les SPE, notamment les avantages découlant du caractère auto formateur des systèmes d'IA, la possibilité de mieux cibler les services des SPE et l'utilisation plus efficace des ressources (humaines et financières). Toutefois, l'utilisation de l'IA présente plusieurs risques pour les SPE, notamment des préoccupations éthiques, le risque de partialité dans les systèmes d'IA, la nécessité de favoriser la transparence et l'explicabilité, ainsi que la résistance potentielle et le manque de compétences du personnel. Tout SPE utilisant l'IA ou prévoyant de développer de telles solutions devrait considérer ces aspects de manière holistique, afin de saisir les avantages potentiels tout en atténuant de manière proactive les risques associés.

Basé sur les réponses à une enquête de l'OCDE, ce document fournit une cartographie complète des cas d'utilisation de l'IA dans les SPE de l'OCDE. Les résultats de cette cartographie indiquent que la moitié des SPE de l'OCDE améliorent les performances et la simplicité d'utilisation de leurs outils et services numériques grâce aux technologies de l'IA. Les principales tendances en matière d'utilisation de l'IA sont les suivantes :

- L'IA est utilisée par les SPE pour soutenir les demandeurs d'emploi tout au long de leur parcours client : des chatbots pour fournir des informations sur la manière de s'inscrire auprès des SPE et sur les services, mesures et avantages disponibles (17 % des SPE), des outils de profilage des demandeurs d'emploi pour mieux comprendre leurs besoins (17 % des SPE), des outils pour guider la gestion de carrière et les stratégies de recherche d'emploi des demandeurs d'emploi (15 % des SPE), des outils pour cibler les politiques actives du marché du travail (PAMT) sur les besoins des demandeurs d'emploi (dans un SPE) et des systèmes d'appariement des offres d'emploi pour recommander des opportunités d'emploi appropriées (20 % des SPE). En outre, le même (ou une partie du même) algorithme d'IA est parfois utilisé pour les différentes fonctions de ces solutions globales, par exemple pour recommander des stratégies de recherche d'emploi, des possibilités de formation, ainsi que des offres d'emploi spécifiques. Ces évolutions devraient se multiplier dans les pays de l'OCDE, car de plus en plus de SPE cherchent à développer des écosystèmes numériques complets pour apporter un soutien personnalisé aux demandeurs d'emploi, avec l'aide de l'IA à chaque étape du parcours d'intégration sur le marché du travail.
- À ce jour, les technologies de l'IA sont le plus souvent adoptées par les SPE pour mettre en relation les demandeurs d'emploi et les postes vacants, comme c'est le cas dans près d'un SPE de l'OCDE sur cinq. L'appariement piloté par l'IA permet aux SPE de prendre en compte des sources de données plus larges, de maintenir l'algorithme d'appariement à jour et de personnaliser les recommandations d'emploi, augmentant ainsi la performance de l'algorithme d'appariement et la simplicité d'utilisation des plates-formes d'appariement des offres d'emploi. En particulier, les SPE utilisent les technologies de l'IA pour faciliter l'appariement basé sur les compétences, notamment

par une intégration plus aisée des taxonomies des professions et des compétences (par exemple, la classification européenne des aptitudes, des compétences et des professions, ESCO). Les progrès des techniques de traitement du langage naturel se sont avérés particulièrement utiles pour faciliter l'adéquation d'appariement par les SPE, en permettant une meilleure identification des compétences détenues par les demandeurs d'emploi et de celles requises par les employeurs, et en améliorant l'adéquation entre les deux. Au fur et à mesure que ces technologies progressent et deviennent de plus en plus accessibles aux SPE, l'amélioration des outils d'adéquation avec l'utilisation de 'IA devrait rester l'un des cas d'utilisation de l'IA les plus courants parmi les SPE.

- L'IA a été de plus en plus utilisée par les SPE ces dernières années pour développer des outils supplémentaires afin de mieux soutenir les employeurs dans le processus d'adéquation des postes. Par exemple, certains SPE utilisent l'IA pour aider les employeurs à créer des offres d'emploi (20 % des SPE), notamment pour classer correctement les professions et aider à rédiger des descriptions d'offres d'emploi sur la base de l'historique des offres d'emploi. En outre, quelques SPE utilisent l'IA pour détecter les illégalités dans les offres d'emploi publiées par les employeurs (dans 7 % des SPE), diagnostiquer les postes vacants qui seront difficiles à pourvoir afin de contribuer à la refonte des offres d'emploi (dans un SPE) et identifier de manière proactive les employeurs ayant une forte probabilité de recrutement (dans un SPE).
- Les outils basés sur l'IA ont également le potentiel de soutenir les SPE dans leurs tâches administratives, telles que la détection de la fraude dans l'administration des prestations. Néanmoins, l'utilisation de l'IA pour aider à la gestion des prestations est limitée dans les SPE de l'OCDE, avec deux cas d'utilisation par les SPE, et il est probable qu'elle le restera en raison de préoccupations éthiques, d'obstacles juridiques (y compris dans l'UE dans le cadre du Règlement général sur la protection des données) et de cas très médiatisés de systèmes mal mis en œuvre.
- Un nouveau cas d'utilisation de l'IA dans les SPE est celui de la production de connaissances, à la fois pour produire et prévoir des informations sur le marché du travail (dans 10 % des SPE), telles que les besoins en compétences, et pour suivre et évaluer les PAMT (dans 5 % des SPE). Bien qu'elle n'en soit encore qu'à ses débuts dans les pays de l'OCDE, il existe un potentiel important pour l'avenir en raison des risques limités pour les individus et de la capacité à produire des analyses plus systématiques et plus poussées. Il s'agit notamment de mieux comprendre les impacts des PAMT sur les sous-groupes grâce à l'utilisation de l'apprentissage automatique dans les évaluations d'impact contrefactuelles et de permettre l'analyse de texte qui a diverses applications, y compris, par exemple, dans l'analyse des données relatives aux offres d'emploi et des données textuelles détenues par les SPE, telles que les plans d'action individuels des demandeurs d'emploi.
- Bien que cela ne soit pas très répandu, quelques SPE de l'OCDE utilisent des données de clics dans leurs outils d'IA. Ces données de clics provenant des interactions d'un demandeur d'emploi avec les services numériques des SPE peuvent être utilisées comme indicateur de la motivation d'un demandeur d'emploi dans les outils de profilage des demandeurs d'emploi. De même, dans le cas des outils d'appariement, les habitudes de navigation d'un demandeur d'emploi sur le portail des offres d'emploi des SPE peuvent être utilisées pour comprendre ses intérêts et ses préférences en ce qui concerne son futur emploi.
- Bien qu'il s'agisse de technologies relativement récentes, les premières applications de l'IA générative et des grands modèles de langage (LLM) par les SPE ont déjà été mises en œuvre ou sont en cours de développement. Ces technologies présentent divers cas d'utilisation potentiels pour les SPE, en particulier dans le développement de solutions interactives telles que des chatbots améliorés et des assistants virtuels pour les clients et le personnel des SPE.

L'adoption d'outils d'IA par les SPE modifie leurs modèles et processus opérationnels, et a donc des implications significatives pour le personnel des SPE, le plus souvent par le biais de changements dans la composition des tâches de leurs emplois. Un impact secondaire est induit par les changements dans les demandes de main-d'œuvre des SPE, y compris en termes de changements potentiels dans les effectifs et les compétences requises. L'impact net de l'adoption de l'IA sur les besoins en personnel des SPE reste à voir jusqu'à ce que les pays soient plus avancés dans leur parcours d'intégration de l'IA. Comme dans le cas d'un changement organisationnel plus large, l'adoption de l'IA par les SPE peut se heurter à la résistance et au manque de confiance du personnel des SPE, notamment en raison des craintes liées à l'impact potentiel de ces technologies sur leur travail. Les SPE doivent être proactifs pour faire face à ces défis potentiels, notamment en fournissant un soutien et une formation adéquats à la fois au personnel et aux clients pendant cette transition.

Pour que l'adoption de l'IA soit réussie et durable, les SPE doivent établir des cadres et des structures pour guider et régir clairement l'utilisation de l'IA au sein des SPE. Ces cadres doivent favoriser la transparence et l'explicabilité des outils d'IA et impliquer les utilisateurs finaux (à la fois le personnel et les clients des SPE) dans le développement de solutions d'IA, afin de garantir que ces solutions répondent aux besoins des utilisateurs finaux et de favoriser la confiance et la transparence dans ces nouvelles technologies. En outre, les initiatives d'IA dans les SPE devraient être suivies et évaluées en permanence, à toutes les étapes de leur cycle de vie, afin d'éviter tout développement biaisé et de comprendre l'efficacité et l'efficience de ces solutions.

L'adoption de l'IA étant encore largement récente dans le monde des SPE et de nombreux autres pays étant susceptibles de s'engager bientôt dans cette voie, l'avantage des possibilités d'apprentissage par les pairs est évident. L'OCDE peut jouer un rôle important en encourageant ce processus et en identifiant les bonnes pratiques, notamment par le biais de travaux futurs sur ce sujet, à la fois entre les pays et au sein de PSE et de contextes spécifiques.

Zusammenfassung

Im Zuge der verstärkten Digitalisierungs- und Modernisierungsbemühungen der letzten Jahre setzen die öffentlichen Arbeitsvermittlungen (öAV) in OECD-Ländern vermehrt auf künstliche Intelligenz (KI), um ihre Aktivitäten und Dienstleistungen für Stellensuchende, von Arbeitslosigkeit bedrohte Personen und Arbeitgebende weiter zu verbessern.

In diesem Zusammenhang bietet KI zahlreiche Chancen für die öAV, einschliesslich der Vorteile, die sich aus der selbstlernenden Natur von KI-Systemen ergeben, sowie die Möglichkeit, die Dienstleistungen der öAV gezielter auszurichten und die (sowohl personellen als auch finanziellen) Ressourcen effizienter zu nutzen. Der Einsatz von KI birgt jedoch auch einige Risiken für die öAV, darunter ethische Bedenken, das Risiko von Bias in KI-Systemen, die Notwendigkeit, Transparenz und Erklärbarkeit zu fördern, sowie potenzielle Widerstände und mangelndes Know-how der Mitarbeitenden. Jede öAV, die KI einsetzt oder die Entwicklung solcher Lösungen plant, sollte diese Aspekte ganzheitlich betrachten, um die potenziellen Vorteile zu nutzen und gleichzeitig die damit verbundenen Risiken proaktiv zu mindern.

Basierend auf den Antworten auf eine OECD-Umfrage liefert dieses Papier eine umfassende Übersicht über die Anwendung von KI in den öAV der OECD-Länder. Die Ergebnisse dieser Bestandsaufnahme zeigen, dass die Hälfte der öAV in OECD-Ländern die Leistung und Benutzerfreundlichkeit ihrer digitalen Werkzeuge und Dienstleistungen mit KI-Technologien verbessert. Folgende Trends bei der Nutzung von KI gehören zu den wichtigsten:

- KI wird von den öAV eingesetzt, um Stellensuchende während des gesamten Prozesses zu unterstützen: Chatbots zur Bereitstellung von Informationen über die Anmeldung bei der öAV sowie über verfügbare Dienstleistungen, Massnahmen und finanzielle Leistungen (17% der öAV), Tools zum Profiling von Stellensuchenden, um deren Bedürfnisse besser zu verstehen (17% der öAV), Tools zur Steuerung des Karrieremanagements und der Strategien der Stellensuche (15% der öAV), Tools zur Ausrichtung aktiver arbeitsmarktlicher Massnahmen auf die Bedürfnisse der Stellensuchenden (in einer öAV) und Job-Matching-Tools zur Empfehlung geeigneter Stellenangebote (20% der öAV). In einigen Fällen wird derselbe (oder ein Teil desselben) KI-Algorithmus für verschiedene Lösungen verwendet, z. B. zur Empfehlung von Strategien für die Stellensuche, Weiterbildungsmöglichkeiten und Stellenangeboten. Diese Entwicklungen werden in OECD-Ländern voraussichtlich zunehmen, da immer mehr öAV darauf abzielen, umfassende digitale Ökosysteme zu entwickeln, um Stellensuchende mit Hilfe von KI bei jedem Schritt ihrer Wiedereingliederung in den Arbeitsmarket individuell zu unterstützen.
- Aktuell werden KI-Technologien von den öAV am häufigsten eingesetzt, um Stellensuchenden gezielt passende offene Stellen zu vermitteln. Dies ist bei fast jeder fünften öAV in OECD-Ländern der Fall. KI-gestütztes Matching ermöglicht es den öAV, mehr Daten zu berücksichtigen, den Matching-Algorithmus auf dem neuesten Stand zu halten und die Jobempfehlungen zu personalisieren, wodurch die Leistung des Matching-Algorithmus und die Benutzerfreundlichkeit der Job-Matching-Plattformen erhöht werden. Insbesondere setzen die öAV KI-Technologien ein, um kompetenzbasiertes Matching zu erleichtern, u. a. durch eine leichtere Integration von Berufs- und Qualifikationstaxonomien (z. B. die Europäische Klassifizierung für Fähigkeiten,

Kompetenzen, Qualifikationen und Berufe, ESCO). Fortschritte bei den Techniken zur maschinellen Sprachverarbeitung („Natural Language Processing“) haben sich als besonders nützlich erwiesen, um die Arbeitsvermittlung zu unterstützen, indem sie eine bessere Identifizierung der Kompetenzen von Stellensuchenden und der von Arbeitgebenden nachgefragten Kompetenzen ermöglichen und dadurch den Abgleich zwischen den beiden verbessern. Da solche Technologien weiter fortschreiten und für die öAV immer zugänglicher werden, wird die Verbesserung von Matching-Tools mit KI voraussichtlich einer der häufigsten KI-Anwendungsfälle bei den öAV bleiben.

- KI wurde in den letzten Jahren von den öAV zunehmend genutzt, um zusätzliche Tools zu entwickeln, die Arbeitgebende beim Job-Matching besser unterstützen. So setzen einige öAV KI ein, um Arbeitgebende bei der Erstellung von Stellenausschreibungen zu unterstützen (20% der öAV), u. a. zur korrekten Klassifizierung von Berufen und zur Unterstützung bei der Abfassung von Stellenbeschreibungen auf der Grundlage früherer Stellenausschreibungen. Darüber hinaus setzen einige öAV KI ein, um illegale Stellenausschreibungen von Arbeitgebenden aufzudecken (in 7% der öAV), Stellen zu identifizieren, die schwer zu besetzen sind, um bei der Umformulierung der Stellenausschreibung zu unterstützen (in einer öAV), und proaktiv Arbeitgebende mit hoher Rekrutierungswahrscheinlichkeit zu identifizieren (in einer öAV).
- KI-basierte Tools haben auch das Potenzial, die öAV bei ihren administrativen Aufgaben zu unterstützen, z. B. bei der Aufdeckung von Sozialleistungsbetrug. Dennoch ist der Einsatz von KI zur Unterstützung der Leistungsverwaltung bei den öAV in OECD-Ländern begrenzt und es gibt nur zwei Anwendungsfälle bei den öAV. Dies dürfte auch so bleiben, da ethische Bedenken und rechtliche Hindernisse (auch in der EU im Rahmen der Datenschutz-Grundverordnung) bestehen und es zu Fällen von schlecht implementierten Systemen kommen kann, die in der Vergangenheit auch in den Medien ein Echo fanden.
- Ein sich abzeichnender Anwendungsfall von KI in der öAV ist die Wissensgenerierung, sowohl zur Erstellung und Prognose von Arbeitsmarktinformationen (in 10% der öAV), z. B. zum Qualifikationsbedarf, als auch zum Monitoring und zur Evaluation von aktiven arbeitsmarktlichen Massnahmen (in 5% der öAV). Obwohl dieser Anwendungsfall in den OECD-Ländern noch wenig verbreitet ist, besteht aufgrund der begrenzten Risiken für einzelne Personen und der Möglichkeit, systematischere und komplexere Analysen zu erstellen, ein erhebliches Potenzial für die Zukunft. Dazu gehört ein besseres Verständnis der Effekte von aktiven arbeitsmarktlichen Massnahmen auf Untergruppen durch den Einsatz von maschinellem Lernen in kontrafaktischen Wirkungsanalysen und die Ermöglichung von Textanalysen. Letzteres hat verschiedene Anwendungen, z. B. bei der Analyse von Stellenausschreibungen und textbasierten Daten der öAV, wie beispielsweise individuelle Wiedereingliederungspläne von Stellensuchenden.
- Einige öAV in OECD-Ländern verwenden Klickdaten in ihren KI-Tools, wobei dies derzeit allerdings nicht weit verbreitet ist. Solche Klickdaten aus der Interaktion eines Stellensuchenden mit den digitalen Dienstleistungen der öAV können in Tools zum Profiling als Proxy für die Motivation der Stellensuchenden verwendet werden. Im Falle von Matching-Tools kann das Klickverhalten von Stellensuchenden auf dem Stellenportal der öAV genutzt werden, um Interessen und Präferenzen in Bezug auf die zukünftige Beschäftigung zu verstehen.
- Obwohl es sich um vergleichsweise neuere Technologien handelt, wurden die ersten Anwendungen von generativer KI und grossen Sprachmodellen („large language models“) von den öAV bereits umgesetzt oder befinden sich in der Entwicklung. Diese Technologien haben potentiell verschiedene Anwendungsfälle für die öAV, insbesondere bei der Entwicklung interaktiver Lösungen wie verbesserter Chatbots und virtueller Assistenten für Kunden und Kundinnen sowie Mitarbeitende der öAV.

Die Einführung von KI-Tools durch die öAV verändert die Arbeitsmodelle und -prozesse und hat daher erhebliche Auswirkungen auf die Mitarbeitenden, vor allem durch Veränderungen in der

Zusammensetzung ihrer Aufgaben. Eine sekundäre Auswirkung ergibt sich aus den veränderten Anforderungen an das Personal der öAV, u.a. im Hinblick auf potenzielle Veränderungen bei der Anzahl der Mitarbeitenden und den erforderlichen Fähigkeiten. Wie sich die Einführung von KI auf den Personalbedarf der öAV konkret auswirken wird, wird sich erst zeigen, wenn die Länder auf ihrem Weg zur Integration von KI weiter fortgeschritten sind. Wie bei umfassenderen organisatorischen Veränderungen kann die Einführung von KI bei den öAV auf Widerstand und mangelndes Vertrauen seitens der Mitarbeitenden stossen, z.B. aufgrund von Ängsten in Bezug auf die möglichen Auswirkungen dieser Technologien auf ihre Arbeit. Die öAV müssen solche potenziellen Herausforderungen proaktiv angehen, u. a. durch angemessene Unterstützung und Schulung von Mitarbeitenden sowie Kunden und Kundinnen.

Für eine erfolgreiche und nachhaltige Einführung von KI müssen die öAV Rahmenbedingungen und Strukturen schaffen, die den Einsatz von KI innerhalb der öAV klar steuern und regeln. Solche Rahmenbedingungen sollten die Transparenz und Erklärbarkeit von KI-Tools fördern und die Endnutzer (sowohl die Mitarbeitenden als auch die Kunden und Kundinnen) in die Entwicklung von KI-Lösungen einbeziehen, um sicherzustellen, dass diese Lösungen den Bedürfnissen der Endnutzer entsprechen, und um Vertrauen und Transparenz in diese neuen Technologien zu fördern. Darüber hinaus sollten KI-Initiativen in den öAV in allen Phasen ihres Lebenszyklus kontinuierlich überprüft und evaluiert werden, um sowohl Bias zu vermeiden als auch die Effizienz und Effektivität solcher Lösungen zu prüfen.

Da die Einführung von KI in der Welt der öAV noch weitgehend neu ist und weil viele weitere Länder sich wahrscheinlich bald auf diesen Weg begeben werden, sind die Möglichkeiten zum gegenseitigen Lernen groß. Die OECD kann eine wichtige Rolle bei der Förderung dieses Prozesses und bei der Erkennung erfolgsversprechender Praktiken spielen, u.a. durch neue Projekte zu diesem Thema, die sowohl länderübergreifend als auch auf den spezifischen Kontext einzelner öAV ausgerichtet sein können.

1 Introduction: Objectives and definitions

1.1. Introduction and objectives

In recent years, Public Employment Services (PES) across the OECD have been increasingly harnessing digital technologies to complement and assist their operations and service provision (OECD, 2022[1]). The digitalisation journey for PES in many countries took a considerable leap during the COVID-19 pandemic when new ways of doing business were required in the face of public health restrictions – some of which have been retained post-pandemic. Nestled among this broader PES digitalisation trend is the adoption of Artificial Intelligence (AI). The OECD defines an AI system as:

> *a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment. (OECD, n.d.[2]; OECD, 2023[3]; OECD, 2024[4])*

With developments in the AI space accelerating in the past few years, innovation and application of AI is now widespread across industries. Thanks to this progress, the development of AI tools has become more feasible for many organisations, including PES. This has led to PES across the OECD exploring how AI and advanced analytics can be used to assist in their service delivery, processes and operations. If developed and implemented appropriately, AI tools have the potential to increase the effectiveness and efficiency of PES in their mission to connect people with jobs.

In this context, the main objective of this paper is to map current AI use by PES across the OECD in their central areas of activity, namely:

- **Understanding jobseeker needs and providing targeted support** – this includes AI solutions to provide information to clients (including via chatbots), identify jobseeker needs using profiling tools, career management and job-search orientation tools and initiatives to aid the targeting of PES supports and measures.
- **Labour market matching and employer services** – this covers AI-powered job-matching systems and other demand-side solutions, including tools to aid the design of vacancy postings, detect illegal vacancies and predict recruitment likelihood.
- **PES administrative activities and knowledge generation**– this includes AI use in the area of benefit administration, fraud detection and solutions to enhance monitoring and evaluation activities of PES.

In doing this, this paper strictly examines solutions using AI (see definitions in 1.2). The utilisation of non-AI powered automation and other forms of advanced analytics that do not learn or adapt over time and are not capable of autonomy are not considered or included in the analysis and will be part of an OECD policy brief on wider PES modernisation efforts that will be published at a later date.

This paper covers 39 countries: 36 OECD member countries (except for the United Kingdom and United States) and 3 OECD accession countries in the European Union (EU): Bulgaria, Croatia and Romania. It combines information from a country-level questionnaire on PES digitalisation and AI use conducted in Spring 2023, along with in-depth consultations with selected countries (Australia, Iceland, Israel, Luxembourg) and a review of the related literature.[1] The consultation with Luxembourg was held jointly with the European Network of Public Employment Services in the context of their complementary study on AI in PES which considers past, current and future lessons for PES practitioners in this domain based on the experience of 11 European PES (European Network of Public Employment Services, forthcoming[5]).

Section 2 of this paper considers the opportunities and challenges for PES associated with the use of AI-enabled technology. Section 3 provides a mapping of AI use in PES across OECD countries, in order to showcase levels of AI adoption across key areas of PES activity. Section 4 discusses the implications of AI tools for PES staff. Finally, Section 5 concludes and presents key considerations for PES in adopting and utilising AI.

1.2. Definitions: Categories of AI and the use of Big Data

AI is an umbrella term, encompassing a wide range of technology and methods, each with their own features and potential applications. As documented further in the paper, AI use by PES in OECD countries not only varies across different areas of PES activity, but also differs in terms of the exact type of AI used. Therefore, before delving further into the individual tools used by PES (as discussed further in Section 3), it is useful to first define the key concepts. The main categories of AI, as illustrated in Figure 1.1, can be defined as follows:

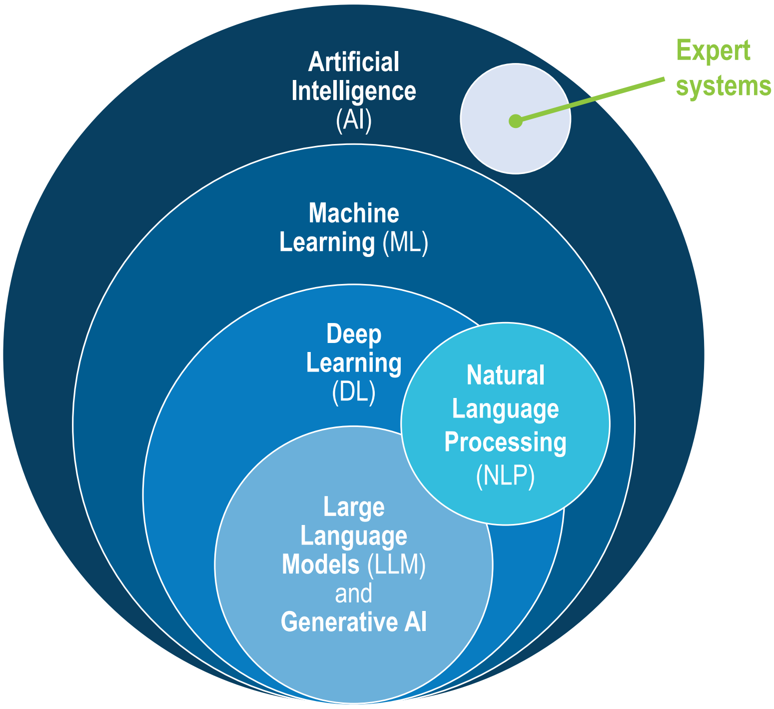
- **Expert systems** or expert models are a basic or narrow form of AI whereby a computer system is trained to reproduce the decision-making process and ability of humans (IBM, 2023[6]). Based on its training data, expert systems apply reasoning to solve complex problems in a rule-based fashion. This rule-based approach often follows an “if-then” procedure, whereby an action is executed (or inference is drawn) conditional on a prescribed rule being met (Grosan and Abraham, 2011[7]).
- **Machine Learning** (ML) is a type of AI whereby computers or software use data to self-learn and improve without the need for explicit instructions or programming (Samuel, 1959[8]). Machine learning can be classified into three types: i) supervised machine learning (classic form of machine learning whereby models are trained using labelled training data), ii) unsupervised machine learning (here the model is provided with unlabelled data, allowing freedom to identify new patterns and trends), and iii) reinforcement machine learning (relies on the model learning through trial and error, rewarding desired actions) (Brown, 2021[9]).
- **Deep Learning** (DL) is a sub-category of machine learning relying on multiple layers of artificial neural networks. These artificial neural networks simulate the learning process of the human brain by emulating the way neurons interact with each other across the many ‘deep’ layers. It attempts to replicate these mechanisms and behaviours seen in the brain using math, resulting in a software that can self-train to perform tasks. In general, deep learning requires significantly less human intervention and achieves comparatively better results with larger volumes of data than standard machine learning methods (OECD, 2021[10]; Berryhill et al., 2019[11]).

[1] Responses to the questionnaire were received from all OECD countries, except the United Kingdom and United States, and OECD accession countries in the EU (Bulgaria, Croatia and Romania). For Belgium, three sub-national responses were received individually (Brussels, Flanders, Wallonia).

- **Natural Language Processing** (NLP) combines both machine learning and deep learning models to process linguistic information. This allows for the analysis of text and enables for language to be recognised, processed and responded to – including across and between languages (Brown, 2021[9]). The linguistic basis of the approach means natural language processing lends itself well to technological applications like chatbots or digital assistants and has the potential to yield further utility when combined with other forms of AI, including machine or deep learning.
- **Large Language Models** (LLMs) and **generative AI** (specifically generative pre-trained transformers, GPTs) represent some of the latest developments in the AI space, gaining significant prominence in recent years. These methods typically use deep learning and neural networks, and in the most basic form generate text by statistically predicting the next word based on the sequence of preceding text. Applications are wide-ranging, including text generation, translation activities and more personalised chatbots or digital assistants (Lorenz, Perset and Berryhill, 2023[12]; Perset, Plonk and Russell, 2023[13]).
- While not a form of AI, **big data** is often a key input into AI tools – providing the fuel from which AI systems can learn and improve. First coined in the early 2000s, the term big data was created to describe the boom in quantity of available data – largely aided by advancements in the technology associated with data recording and storage. Big data differs from traditional data in that it can feature structured and/or unstructured data, that cannot be managed, processed or analysed using traditional approaches. Big data is often described through the 'Four vs.': volume (quantity and scale of data), variety (scope and heterogeneity of data), velocity (speed of data generation) and veracity (data accuracy and reliability) (OECD, 2021[10]; Forbes, 2022[14]). It is important to note that the wealth of administrative data in PES registers are generally distinct from big data. Data in PES registers are more systematic and structured in nature, whereas big data can be comparatively more chaotic and are often found or observed, rather than collected. For PES, the most relevant forms of big data for their operations, include – inter alia – job vacancy postings (text) and internally-generated click data from clients' interactions with PES digital platforms.

Figure 1.1. Under the umbrella of AI, various sub-categories of methods exist

Main forms of AI and their interlinkages



Source: Authors' illustration, adapted from OECD (2019[15]), Artificial Intelligence in Society, https://doi.org/10.1787/eedfee77-en.

The field of AI, along with its capabilities, is rapidly and constantly evolving. This includes significant developments in the area of generative AI and large language models. A prominent example of these advances in the field of generative AI is ChatGPT – now a household name. As countries, organisations and individuals get to grips with the potential uses and risks of generative AI and large language models, so too is the public sector – including PES. While the timing of this study means that the full implications of such tools for PES are still uncertain, the potential applications of these innovations to the provision of employment services and associated back-office operations or processes are numerous (Box 1.1). However, as with other uses of AI, an assessment of the associated risks and related action to minimise risks will be necessary for PES in the adoption or development of such AI tools.

Box 1.1. The recent boom in generative AI and large language models (LLMs) may yield significant benefits for PES

The end of 2022 and early 2023 saw the emergence of several generative AI tools, including ChatGPT, Bard, Microsoft Bing AI, and others. These tools have quickly gained prominence, bringing with them widespread applications and implications for society. For PES, multiple potential uses can be envisaged both through generalised (open-source) or custom models, including:

- Enhanced chatbots or virtual assistants to provide information and recommendations to jobseekers and employers (including in multiple languages);
- Virtual assistants to assist the work of PES staff, including generating individual action plans for jobseekers and drafting responses to emails;
- Analysis of unstructured text-based information collected by PES databases (e.g. data from individual action plans of jobseekers);
- Sentiment analysis of customer feedback on services and measures (i.e. using AI to analyse user feedback data, for example from emails, to determine whether they are positive, negative or neutral);
- Support to employers in drafting the content of job vacancies;
- Content generation, including informational material on PES supports and measures.

For PES, generative AI and LLMs provide a significant opportunity to make better use out of already limited resources. This includes human resources, where such tools have the potential to facilitate PES staff to free up time and focus on more complex non-routine tasks. However, just like other AI tools, generative AI and LLMs also come with their own set of risks, some of which are particularly acute for public sector organisations such as PES. This includes, in particular, data protection, security concerns and the echoing of biases in the underlying training data (see Section 2 for a wider discussion of the opportunities and challenges for PES associated with AI use).

Furthermore, open-source transformers, such as BERT (Bidirectional Encoder Representations from Transformers), provide further opportunities for PES and enhanced accessibility to these technologies. In addition, the inspectable nature of such open-source AI models allows for comparatively higher transparency for PES, compared to proprietary AI models which are often black box models (see Section 2.2.1 for more on black box AI models).

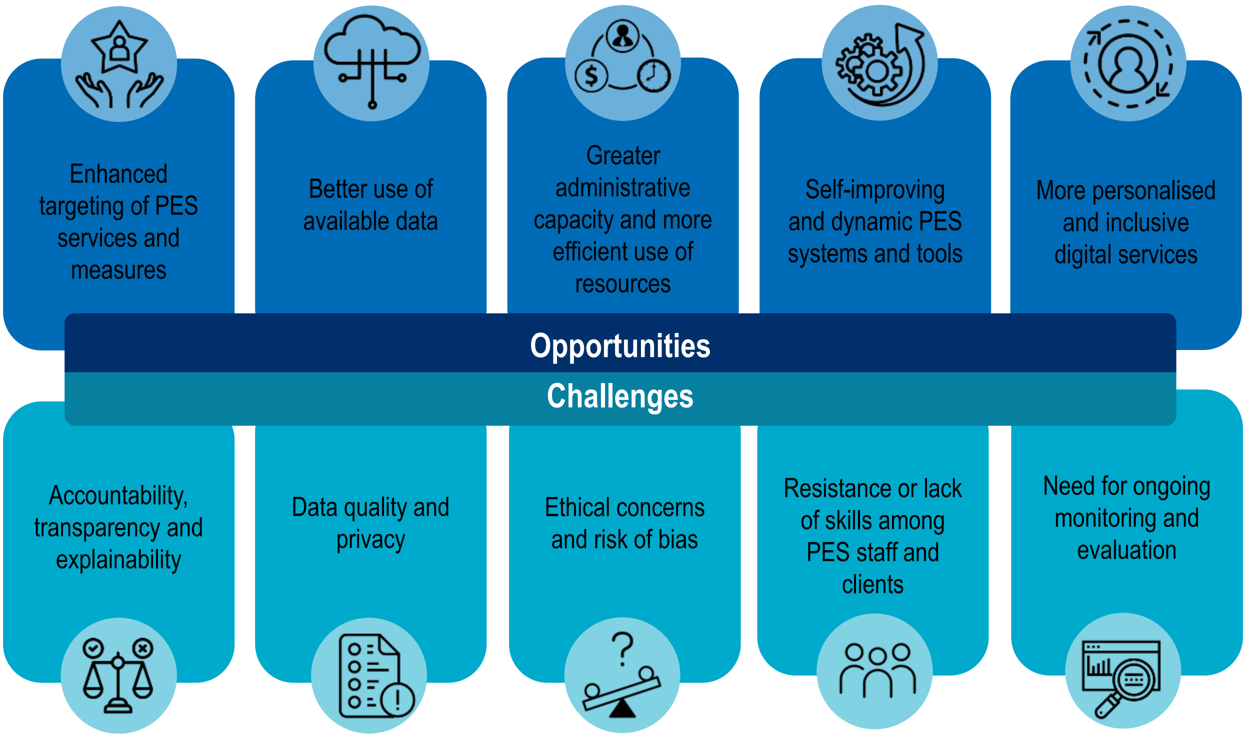
In practice, across OECD countries, the Austrian PES was the first to rollout a generative AI solution for client use. Since early 2024, the Austrian PES has implemented a ChatGPT enabled chatbot to provide information on training and career orientation to jobseekers. However, this innovation came under criticism soon after launch, including due to reports that the recommendations to users generated by the chatbot perpetuated gender biases.

Source: Lorenz, Perset and Berryhill (2023[12]), *Initial policy considerations for generative artificial intelligence*, https://doi.org/10.1787/fae2d1e6-en; Perset, Plonk and Russell (2023[13]), As language models and generative AI take the world by storm, the OECD is tracking the policy implications, https://oecd.ai/en/wonk/language-models-policy-implications; Council of the European Union General Secretariat (2023[16]), ChatGPT in the Public Sector – overhyped or overlooked?, https://www.consilium.europa.eu/media/63818/art-paper-chatgpt-in-the-public-sector-overhyped-or-overlooked-24-april-2023_ext.pdf; AMS (2024[17]), AMS Berufsinfomat, https://www.ams.at/arbeitsuchende/aus-und-weiterbildung/berufsinformationen/berufsinformation/berufsinfomat; Köver (2024[18]), AMS erntet Hohn mit neuem KI-Chatbot, https://netzpolitik.org/2024/diskriminierung-ams-erntet-hohn-mit-neuem-ki-chatbot/

2 Opportunities and challenges for PES in adopting AI

AI has the potential to offer various opportunities and benefits for PES in aiding their mission to connect people with jobs. These potential benefits include: the self-improving and dynamic nature of AI tools; the scope for PES to provide more personalised and inclusive digital services; enhanced targeting of PES services and measures; enabling better use of available data; and boosting the administrative capacity of PES, contributing to more efficient use of resources. This section discusses these benefits, while also highlighting the need to address some of the central challenges or risks faced by PES in the domain of AI (Figure 2.1) – including: the need to provide accountability; transparency and explainability mechanisms; coping with data quality and privacy concerns; the need to proactively address the risk of bias; addressing potential resistance and lack of skills among staff and clients; and the importance of ongoing and rigorous monitoring and evaluation. Each individual PES should consider these matters together and, when adopting AI solutions, should attempt to strike a balance that manages or mitigates risks, while capitalising on the potential benefits.

Figure 2.1. Adopting AI presents a number of opportunities and challenges for PES



Note: PES – Public Employment Services.
Source: Authors' illustration.

2.1. Key opportunities for PES in adopting AI

The adoption of AI presents several potential benefits for PES. This section explores some of the central prospective opportunities for PES in adopting AI in its operations and processes. In decision-making regarding the adoption of AI by PES, these opportunities should be considered holistically and along with the risks and challenges associated with these technologies.

2.1.1. Self-improving and dynamic PES systems and tools

Unlike traditional software and computing systems, AI systems can self-learn. For PES, the application of self-learning systems presents various advantages, including the ability to gradually improve their performance over time, as they encounter new situations and data. For example, an AI-powered PES chatbot can continuously learn as they interact with larger volumes of users. Continuous learning and improvement can be integrated into AI systems by incorporating feedback loops and backpropagation algorithms, which mimic the learning process of the human brain and iteratively adjust the model as needed (Gomede, 2023[19]).

AI systems are also well equipped to operate in dynamic environments and can identify and flexibly respond to changes in real-time. Such agile systems may be advantageous for PES, due to the dynamic labour market backdrop against which they operate – including fluctuating economic and labour market conditions and changes to skills and occupations in demand by employers.

2.1.2. Enabling more personalised and inclusive digital PES services

Users of public services are progressively demanding more responsive and personalised services, while also having higher expectations of the digital capacities of public services in an increasingly digitalised world (Ubaldi et al., 2019[20]). AI provides an avenue to achieve this, with various public organisations using Natural language processing (NLP) and other forms of AI to provide personalised services to their users (Berryhill et al., 2019[11]). For PES, this same opportunity exists, allowing services to be tailored to the needs of the individual client even when provided through online or digital self-service channels. AI enabled digital platforms can do this by using information input by clients, along with their usage history and patterns in order to tailor content and offerings to their individual needs. In addition, AI can enable more efficient client experiences for users of PES services and can contribute to easing and shortening the often-lengthy administrative procedures involved in accessing services and supports.

In communicating with clients, AI offers PES a route to personalised automated communication and messaging and increased levels of engagement. AI-enabled chatbots, unlike traditional rule-based chatbots, are not restricted to scripted conversations based on pre-defined rules. Instead, chatbots powered by AI can carry out more complex conversations with clients, providing more personal responses and responding to more nuanced requests. This includes AI-powered chatbots operating in a protected environment with access to a client's information which can enable more individualised and complex support, provided associated risks regarding data protection and privacy are carefully considered and addressed (see also the discussion in Section 2.2.2).In addition, AI-powered chatbots can be powerful informational and guidance tools for PES to support their clients in a fast and efficient manner, including outside of regular business hours. Despite these comparative advantages over traditional conversational bots, the ability for unresolved queries to be escalated to a human (i.e. a PES staff member) will still remain a feature of many AI-powered chatbots implemented by PES.

AI also has the potential to improve accessibility of PES services. For example, AI can assist in, among other things, automatically translating documents or services (including via chatbots), automating captions and subtitles on audio-visual content, enhancing assistive technologies, and testing the accessibility of websites and digital tools.

2.1.3. Aiding the targeting of PES services and measures

To provide effective services to clients, PES must first understand their individual needs. This is particularly the case in serving the needs of vulnerable groups facing labour market disadvantage, where individualised and targeted services are essential in addressing their often-complex needs and barriers to employment (OECD, 2021[21]). AI tools can assist in this domain, facilitating more advanced analysis of data to enhance the understanding of the different segments of people within the caseload of the PES and their associated needs (United Nations, 2022[22]).

For many PES, a key step in the initial counselling and needs assessment of clients is the application of a profiling or segmentation process – often operationalised in the form of a digital tool. Profiling tools allow PES counsellors to identify both those jobseekers who will easily find a job with limited assistance and those who will require more time and intensive support to do so (OECD, 2018[23]). These tools are particularly important for clients from vulnerable groups, so that intensive services can be targeted at those that need and would benefit from them most. Such tools enhanced by AI enable the application of more complex algorithms and allow the models to encompass wider data sources, including click data from jobseeker interaction with PES digital sites or platforms in order to integrate data on jobseeker browsing patterns. The results of these tools help the PES and counsellors to target active labour market policies (ALMPs) more effectively. A discussion of PES in OECD countries using AI to support client profiling and in turn the targeting of services can be found in Sections 3.2.2 and 3.2.4.

Furthermore, AI can allow for more data-driven and systematic assessments and recommendations regarding jobseekers and their labour market integration pathway. This includes any differences in decision-making across caseworkers and potentially improving fairness, through the mitigation of any possible bias or discrimination.

2.1.4. Enabling PES to make better use of available data

AI tools and solutions offer the potential for PES to make better use of available data in PES and data from wider sources.

First, AI can enable PES to manage, process and use data in a timelier and more automated fashion. With PES typically holding vast amounts of historical and up-to-date data, AI presents opportunities for real-time analytics (OECD, 2022[1]). Vast amounts of real-time data can be analysed and learned from more quickly than traditional methods, allowing for more agile operational and policy decision-making. In addition, AI can assist PES in making use of a wider range of data such as unstructured and big data. For PES, such data could include click-data and browsing behaviour of jobseekers using digital PES tools and other text-based data (e.g. from CVs and job advertisements). This capability broadens the analytical horizon for PES. As holders of large amounts of administrative data, AI also presents opportunities for PES to improve data management – a significantly labour-intensive task – across the areas of data classification, cataloguing, quality, security and integration (Davenport and Redman, 2022[24]).

AI-powered sentiment analysis also has the potential to provide PES with a better understanding of the experiences of their customers (both jobseekers and employers) with the supports and services they receive. While PES in many countries already engage in some customer satisfaction activities (e.g. via questionnaires), conducting these activities and examining their results can be time-consuming and resource-intensive. AI has the potential to assist with these activities, including in analysing the results of customer surveys and other forms of contact with clients (e.g. through chatbots, emails, etc) to better understand the experiences of clients in their engagement with the PES. Supplementing this work with AI provides various opportunities for efficiency gains, including by allowing PES to conduct such activities more regularly and on larger samples of their customer base.

AI also has the potential to transform how PES assess and evaluate their measures and services provided, including through rigorous counterfactual impact evaluations. This can take place in one of two ways, either by using AI methodology (such as machine learning) to enhance causal inference activities or by using an AI-driven system to produce the analysis. In this first domain, recent literature indicates that causal machine learning has the potential to yield various benefits for policy evaluation, particularly in better estimating the heterogeneity of effects, or how policies impact different groups of people (Athey, 2019[25]; Lechner, 2023[26]; Cockx, Lechner and Bollens, 2023[27]). The evidence created through these efforts can greatly assist in informing the design and targeting of measures and supports offered by PES. The second avenue through which AI can assist PES evaluation activities is through the development and implementation of AI systems to conduct impact evaluations. While few PES engage such in AI-enabled evaluation activities (see Section 3.4.2 for use cases), opportunities exist for PES to both enhance the insights driven from this work, particularly regarding sub-group impacts, and to have more systematic and regular evaluations through dedicated evaluation tools.

AI also has wide potential uses in producing predictive analytics, whereby predictions about future events or trends are made based on extrapolations from historical data. For PES, predictive AI algorithms have the potential to enhance a number of services and activities (Körtner and Bonoli, 2021[28]). Predictive algorithms can be applied to profiling exercises (in order to predict a jobseeker's likelihood of becoming long-term unemployed), targeting (to predict what measures will work best for a given jobseeker's needs) and in matching (to predict successful matches between a jobseeker and a vacancy) – a discussion of current applications of these by PES in OECD countries can be found in Section 3. At the strategic level, predictive AI has the potential to assist an organisation in enhancing their anticipatory capabilities (United Nations, 2022[22]). This can enable PES to become more agile and proactive in its decision-making and planning and can help to better align services offered with the needs of clients and the labour market.

AI can also be used to detect anomalies in both data and systems. For PES, this could be particularly relevant to the processing of applications (for both benefits and labour market measures) in order to identify any potential issues or suspected fraud (Section 3.4.1). This can also be expanded to fraudulent use of online services or tools. However, the risk of poor implementation of such initiatives are substantial, including wrongful sanctioning and associated distress for affected clients.

2.1.5. AI can help PES boost administrative capacity and promote a more efficient use of human and financial resources

Applications of AI by PES presents the potential for more efficient and effective use of PES resources. These avenues include enhancing the human resource capacity of PES, including by taking over administratively heavy or repetitive tasks or by augmenting the performance of workers with AI-powered tools that assist elements of their work.

AI solutions have the potential to help with time-intensive and tedious administrative tasks, reducing the potential for errors and allowing staff to focus their time on more important and high-value work which cannot be delegated to AI or other forms of technology (Salvi Del Pero, Wyckoff and Vourch, 2022[29]), including allowing counsellors to spend more time on clients with complex needs. For example, in providing information to customers (citizens, jobseekers and employers), AI-based chatbots can be a significant resource for PES – allowing staff to focus on more difficult cases or other tasks. In addition, chatbots have the added value of providing instantaneous support 24 hours a day. This can be particularly important when PES human resources come under additional pressure, including – for example – during the COVID-19 pandemic (see section 3.2.1 for a further discussion of chatbots).

In other cases, AI tools or systems working side-by-side with PES staff have the potential to yield various benefits, including staff empowerment and increased productivity. In a recent workplace study, Brynjolfsson, Raymond and Li (2023[30]) examine the impacts of a generative AI assistant to aid workers in the contact centre of a software firm (Box 2.1). The results of the study indicate that access to the AI tool both enhanced the productivity of support agents, but also increased the speed at which less tenured staff learned. In addition, in contrast to literature on the impact of previous waves of technological adoption, the positive productivity effect of the generative AI tool was found to be even higher among less-skilled and less-experienced agents. Such evidence suggests, that if implemented correctly, AI tools to assist PES staff could yield productivity gains and imbed better overall performance – particularly in the area of client support and engagement.

Box 2.1. A workplace study showed that access to a generative AI tool boosted worker productivity, particularly for low-skilled workers

Brynjolfsson, Raymond and Li undertook a study that saw a real-world deployment of generative AI in the workplace. More specifically, the authors staggered the introduction of a conversational assistant in a contact centre with 5 179 support agents, working in a Fortune 500 software firm.

The assistive tool developed using a type of GPT solution, that uses large language models built by OpenAI. The tool monitored chats received by the contact centre and provides suggested responses to agents in real-time. Agents still had responsibility and autonomy over conversations and could take on board or ignore the suggestions of the AI assistant as they wished.

The main results of the study include the following:

- Having access to the AI assistant boosted worker productivity, resulting in a 14% increase in the number of chats successfully resolved by an agent per hour. This was driven by a reduction in the average handling time of a chat and an increase in the share of chats resolved successfully.
- For less-skilled or less-experienced agents, significant productivity enhancements were seen, including a 34% increase in the number of successful resolutions per hour.
- Newer agents that had access to the AI tool were more quickly able to learn. For example, these agents with two months tenure had the same productivity as their counterparts with more than six months experience.

The mechanisms driving these results were found to include increasing adherence rates, or how closely a support agent follwed the tool's recommendations, over time. In addition, agents using the AI tool experience long-lasting learning; meaning that even during software outages, where the tool is temporarily unavailable, agents perform better in terms of productivity than compared to their pre-AI level.

Source: Brynjolfsson, Raymond and Li (2023[30]), *Generative AI at Work*, https://www.nber.org/system/files/working_papers/w31161/w31161.pdf.

On the side of financial resources, while the upfront costs of developing and implementing AI systems and tools may be high, in the long run these solutions have the potential to generate cost efficiencies, or even savings, for PES if implemented successfully. Such savings have the potential to be realised through enhanced organisational efficiency, increased productivity, avoiding duplication of work, optimised processes and significant time savings. In addition, AI algorithms and systems can enable better financial resource management, including control and fraud detection activities – in particular in cases where the PES are responsible for the administration of benefits.

2.2. Central challenges and risks faced by PES in utilising AI

The emergence of AI and its growing prevalence has come with various challenges and risks. While many of these risks are not only specific to PES, but to the use of AI more generally, they are particularly acute for PES as public organisations and given the impact of their work on citizens. This section discusses some of these key challenges for PES in adopting AI, which should be considered in tandem with the already discussed opportunities.

2.2.1. Accountability, transparency and explainability should be central to PES AI use

As established in the OECD's AI principles, accountability, transparency and explainability are key pillars in the responsible and trustworthy use of AI and should be central to the work of PES in this domain (OECD, 2023[3]). Similarly, the new EU AI Act also underpins these factors as crucial to the development and use of safe and trustworthy AI systems (Council of the European Union, 2024[31]).

AI actors – organisations and individuals that design, deploy or operate AI – should be accountable for ensuring the proper functioning of AI systems (OECD, 2023[3]; OECD, n.d.[32]). Given the nature of PES and the impact of its work on clients, establishing accountability for decision-making and results of AI systems and tools is crucial. This requires the creation and implementation of governance frameworks that define clear lines of responsibility for AI systems along their entire lifecycle (OECD, 2021[10]). Such governance frameworks act as an essential enabler of trustworthy AI in the public sector (OECD, forthcoming[33]) and for PES could either be internally or on a government or public sector-wide basis.

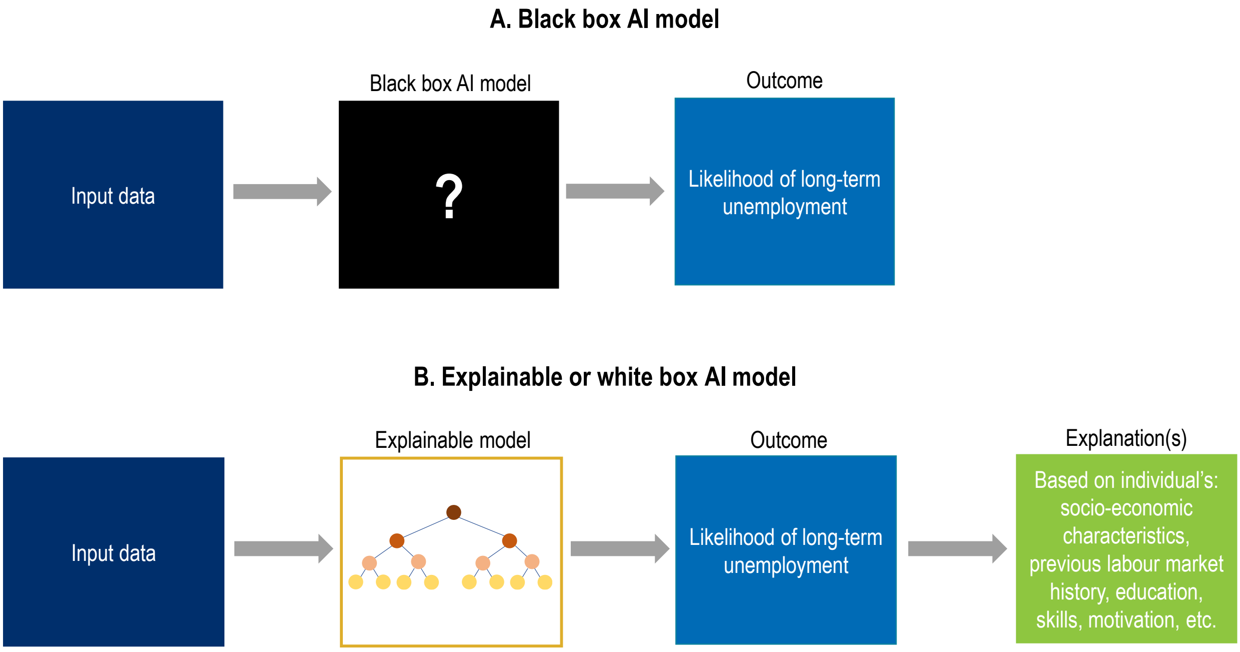
The effectiveness of accountability mechanisms is likely to increase with the availability of information on PES AI use and activities – enabling external scrutiny (Berryhill et al., 2019[11]). Therefore, PES should commit to promoting transparency surrounding their AI use, including to enhance awareness and understanding among key stakeholders (crucially PES clients and staff) of how AI is used and outcomes generated. However, efforts by PES to promote transparency and explainability in their use of AI need to be carefully balanced against the risk of facilitating fraud and intellectual property rights.

Well-designed structures to foster transparency around AI use within PES can also aid in creating greater explainability and trust in AI outcomes among PES clients and staff. However, as AI and associated algorithms have become more advanced in recent years, this has contributed to difficulties in explaining and interpreting the workings and results of AI models. Such complex AI systems are often commonly referred to as "black box" models (Figure 2.2, Panel A), with the process and logic (i.e. the how and why) behind the results and decision-making remaining opaque (Berryhill et al., 2019[11]). While some AI actors value the results more than the process, for public organisations including PES, explainability remains crucial due to the impact of the systems on citizens and to ensure reasonable levels of accountability and transparency (Rudin, 2019[34]). In the EU, these concerns have been addressed in legislation, specifically the EU's General Data Protection Regulation (GDPR) and the new EU AI Act, due to the fact that black box systems limit the autonomy of citizens and breach the right of citizens for explainable and challengeable decisions (European Parliament, 2020[35]).

Therefore, the "white box" approach is more favourable for PES, requiring inherently interpretable models and embedding the values of transparency and explainability into the system. For example, for PES using AI to support their profiling of jobseekers, an explainable or "white box" model will allow both the client and counsellor to better understand the outcome of the tool (i.e. the jobseeker's predicted likelihood of long-term unemployment) and the factors that contributed to this AI-generated outcome (Figure 2.2, Panel B). This can include transparency around variables included in AI systems and associated weightings in the overall model (Salvi Del Pero, Wyckoff and Vourch, 2022[29]). For example, in the case of a profiling tool, understanding how the status of certain variables (e.g. educational attainment) contributes to the final profiling score.

Figure 2.2. In contrast to black box models, explainable AI models enable better transparency and explainability

Illustration of black box and explainable AI models using the example of a profiling tool, which predicts a jobseeker's likelihood of long-term unemployment



Source: Authors' illustration.

2.2.2. Data quality and privacy

Data is the central input for most AI models and the fuel that enables them to run and learn. PES hold extensive volumes of administrative data mainly collected through the interaction of clients –jobseekers, employers and workers – with their services and measures. However, the quality and readiness of data for use in AI models cannot be taken for granted, especially when integrating various datasets and sources. This means that steps must be taken to continually verify the accuracy, reliability and appropriateness of data inputs to AI systems (Berryhill et al., 2019[11]; Desouza, Krishnamurthy and Dawson, 2017[36]), which allow PES to proactively identify and address errors, as well as bias present in the data (as discussed in section 2.2.3). This is also especially important in the use of big data, where more data does not necessarily automatically mean better data. High quality results from AI systems hinge on high quality training and input data, requiring effective data collection, validation and governance frameworks within PES.

In addition, due to the personal data held by PES, its use, including in AI systems in particular, may be of concern for citizens. In this domain, PES must be aware of obligations regarding data privacy and protection, including national and international legislative and regulatory requirements (including GDPR in the EU). Although not explicitly mentioned in the GDPR, many of its elements are pertinent to the field and use of AI, including the principles of fairness and transparency (European Parliament, 2020[35]). In addition, GDPR deals with automated decision-making. In this regard, PES must be committed to guaranteeing data protection and privacy in its AI use, as well in its data processing more widely. In some countries, data strategies have been implemented by governments to facilitate access to rich and accurate data, while abiding by privacy and ethical requirements, such as in New Zealand where the Government has implemented data management principles (Berryhill et al., 2019[11]). However, it remains to be seen how effective existing legislation will be at fully protecting data and privacy in the age of AI. Case law is limited and specific issues still remain, including through the ability of AI to infer sensitive information on citizens from non-sensitive data (OECD, 2023[37]; Wachter and Mittelstadt, 2019[38]).

PES should also be aware of the implications of latest developments in the field of AI, particularly third-party generative AI tools, on data protection and privacy issues. Generative AI models are largely trained on data generated through web scraping, whereby large swathes of data are mined from internet sites. This raises data privacy and ethical concerns, as such activities do not necessarily involve obtaining consent from data subjects (CEDPO, 2023[39]). Furthermore, there is also a risk that generative AI can leak both information from its training data (Ray, 2023[40]) or sensitive information input by users when using the applications.

2.2.3. The risk of bias within AI systems should be proactively addressed by PES

Bias has different definitions in different contexts, including in statistics. In the AI space, bias refers to models that generate systematically unfair outcomes, including giving preferential treatment to some groups over others or upholding certain stereotypes (Best and Rao, 2022[41]).

Biases within AI models are almost always human in origin, which can then be replicated by the AI model. For example, in the realm of PES, a labour market matching tool, designed to match jobseekers with vacancies, developed on unrepresentative training data may show bias against certain groups in its recommendations. A prominent example of this in the private sector is Amazon’s AI recruitment tool, recalled in 2018, which showed significant bias against women due to being trained on historical data of recruitments which were biased towards males (Dastin, 2018[42]; Broecke, 2023[43]).

Mitigating biases and discrimination in AI systems is extremely important, particularly for PES, due to the sensitivities of their work and implications of results for clients. Therefore, fairness must be prioritised at each stage of the lifecycle of AI tools and systems developed and implemented by PES. This includes avoiding bias in the design and development stages, but also post-deployment by closely monitoring and auditing algorithms and their outputs on an ongoing basis to ensure they remain equitable and do not develop biases over time (Ota-Liedtke and Raghunath, 2022[44]).

2.2.4. Resistance and lack of skills among PES staff and clients

The introduction of AI in organisations, including public ones such as PES, can often be met with some resistance and scepticism from staff members, PES clients and the general public. This can be driven by a number of factors, including overall resistance to change and new practices or fear that these developments may threaten their employment (in the case of staff).

If left unaddressed, such negative sentiment sentiment can jeopardise the potential benefits of AI systems and tools and can lead to low adoption rates, avoidance or rejection among staff (Cappuccio et al., 2023[45]). For PES, proactive steps should be taken to mitigate the risk of such sentiment among employees and to build trust in AI tools. This is particularly important to ensure adoption of tools that will require PES staff to work alongside them, such as profiling or matching tools. Some measures to promote trust and acceptance of AI systems include involving PES staff in decision-making surrounding AI solutions and fostering open communication and transparency (for a more detailed discussion see Section 4.2).

More generally, a lack of skills among workers still represents a significant barrier to AI adoption within organisations, highlighting the importance and need for adequate training (OECD, 2023[37]). Within PES, this is the most common challenge faced in their digitalisation journey, reported by more than three-fifths of countries. This is particularly important where the introduction of AI solutions generates a skills gap among staff. For PES, proactive steps should be taken to close this skills gap, in order to promote greater understanding and more effective use of AI tools. In addition, where some tasks have been freed up by AI systems, this can give workers an opportunity to improve their skills in new areas.

For PES clients, particularly jobseekers, the introduction of AI solutions may be met with similar sentiments of resistance or distrust. Therefore, PES should be transparent in their use of AI and how it will impact clients. In addition, where clients are the end-users of AI tools, digital literacy will be a determinant of the client's take-up and success in using such tools – as is the case in digital PES tools and services more widely. Clients without sufficient digital skills or means of access risk being left behind or disadvantaged in these developments (OECD, 2022[1]). PES should be aware of this risk and identify those clients with such barriers so that support can be provided, including through the provision of digital skills training, guidance from caseworkers and, where relevant, alternative routes to access services.

Furthermore, building the ability for human determination and oversight into all AI systems developed by the PES, may also help building trust in these new technologies. Fully autonomous AI systems would represent legal issues (see Section 5), but may also further contribute to distrust and resistance from both PES staff and clients (OECD, 2023[37]). Allowing human determination means that PES staff can still retain their sense of agency and can also contribute to greater trust among PES clients from knowing that humans are still involved in all PES processes.

2.2.5. The need for ongoing monitoring and evaluation

Just like other policy innovations introduced by PES, AI systems and tools require rigorous and regular monitoring and evaluation. Positive performance in the development and testing phase cannot be assumed to automatically translate into the post-implementation period, requiring ongoing quality assurance efforts in order to ensure that AI applications are not having undesired impacts.

After implementation, AI systems may encounter data that deviate from the original training data on which they were developed, risking what is known as "model drift" or degradation (IBM, 2020[46]; IBM, n.d.[47]). These changes to the input data can risk deteriorating the quality of the outputs and the overall AI model performance. In order to mitigate the impacts of any potential drift, model performance and outputs must be closely monitored. In addition, detection mechanisms can be put in place, including automated drift monitoring to detect any divergence in the data or outliers in the results beyond a defined threshold.

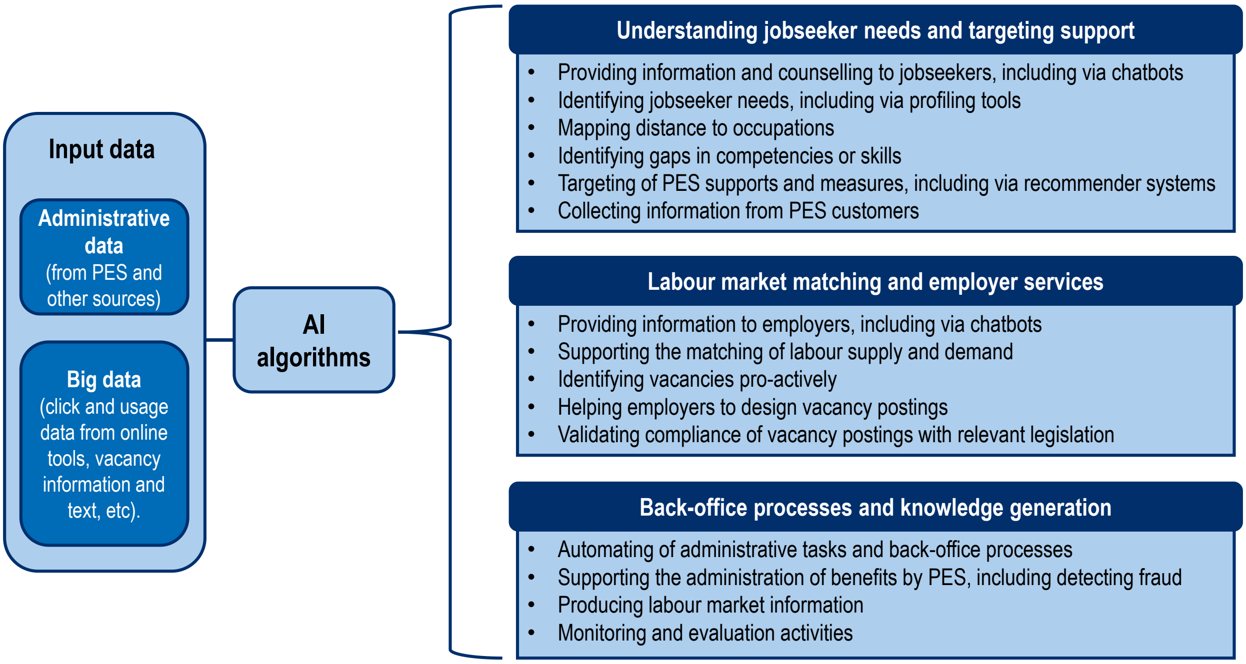
In addition to monitoring, formal evaluations of AI systems and tools implemented by PES are essential to ensure they are performing as intended (OECD, 2022[1]). These efforts can include counterfactual impact evaluations to causally measure the impact of an AI tool, process evaluations to identify the integration of an AI tool or system within PES operational processes and cost-benefit analyses to weigh the costs of the innovation against the benefits (OECD, 2020[48]). In addition, randomised controlled trials offer a route for PES to test new systems or tools and to measure their associated effect, prior to full roll-out.

Such monitoring and evaluation activities, along the entire lifecycle of an AI system or tool, are essential for PES to ensure the ongoing performance and reliability of AI models and their associated results. Furthermore, PES should ensure the results of these exercises have an impact, including by amending or removing algorithms that are not performing as desired.

3 Mapping AI use in PES

AI presents the opportunity for PES to complement, augment and enhance their service provision and operational activities. Utilising PES administrative data, and in some cases wider sources including big data, AI algorithms have potential for application across many key areas of PES activity (Figure 3.1). This section seeks to provide an overview of actual AI implementation by PES. It first provides a high-level overview of AI use in PES across countries, followed by a detailed account of the AI tools used by PES in their main areas of activity, namely: i) understanding jobseeker needs and provision of support, ii) labour market matching and employer services, and iii) back-office processes and administrative activities.[2]

Figure 3.1. AI presents various opportunities for PES across central areas of activity



Source: Authors' illustration.

3.1. High-level overview of AI use in PES across the OECD

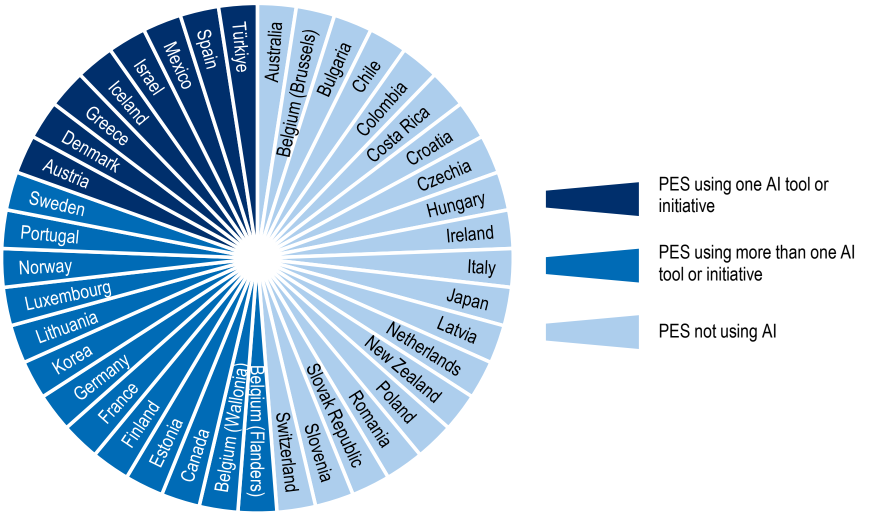
While its potential is vast, actual implementation and use of AI to support PES activities is not yet commonplace across countries, with one-in-two (51%) of OECD PES having implemented AI solutions at

[2] AI use cases presented in this section are based on responses to an OECD questionnaire received from all OECD countries, except the United Kingdom and United States, and OECD accession countries in the EU (Bulgaria, Croatia and Romania). For Belgium, information was received from its three regional PES (Brussels, Flanders, Wallonia) and is reported and analysed separately in this paper.

the time of writing (Figure 3.2).[3] This includes one-fifth of PES using one AI tool or initiative and one-third (32%) having implemented more than one tool or initiative to aid their activities. These AI usage rates can be expected to increase in the coming years, as several countries have indicated having plans or developments underway.

Figure 3.2. Half of PES have implemented AI initiatives

Status of AI implementation in PES, by country/region



Note: PES tools planned or under development are not counted in these statistics, only AI solutions live or implemented at the time of writing. This figure is based on information from 41 PES in 39 countries, with information from the three sub-national Belgian PES reported separately.
Source: Authors' calculation based on responses to OECD questionnaire on digitalisation and AI use in PES.

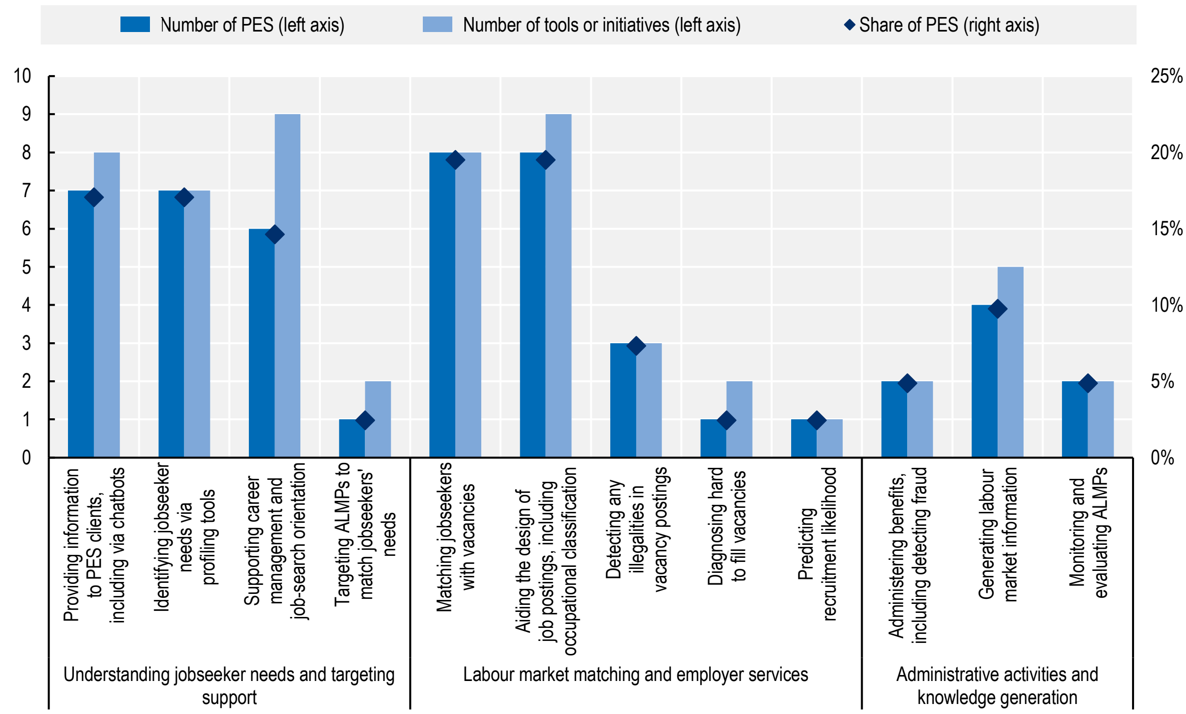
Within the half of OECD PES that have implemented AI systems and tools, their uses are spread widely across all central areas of PES activity (Figure 3.3) and are discussed in detail in the sections that follow. AI usage across the different aspects of PES operations are mapped by country in Annex A. Overall, the areas with the highest rates of PES AI adoption by countries are:

- Matching tools that assist in recommending matches between jobseekers and vacancies (in eight or 20% of PES);
- Tools to aid the design of vacancy postings, including occupational classifications (in eight or 20% of PES);
- Profiling tools that assess a jobseeker's job finding prospects (in seven or 17% of PES);
- Tools to provide information to PES clients, most commonly via chatbots (in seven or 17% of PES);
- Tools to aid jobseeker career management and job-search orientation (in six or 15% of PES).

[3] The mapping conducted in this chapter applies the definition of AI outlined in Section 1.1. Other algorithmic solutions outside of this definition used by PES in OECD countries are not included in this mapping or the associated statistics.

Figure 3.3. AI is being used across all key areas of PES activities

Number of PES, number of tools or initiatives and share of PES using AI by area of PES activity



Note: Share of PES refers to the percentage out of the total number of responding PES, whether they use AI or not. This figure is based on information from 41 PES in 39 countries, with information from the three sub-national Belgian PES reported separately.
Source: Authors' calculation based on responses to OECD questionnaire on digitalisation and AI use in PES.

3.2. AI use to understand jobseeker needs and provide targeted support

This section explores how AI solutions can be used by PES along the customer journey, providing information to clients via chatbots, understanding jobseeker needs through profiling tools, and providing personalised support via tools for career management, job-search orientation and targeting measures.

3.2.1. Providing information to PES clients via chatbots or virtual assistants

For many jobseekers, the first step in their journey is often seeking information about the PES, potential supports available to them and what steps they need to follow to register with the PES. In addition to static information resources, such as content available on PES webpages, PES are gradually deploying more interactive solutions. This includes AI-based chatbots to provide information about the services and measures they offer, the rights and obligations of their clients, registration with the PES and all other possible interactions with clients. In addition, AI chatbots can be used to provide vocational guidance and counselling to clients (see example in Section 3.2.3). Chatbots for information provision can be classified in two (non-mutually exclusive) categories according to their intended end-users and scope of knowledge:

- They can be used either by PES customers in self-service mode (hereafter "external chatbots") or by caseworkers to help them answer customer queries (hereafter "internal chatbots").
- They can either follow a provider-centric approach, containing information about PES activities only, or follow a user-centric approach, providing information about several public organisations.

Recent advances in the field of AI have considerably boosted the performance of chatbots and other virtual assistants. Traditional (non-AI) chatbots are still limited in their ability to answer customers' queries, as they rely on rigid and rule-based algorithms (Van Noordt and Misuraca, 2019[49]). They merely aim at providing general answers to frequently asked questions, but fail to answer queries that are not specific or clear enough. Thanks to recent advances in natural language processing, AI powered chatbots have a far greater ability to read and comprehend human language, can process larger amounts of information extracted from various documents and can have human-like conversations with users (see Annex B). Such tools therefore have the potential to yield a double dividend: improve the visibility and transparency of the services offered for PES customers while freeing up time for PES staff to concentrate on their core mission; helping jobseekers to find jobs and employers to fill vacancies. This added value of external chatbots to assist PES clients was particularly visible during the COVID-19 crisis, at a time when PES worldwide faced a rapid surge in unemployment (Miller, 2021[50]). The deployment of chatbots took a leap forward and helped PES staff handle a massive influx of queries.

At present, among the several PES using AI-assisted chatbots, the vast majority sit in the category of external chatbots – assisting clients (jobseekers and, in some cases, employers) to access information about available services and measures (Table 3.1).

Table 3.1. While traditional rule-based chatbots remain prominent, several PES are engaging in AI-driven applications

Key features of AI-based chatbots, by country

	Type of chatbot	End-user	Scope	Type of AI
Finland (*Tarmo*)	External	Jobseekers & employers	Providing information on PES services and measures	Conversational AI
Finland (*Aino*)	External	Jobseekers & employers	Providing information to foreign workers interested in working in Finland and to employers interested in recruiting from Finland.	Conversational AI
Greece	External	Jobseekers & employers	Providing information on PES services and measures	Natural language processing
Iceland	External	Jobseekers & employers	Providing information on PES services and measures	Conversational AI (including deep learning and natural language processing methods)
Lithuania	External	Jobseekers & employers	Providing information on PES services and measures	Natural language processing and generative AI (ChatGPT, internally)
Norway	External	Jobseekers & employers	Providing information on PES services and measures	Conversational AI (including deep learning and natural language processing methods)
Portugal	External	Jobseekers & employers	Providing information on PES services and measures	Natural language processing
France	Internal	PES staff	Drafting responses to customer queries received by email	Not specified

Note: Not specified refers to cases where the type of AI model was not provided by the responding authority.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

External chatbots to assist PES clients

The PES in Norway and Iceland are employing the use of AI-powered virtual assistants or chatbots to provide information to jobseekers and employers – seeing significant benefits to capacity during the COVID-19 crisis period. Both countries have implemented AI-enabled virtual assistants to assist PES clients with the help of Boost.AI, a Norway-based company providing AI solutions to organisations globally.

- **Iceland's** PES introduced its chatbot *Vinný* in July 2020 in the midst of the COVID-19 pandemic. In training the chatbot, the PES conducted an analysis of email and phone traffic to identify the key areas they wanted it to cover. Initially limited to more general matters, in particular the claiming of unemployment benefits in the early days of the pandemic, *Vinný* can now provide information to both employers and jobseekers alike on a wide variety of services, measures and benefits available. *Vinný* handles approximately one-third of all queries received.
- In **Norway**, the PES has had in place a chatbot, *Frida*, since 2018 which utilises conversational AI (specifically natural language processing) to provide information to clients (OECD, 2023[51]; Boost AI, n.d.[52]). Faced with a 250% increase in queries upon the onset of the pandemic, Frida provided the necessary leverage in capacity – handling a query caseload equivalent to 220 full-time employees and resolving 270 000 enquiries in the pandemic's initial weeks alone. *Frida* successfully resolved 80% of cases without the need for human intervention, with only one-in-five queries requiring escalation to a human support representative. In addition to providing much-needed information and support to citizens in a quick and efficient manner during this crisis period, *Frida* allowed the Norwegian PES to make better use of its resources – especially at a time where they were already over-stretched. This mitigated the need for significant scaling up of human resources and greatly alleviated pressure on staff.

Also in the Nordic region, the PES in **Finland** has two external chatbots in place. First, the chatbot *Tarmo* provides support to both jobseekers and employers on frequently asked questions related to the services of the PES and in particular those available through the *Job Market Finland*: the e-services and matching portal of the PES. The second chatbot, *Aino*, instead focusses on national talent attraction efforts, i.e. those activities aimed at attracting labour from abroad. Here, international workers can engage with the chatbot in English to receive relevant information regarding working or studying in Finland, as well on the services and vacancies on offer through the PES. In addition, the chatbot can also assist employers based in Finland with their queries relating to hiring from abroad.

The **Greek** PES has also been utilising an AI chatbot to provide information to clients since 2022. *Daphne* utilises natural language processing to assist citizens and employers with their queries concerning PES services and measures. The tool relies solely on training data input by the PES; with question-and-answer files able to be updated by PES staff to reflect the latest information. Plans are already in place to develop a successor to *Daphne*, with the aim being to develop and implement a more sophisticated AI chatbot that will act as a digital employment counsellor. While the exact details are yet to be finalised, the aim is to implement a tool that will provide more personalised and tailored information and engagement with jobseekers on the services, measures and unemployment benefits available to them – including tailored recommendations for suitable training options.

In **Lithuania**, the PES has had in place an AI-powered chatbot since the end of 2023. The chatbot, *EMA* (a common Lithuanian name and an abbreviation of the chatbots' values: empathy, politeness, and responsibility). While still new and further development planned, the chatbot provides jobseekers and employers on key topics related to PES services and measures using natural language processing. Internally, the chatbot trainers are also supported by a ChatGPT (generative AI) plugin to generative additional possible scenarios, in order to enhance the ability of the chatbot to respond to a broader set of queries and provide more targeted responses. In the near future, the PES plans to expand ChatGPT capabilities, trained on PES data, in order to be able to provide clients with career counselling and job-search advice.

The **Portuguese** PES recently introduced a virtual assistant chatbot in March 2024. Using natural language processing, the assistant provides answers to queries received from jobseekers and employers on several key measures provided by the PES. The plan is for the chatbot to eventually be able to answer queries relating to the full set of ALMPs provided by the PES.

Internal chatbots to assist PES staff

External bots cannot deal with all enquiries from jobseekers and employers, for various reasons. Certain queries may remain too complex or too specific for these tools to provide an accurate and comprehensive answer. In addition, the existing digital divide prevents some cohorts of PES clients (e.g. older people, micro-firms in rural areas) to access or use effectively self-service tools available online. Furthermore, in-person contacts with caseworkers may continue to be the best entry point into the PES for people with severe labour market difficulties, especially those who face multiple disadvantages and those from vulnerable situations. In addition, such groups are significantly less likely to make contact or reach out to the PES themselves for support. A more human touch is still necessary to help those people effectively and smart bots currently lack the soft skills needed to do this. These tools also lack the tacit knowledge of an experienced caseworker, which remains difficult to codify even for an AI-based tool.

The shortcomings of external chatbots have led some PES to implement smart virtual assistants for internal use only. These internal bots help PES staff manage customer queries more efficiently and answer them more rapidly, whilst keeping human empathy and human know-how in the loop. AI-powered internal virtual assistants are less commonplace in PES than external ones – with such measures in place or in development in only two countries so far. In **France**, the PES uses a smart tool to sort messages received from customers by analysing their content.[4] The tool, called "Contact via Email", identifies queries containing simple or standard issues and recommends pre-defined answers for the counsellor to send back. The counsellor can then either modify the draft message, use it as it is, or reject it altogether. Compared with chatbots designed to be used by PES customers in self-service mode, "Contact via Email" is more flexible as it enables caseworkers to personalise the answer if needed, thereby adding a human touch, while enabling them to respond to frequently asked queries easily and quickly. While not yet deployed at the time of writing this paper, the PES in **Luxembourg** is developing an email bot powered by natural language processing. The project arose from the need to be more efficient with PES resources, particularly in the contact centre which receives thousands of calls and emails per day. Therefore, the tool, when implemented, should relieve staff in the PES contact centre from many of the most standard and easy to address queries. As in the French case, Luxembourg's email bot will draft a response, with the human counsellor having responsibility to validate, edit and ultimately send the reply.

The choice between external and internal smart bots may reflect a broader policy choice in terms of service delivery models. In France, for example, the use of AI for internal chatbots only aims to ensure that in-person contacts remain a core component of the service delivery model for all jobseekers, as from the very beginning of their unemployment spell. This is a key aspect of the implementation strategy for AI-based tools, which is reflected in the "Charter for Ethical AI" published by the French PES in 2022 (Pôle emploi, 2022[53]). In other cases, various external smart tools – including chatbots – are made available to customers in self-service mode with the aim of developing a "digital first" approach to service delivery.

External user-centric chatbots to provide guidance on cross-government services

One of the greatest promises of smart bots is to enable citizens to navigate more easily the various public institutions and organisations that can help them – which often tend to work in silos. User-centric chatbots, designed to deal with enquiries that cut across various policy areas, are particularly well-suited for the most vulnerable jobseekers who require holistic and multi-disciplinary support from different institutions (OECD, 2021[21]). These tools can also be helpful for jobseekers seeking to enter the labour market via the

[4] The French PES is, at the time of writing, undergoing a significant reform. The AI use cases presented in this paper represent the situation prior to the reform.

entrepreneurial route by setting up their own business, which often comes with various administrative procedures required by different public bodies. User-centric chatbots reduce time spent searching for information on different websites and lower the risk that users miss important information about the various support measures they could be entitled to, or about the various obligations they may have to comply with (in addition to what is provided or requested by the PES itself).

Ultimately, these kind of chatbots might help different public bodies work together rather than separately. It is however worth noting that while technologies have long been expected to help break down silos within the public sector (as soon as the first waves of digitalisation took place), this has not materialised (Van Noordt and Misuraca, 2019[49]). The same could apply to user-centric chatbots, which are not yet widely used. Their development requires a coordinated approach in terms of digital strategy and information systems, which can still be difficult to achieve between different agencies. Against this backdrop, governments are implementing open data initiatives that encourage public institutions to share their digital apps and data in order to promote citizen-centric services (Van Noordt and Misuraca, 2019[49]). These initiatives could facilitate the development and deployment of cross-government user-centric smart tools, similar to those already in place in **France** and **Latvia** (Box 3.1).

Box 3.1. User-centric smart bots can help break down silos between public organisations

NOA, the French chatbot that helps new entrepreneurs with a wide range of administrative procedures

In France, a chatbot called NOA has been deployed on the websites of six public organisations, including the French PES, to reduce the administrative burden for individuals when setting up a new business in the Paris region. NOA covers a wide range of administrative issues, including fiscal aspects, trademark applications, import/export licences, and social obligations. It also provides information on various support measures that start-ups may be entitled to, in cash (e.g. hiring subsidies, tax relief, export subsidies, regional grants) or in kind (e.g. business incubators that provide facilities or premises), whether at national or regional level.

Zintis, the Latvian virtual assistant promoting unified access to state and municipal institutions

Introduced in 2020, *Zintis*, the AI-powered chatbot is part of the Latvian government's initiative to provide unified platforms for government and local authorities. *Zintis* is a virtual assistant currently available on the home pages of over 54 Latvian public authorities, including the Latvian PES. Based on training data from across institutions and integration into cross-government IT systems, *Zintis* can answer queries from citizens on cross-cutting issues – meaning the citizen does not need to know what institution to go to for various queries. In addition, with direct access to Latvia's open data portal, *Zintis* can access the latest available information at all times.

Source: Prefecture of Paris and Île-de-France (2019[54]), Le chatbot NOA, une nouvelle offre de service pour les start-up, https://www.prefectures-regions.gouv.fr/ile-de-france/Region-et-institutions/L-action-de-l-Etat/Economie-et-finances-publiques/Innovation-Recherche/Le-chatbot-NOA-une-nouvelle-offre-de-service-pour-les-start-up; Latvian Cabinet of Ministers (2023[55]), *Virtual assistant: Zintis*, https://www.mk.gov.lv/en/virtual-assistant-zintis; European Language Resource Coordination, (2023[56]), *ELRC Workshop Report for Latvia: Deliverable D3.2.28, Task 3*, https://www.lr-coordination.eu/sites/default/files/Latvia/2022/ELRC3_Workshop%20Report%20Latvia_Public.pdf.

3.2.2. Identifying jobseeker needs via profiling tools

By assessing the propensity of a jobseeker to return to employment, profiling tools are an important first step for PES in identifying the needs of jobseekers and targeting the appropriate provision of services and measures (OECD, 2018[23]). Profiling tools allow PES to proactively identify newly registered jobseekers who may need additional intensive support to re-enter work, enabling PES to target resources to where they are needed most. In addition, the early identification of the most vulnerable or at-risk jobseekers is key to reducing their likelihood of long-term unemployment.

Profiling tools can be separated into three main categories: i) rule-based profiling that uses established criteria (e.g. education and skills) to classify individuals into client groups; ii) counsellor-based profiling that relies on counsellors' own judgement; and iii) statistical profiling that uses a statistical model to assess labour market disadvantages (Desiere, Langenbucher and Struyven, 2019[57]).[5] In practice, PES can often employ a combination of these different approaches. In classifying jobseekers according to their job prospects, statistical profiling tools are typically comprised of two key features (see Annex B for a more detailed discussion). First, a prediction model estimates a jobseeker's employability based on an ideally rich dataset to take account of, among other things, the jobseeker's characteristics and labour market history. Second, the PES establishes operational thresholds which dictate, based on the outcome of the predictive model, which group a jobseeker is assigned to. This in turn informs the appropriate provision of services and supports.

AI has the potential to improve the predictive power of data-driven profiling tools. While standard regression models are still widely used, these models need frequent adjustments and revisions to remain accurate in a constantly evolving labour market. Thanks to their dynamic feature, machine learning techniques make it much easier to update and revise prediction models, as more recent data or new explanatory variables become available. In addition, AI, together with advances in computing power, allow more sophisticated prediction models to be utilised (e.g. Artificial Neural Networks, or complex decision trees such as Gradient Boosting Machines and Random Forest models), which can capture more complex relationships between variables and, therefore, achieve higher levels of accuracy or precision (Traverso et al., 2019[58]; Dankers et al., 2019[59]). In short, AI-augmented profiling tools are more flexible, which could enable them to make better use of available data at any point in time.

The use of statistical profiling by PES is increasingly commonplace, but the use of AI to supplement profiling activities is still in its infancy (Körtner and Bonoli, 2021[28]; Griffin et al., 2020[60]). Nevertheless, enhancing jobseeker profiling tools with AI technologies is picking up pace and this paper identifies seven PES with established use of AI to assist profiling (Table 3.2), with at least three other countries currently developing AI-powered profiling methods.

[5] AI-enabled profiling is usually referred to as statistical profiling, albeit most often, the underlying model is not a statistical model but a much more sophisticated prediction model.

Table 3.2. Seven OECD PES currently have AI-driven profiling solutions in place

Key features of the AI-based profiling solution, by country/region

	Type of AI	Main data used		
		Jobseeker characteristics	PES administrative data	Local labour market data
Flanders, Belgium	Random forest model (subset of Machine Learning)	X	X	
Wallonia, Belgium	Light gradient boosting machine (subset of Machine Learning)	X	X	
Estonia	Gradient boosting model (subset of Machine Learning)	X	X	X
France	Not specified	X	X	X
Lithuania	Random forest model (subset of Machine Learning)	X	X	
Portugal	Extreme Gradient Boosting model (subset of Machine Learning)	X	X	
Türkiye	Machine Learning	X	X	

Note: Click data refers to information gathered from a jobseeker's use of online services and platforms of the PES. Not specified refers to cases where the type of AI model was not provided by the responding authority.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

The PES of **Flanders, Belgium** (VDAB) stands out as an early adopter of AI for the use of profiling, launching the first prototype of its AI-enabled *Next Steps* tool in early 2017. This initiative was born out of VDAB's innovation lab, established in 2014 with the aim of boosting the digital and analytical capabilities of the PES (European Commission, 2017[61]). *Next Steps* was a statistical profiling tool enhanced by a random forest model (a type of machine learning algorithm) to estimate a jobseeker's likelihood of remaining unemployed for six months or more (Desiere, Langenbucher and Struyven, 2019[57]; OECD, 2018[23]). The model was built on a number of data sources, including the jobseeker's socio-economic characteristics, their labour market history, their employment preferences (e.g. occupation, sector, geographic location) and administrative data gathered during current and previous unemployment spells. In addition, the prototype used click data from the jobseeker's interactions with VDAB's online services, including vacancy browsing patterns and usage of the job mediation platform which can be used as an indicator for the jobseeker's motivation (Broecke, 2023[43]). *Next Steps* was designed to be a dynamic tool, with both jobseekers and counsellors having the ability to update input data at any time – meaning that profiling scores are kept up to date in real-time. Based on the results of the profiling exercise, jobseekers were classified into one of five groups according to their risk profiles, allowing counsellors to identify and prioritise those jobseekers that will likely require more intensive assistance. Based on the *Next Steps* prototype, a predictive AI profiling model, *Kans-op-werk* (chance of employment), was put into production in 2018. In developing *Kans-op-werk* the decision was taken to proceed without the inclusion of click data in the model, including due its incomplete nature (only job-search conducted while logged into the PES portal is captured).

A recent empirical study shows that *Next Steps* predicts more accurately the risk of long-term unemployment as compared to a simple rule-based approach classifying all low-skilled jobseekers at high risk (Desiere and Struyven, 2021[62]). The study found that 66% of jobseekers are correctly labelled as high- or low-risk jobseekers by the *Next Steps* AI solution, whereas this proportion reaches only 58% when using the rule-based method. However, the study also found that the *Next Steps* tool discriminates against people with a migrant background, who are 2.6 times more likely to be wrongly labelled as high-risk jobseekers than their native peers – compared to 1.8 times more likely using the rule-based approach. Nonetheless, it is important to note this evaluation has a key limitation – the study merely compares the results of a predictive profiling model to a simple rule-based model but does not take into account associated profiling practices. In particular, it does not factor in the behaviour and insights of caseworkers who, in some cases, may overrule classifications or spot misclassifications generated by the profiling tool.

Similarly, the PES in **Türkiye** also structures its profiling method upon a jobseeker's risk of remaining unemployed for more than six months. Here, this risk is calculated on a set of 27 variables (such as age, gender, educational status, employment history, willingness to look for a job, etc) and is subject to decision tree machine learning model. Based on this calculation, jobseekers are then assigned to one of three categories (low, medium, or high risk), allowing for more personalised and targeted counselling and provision of ALMP measures.

In another region of Belgium, **Wallonia**, the PES enhanced its jobseeker profiling solution with the addition of AI in 2022. This initiative forms part of a wider reform in how the Walloon PES (*Forem*) supports jobseekers – channelling jobseekers into four support streams based on the profiling results and the jobseeker's digital skills (Forem, 2022[63]). The profiling tool takes into account the professional history of the jobseeker, their socio-demographic characteristics, data from the interaction with *Forem* and any relevant training over a time horizon of two years prior to their current registration with the PES, in order to predict the jobseeker's job proximity (i.e. their likelihood to find employment within six months). The tool runs on a machine learning model, more specifically a light gradient boosting machine (LightGBM) that uses decision tree learning algorithms (Microsoft Corporation, 2023[64]). *Forem* counsellors then take the profiling results into account along with their own expertise to assign a jobseeker to the appropriate support stream.

The **Estonian** PES (EUIF) has been profiling jobseekers using AI-powered methods since 2020. The tool *OTT* was developed to be a decision-support tool for counsellors and utilises machine learning, specifically gradient boosting, to assess a jobseeker's probability of re-entering the labour market. It does so using approximately 60 variables which take account of both the individual jobseeker's profile along with wider labour market trends, including the levels of vacancies and jobseekers in a given region (Korniltsev, 2021[65]). For each jobseeker, *OTT* calculates their probability of finding a job, their probability of returning into unemployment and identifies the (key) factors contributing to their probability of moving into employment (Leinuste, 2021[66]). This assists counsellors in deciding the most suitable channel of support (online, telephone or in-person), frequency of engagement and the appropriate services and measures to suit the needs of the individual jobseeker. Although fully operational, *OTT* is in constant development as training data are updated every three months, which in turn requires (manual) retraining of the underlying prediction model. EUIF is also supporting ongoing research to develop a prediction model for disadvantaged workers, which would assess their probability of job loss in order to prepare them for career transitions early on if necessary. Comparing the expected diagnosis by *OTT* with how jobseekers moved into employment in reality, the tool performs extremely well – having an accuracy of over 95% (Leinuste, 2022[67]).

In **Portugal,** a project with the Nova School of Business and Economics (Universidade Nova de Lisboa) saw the development of a dynamic assessment system to predict a jobseeker's likelihood of becoming long-term unemployed (Nova School of Business and Economics, 2020[68]). The design process fostered a user-oriented approach, including PES counsellors' feedback in the development of the tool. The final model, an XGBoost or Extreme Gradient Boosting model,[6] was chosen on the basis of performance, fairness (i.e. less bias) and explainability, and replaces a previous logistic regression model in place since 2012. The model builds on the data employed in the previous model (age, employment history, educational attainment, geographic location, social support receipt) and adds a wide range of additional variables including, inter alia, the history of interventions provided, category of disability where relevant and

[6] https://www.nvidia.com/en-us/glossary/data-science/xgboost/

information regarding the desired job of the jobseeker (including whether they have appropriate experience). The output of the model assigns a jobseeker to either the low-, medium- or high-risk group based on defined thresholds.

Since 2021, counsellors in the **Lithuanian** PES are supported by an AI-based profiling tool combining statistical methods and machine learning to assess a jobseeker's probability of becoming long-term unemployed (OECD, 2022[69]). This new tool draws on PES administrative data, replacing a previous profiling tool which relied solely on a set of 22 prescribed questions that the counsellor would cover with the jobseeker during their initial meeting. The individual's risk profile is assessed using a random forest model and employing data from approximately 30 data registers, with the results assisting counsellors to identify the appropriate supports to meet the needs of the jobseeker. Finally, individual action plan (personalised plans to access employment, *PPAE*) in the **French** PES are developed jointly by the counsellor and the jobseeker, outlining the mutual responsibilities and actions each will take towards finding employment (Pôle Emploi, n.d.[70]). A key input to this process and the development of a tailored labour market integration pathway for the jobseeker is the result of a profiling tool supported by AI. This tool uses a predictive model to estimate the likely time it will take a jobseeker to find work – taking into account the profile of the jobseeker and the local labour market dynamics.

Several countries are also currently in the process of developing AI-based solutions for profiling and segmenting jobseekers, including Croatia, Luxembourg, Slovenia and Switzerland. In **Luxembourg**, the PES is currently developing an AI-based profiling tool to replace its current rule-based model, which will estimate a jobseeker's probability of returning to employment after three, six and twelve months of unemployment. In the development process, several AI techniques are being tested – with dual consideration being given to both the quality and explainability of results. The PES in **Slovenia** is developing an AI-based profiling tool to estimate the likely time-to-employment of a jobseeker (in number of days) using semi-supervised learning; a sub-category of machine learning (Andonovikj et al., 2024[71]). The model is being trained on the PES data, containing attributes of the jobseeker, including information on their socio-economic characteristics, their work readiness (educational attainment and health profile), the regional labour market situation and all available labour market history. In **Switzerland**, the potential effectiveness of applying natural language processing techniques to aid the matching of jobseekers with vacancies is currently being explored through the use of pilot projects.

In some countries, jobseeker profiling tools have come under criticism for various reasons. These include concerns due to additional strict conditions set on data processing activities for profiling purposes in the GDPR and sensitivities surrounding the term “profiling”. This highlights the need for transparent communication by PES surrounding their use of digital and AI tools, including on what data are used and how they impact decision-making. In addition, this underpins the important role of human determination (or a human in the loop) in the use of digital and AI tools (OECD, 2023[37]). PES communication should clearly state the solely advisory role of such tools and systems, with decision-making responsibility still resting in the hands of counsellors.

3.2.3. Supporting career management and job-search orientation

One of the key tasks of PES is to support jobseekers in their job-search efforts and career decisions, helping jobseekers to identify career goals meeting their interests and skills. A critical first step to assisting jobseekers in their job-search and career management is helping them to accurately identify the skills they possess. However, in a constantly evolving labour market, PES clients may not always know how best to describe themselves, in a way that is attractive to employers, in line with current labour market trends and accurately captures their skillset (Vänskä, 2020[72]). Some jobseekers might not even know what kinds of jobs could best suit them. AI-powered smart bots have been developed to help PES clients and staff with these tasks (Table 3.3), enabling better mapping of jobseeker skills and identifying suitable occupations and career pathways, potentially via reskilling and upskilling to close any skill gaps (Broecke, 2023[43]). In some cases, the skills mapping component of these tools, or indeed the algorithms that enables this, are used as inputs to other tools within the PES, such as job matching tools (Section 3.3.1) or recommender tools that identify specific training courses suitable for the individual jobseeker (Section 3.2.4).

Table 3.3. Several PES are using AI to assist career management and job-search orientation

Key features of the AI solution, by country/region

	Objective	Type of AI
Austria (*Berufsinfomat*)	Chatbot to provide career guidance to jobseekers, including information on occupations, education and training	Generative AI (ChatGPT)
Flanders, Belgium (*Jobbereik*)	Helps jobseekers to visualise how the skills they possess map onto occupations	Deep learning combined with graph analytics
Flanders, Belgium (*Competentiecheck*)	Helps citizens to evaluate the relevance of their current skills against the competencies associated with a selected occupation	Deep learning and graph analytics
Flanders, Belgium (*Competentiezoeker)*	Acts as an input to other digital tools (including matching tool), to extract competencies from a jobseeker's profile and within vacancies posted by employers	Deep learning
Flanders, Belgium (*Orient*)	Suggests occupations and jobs that a jobseeker could consider given their areas of interest and work preferences.	Deep learning
Denmark	Analyses job postings to identify skills in demand by employers in order to inform counsellors in their provision of career management and job-search support to jobseekers	Machine learning
France	Automatically analyses the CV of a jobseeker to identify skills. Also suggests areas for upskilling/reskilling.	Not specified
Korea	Generates a competency assessment based on the profile of the jobseeker and current labour market demands. Also provides job recommendations and suggestions for career development	Expert system
Sweden	Suggests potential occupations to jobseekers based on their current competency profile	Machine learning, deep learning, graph analytics and natural language processing

Note: Not specified refers to cases where the type of AI model was not provided by the responding authority.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

The PES in **Flanders, Belgium** (VDAB), has built the *Jobbereik* (Job Reach) tool which assists jobseekers to visualise how well their current competencies and skills map to potential occupations using data from job vacancies (Broecke, 2023[43]; VDAB, 2021[73]). Using deep learning and graph analytics, *Jobbereik* presents potential occupations and jobs that the jobseeker could pursue, not only based on their input occupations, but more widely – taking into account core transferable skills that can be useful in other occupations and industries. This tool therefore provides significant benefits in supporting job mobility and job transitions. In further improving the tool, VDAB is currently developing additional functionality that will enable *Jobbereik* to suggest possible training and education programmes to help close the skills gap between the jobseeker and a given occupation. A separate but similar AI-based tool, *Orient*, has also been implemented by VDAB to help clients explore potential suitable occupations based on their interests and preferences regarding working conditions. This online service produces results using a questionnaire on preferences completed by the jobseeker and the VDAB taxonomy of occupations and skills. Other AI tools in this domain currently implemented by VDAB include:

- *Competentiecheck* (Competency Check): This tool aims to help citizens understand their skills and competencies in the context of a dynamic labour market. Users of the tool input an occupation and are then asked to evaluate themselves against the top competencies associated with this role, in order to assess whether their skills are up-to-date and remain relevant (VDAB, n.d.[74]). Based on this, *Competency Check* provides training and job suggestions (both based on current skills and those attainable via skills upgrading).

- *Competentiezoeker* (Competency Extractor): In the background of *Jobbereik* and several other VDAB tools, the AI-powered *Competency Extractor* analyses information input by users into the platform or their CV in order to extract the jobseeker's skills based on their previous work experience (VDAB, n.d.[75]). The tool is also used to identify the competencies within a job advertisement drafted by an employer.

Similarly, the PES in **Sweden** has also deployed an AI solution to aid jobseekers in deciding their career path. Here, various AI methods contribute to a system that recommends potential occupations to a jobseeker that leverage their existing competencies. In addition to providing new career route ideas, the tool can also provide recommendations of suitable vacancies from the Swedish national job board. Further updates to the AI tool are planned, including to further expand its scope to, among other things, incorporate additional data sources, provide recommendations to training and provide more specialised job recommendations to jobseekers with a disability.

The *JobCare* service of the **Korean** PES is an AI-based job counselling support tool introduced in 2021, focussing on career orientation and guidance. *JobCare* uses rule-based AI, which is a type of expert system, whereby decisions are made according to predetermined rules. Using both the jobseeker's information and data collected from private job advertisements, *JobCare* produces an individual competency assessment, which it then uses to provide jobseekers with job recommendations and a career development roadmap, including potential areas for upskilling and reskilling (Kim, 2023[76]; OECD, 2023[77]). The tool can be used independently by jobseekers or together with counsellors, as part of a counselling meeting, (OECD, 2024[78]).

In **France** the PES uses AI to engage in automatic CV analysis to map a jobseeker's skills based on their prior work experience and through concordance with the Operational Directory of Occupations and Jobs (ROME). In addition, the tool can identify potential areas for upskilling and reskilling and is available to counsellors who can utilise or reject the suggestions at their own discretion.

Two other countries are taking a slightly different approach to utilising AI to enhance career management and job-search orientation services provided to jobseekers through the use of an interactive career guidance chatbot and AI-assisted labour market intelligence:

- The PES in **Austria** became the first to implement a generative AI solution for client use, rolling out a ChatGPT-powered chatbot in January 2024 (*Berufsinfomat*). The chatbot aims to provide career-related guidance to citizens, including information on occupations, education and training (AMS, 2024[17]). The chatbot builds on several other tools of the Austrian PES, including its career information system, occupational lexicon (a professional dictionary website which provides information relating to different professions, including career prospects, expected earnings, etc.) and training compass (a key resource for PES clients to obtain information on training and education opportunities). Shortly after launch, the chatbot sparked criticism, including due to reports that it produced gender biases in its recommendations for users, despite the apparent inclusion of a rule to not differentiate on the basis of gender (Köver, 2024[18]).
- In 2020, the **Danish** PES implemented an AI tool to measure the skills currently demanded by employers (OECD, 2022[1]; Westh Wiencken Vizel and Opstrup Hansen, 2021[79]). Using machine learning, the tool analyses text from job advertisement postings and creates an index of the most popular skills among employers at a given moment. The tool has dual objectives. First, to aid PES counsellors to better understand the trends in the labour market, enabling them to better guide their clients towards relevant job and education or training opportunities. Second, it seeks to assist education and training providers in assessing the labour market relevance of their offerings.

The PES in **Portugal** has plans underway to utilise AI in aiding career management and job-search support of jobseekers. Specifically, the aim is to create a virtual assistant that can assist a jobseeker in preparing to apply for a vacancy, including by screening their suitability against requirements and in aiding them to prepare their CV and cover letter.

3.2.4. Targeting ALMPs to match jobseekers' needs

In case finding a good job fast is unlikely due to specific employment barriers (e.g. indicated by jobseeker profiling tools) or skill gaps (e.g. indicated by skills mapping and career management tools), suitable measures and services might be relevant to address jobseeker's needs for additional support. Data-driven digital tools can help PES to better target and personalise its ALMP provision. To date, across the countries studied, the PES in **France** is the only PES employing AI methods for this purpose, with two solutions in place – one for counsellors and one for jobseekers. However, scope exists for many PES to further enhance some existing tools using AI, including jobs-search orientation and career management tools (such as those discussed in Section 3.2.3), by linking them with more specific recommendations for ALMPs, in particular training.

France Travail is providing AI-assisted decision support to counsellors through the *Mon Assistant Personnel* (MAP – My Personal Assistant) tool. This digital user interface, first introduced as a pilot in 2017, brings together in one space various functionalities to assist the work of the PES counsellor (Chapuis, 2018[80]). The tool uses various types of AI (reinforcement learning, machine learning and an expert model), allowing employment counsellors to access automated analysis of jobseekers' CVs and to receive tailored recommendations for supports and job opportunities based on the profile of the jobseeker. The aim of the tool is not to replace, but rather assist, human decision-making – allowing the counsellor to spend time saved on other important tasks.

A second tool to recommend and assist the targeting of support exists is used by *France Travail*, but this time with the end-user being jobseekers themselves. This tool (*Personalised Recommendations*) is situated within the jobseeker's personal space within the online portal of the PES. As in the case of the previous tool, this tool for jobseekers uses reinforcement learning (a sub-category of machine learning) and an expert model to provide jobseekers with recommendations for services and measures – including suitable training opportunities, available workshops (to improve CV and interview skills, for example) and events organised by the PES.

3.3. AI-powered labour market matching and employer services

The ultimate objective of PES is to facilitate labour market matching: finding jobseekers good jobs and employers the staff they need. As such, digital tools to facilitate job matching are central within PES digital infrastructure and for many PES have been the first part of their digital infrastructure to be enhanced by AI technologies. To further support the quality and performance of job matching services, AI technologies have been also increasingly used within related digital solutions for employers – including to assist employers with designing vacancy postings and identifying vacancies that may be hard to fill.

3.3.1. Matching jobseekers with vacancies

Digital advancements in recent years have seen PES across the OECD deploying digital tools to aid jobseekers find suitable vacancies and employers meet their staff needs (OECD, 2022[1]). The specifications of these matching tools, requiring analysis of the similarities between a jobseeker's profile and the vacancy description, mean that matching tools employed by PES lend themselves well to being enhanced by AI methodology. Traditional vacancy matching tools rely on strict one-to-one correspondence by each matching (or filtering) criterion, which can have low performance in identifying good matches due to the limited information these tools can take into account, particularly in the context of constantly evolving labour markets and occupations. AI-assisted matching offers the potential to take into account wider data sources, including click data, and can better capture the congruence between jobseeker profiles and job descriptions – enabling wider and more accurate matching opportunities (Broecke, 2023[43]; World Bank, 2023[81]). Most importantly, AI can facilitate competency-based matching and better considering jobseeker's interests to generate higher quality and more personalised matches (OECD, 2024[78]). In addition, AI can be deployed in vacancy matching tools to enhance user experience and facilitate using competency and skill taxonomies that rely on up-to-date labour market information (OECD, 2024[82]). This study identifies eight PES across OECD that have rolled-out AI matching solutions (Table 3.4). For a number of these tools, countries introduced AI to pre-existing tools in the course of revisions and updates.

Table 3.4. Eight PES in OECD countries have implemented AI-driven vacancy matching solutions

Key features of the AI-based matching solution, by country/region

Country	Type of AI	Types of data used		
		Jobseeker profile information	Vacancy information	Click data
Flanders, Belgium	Deep learning and natural language processing	X	X	X
Canada	Natural language processing and expert system	X	X	
Finland	Natural language processing	X	X	
France	Machine learning	X	X	
Israel	Machine learning	X	X	
Korea	Machine learning	X	X	X
Mexico	Machine learning	X	X	
Sweden	Machine learning, deep learning, graph analytics and natural language processing	X	X	

Note: Click data in this context refers to jobseeker browsing patterns on the PES vacancy platform.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

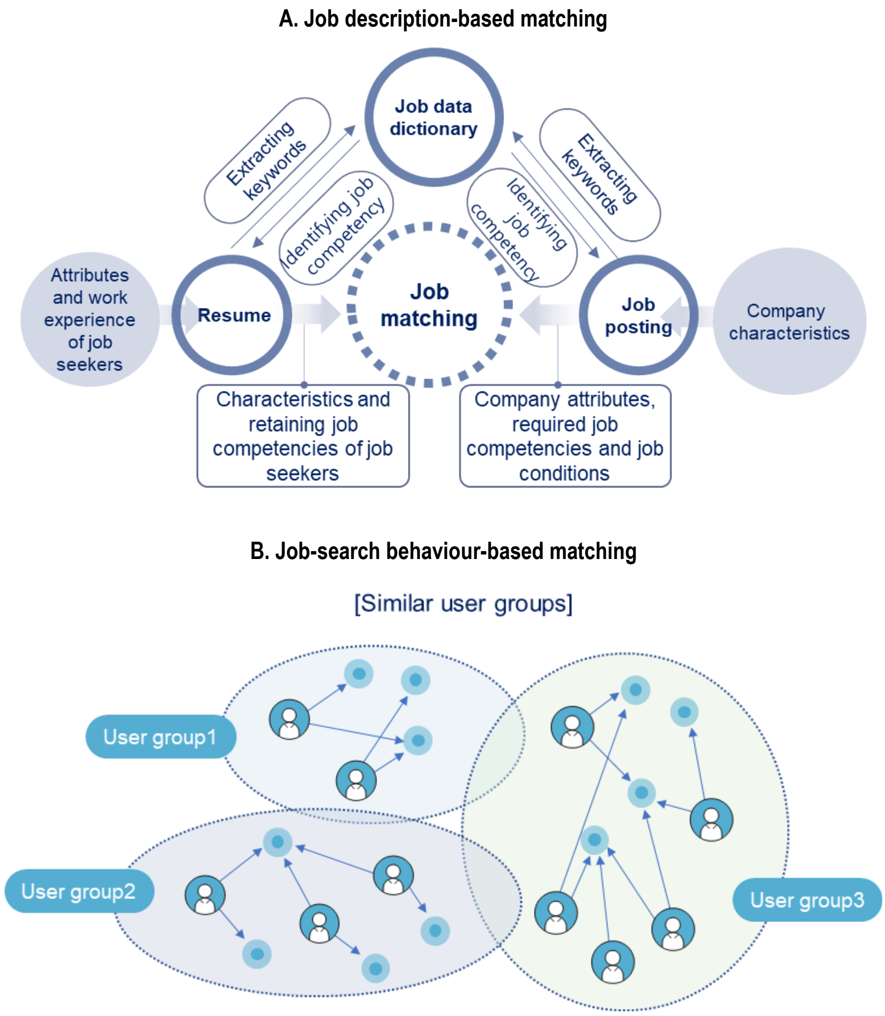
Job Bank is **Canada's** national employment service's online platform, available via the web or mobile application. Since it was first introduced in 2014, Job Bank has evolved gradually with new enhancements and functionalities – this includes its *Job Match* functionality which has undergone various iterations since its first introduction in 2015 (Employment and Social Development Canada, 2021[83]). The AI-powered tool utilises both natural language processing and an expert system; which is a computer system or program designed to make decisions and/or solve given problems – in this case finding suitable matches between jobseekers and job vacancies. Information on jobseekers is gathered when they create their profile, where they indicate information including their educational attainment, skills and previous professional experience. Based on this, the tool assigns a star rating (from one to five) to each match, a higher number indicating a stronger compatibility between the jobseeker and the vacancy (Canadim, 2023[84]). On the employer side, when an employer adds a new job advertisement, *Job Match* identifies suitable jobseekers, keeping their identity anonymous, and provides the employer with a comparison chart showing the suitability of the person relative to the job requirements.

In the **Flemish region of Belgium**, VDAB has been using AI to support its labour market matching function since 2018. Initially, this began with *Jobnet*, a self-learning algorithm developed to produce semantic matching between jobseekers and available vacancies (VDAB, 2021[73]). This was further built on in 2021, with the launch of a new AI-powered matching solution, *Talent API*, combining deep learning and natural language processing capabilities. The tool generates targeted job offers to jobseekers based on their profile (geographic location, previous work experience and skills) and vacancy text – including synonymous words in job advertisements to generate a broadened set of potential matches (OECD, 2022[1]). In addition, the application takes into account the browsing behaviour of the jobseeker as they explore vacancies, in order to identify similar opportunities to those they have already examined. Each individual jobseeker profile and job vacancy are then translated into unique high dimensional vectors, with similarity scores generated across the aforementioned several aspects of job matching characteristics. Unlike its predecessor, *Talent API* is a more transparent matching tool; by showing the matching scores across the different dimensions to the jobseeker, thereby providing justification for the suggested matches produced (OECD, 2021[85]).

In **France**, the PES has long been using digital tools to enhance the job matching process. The vacancy matching algorithm uses machine learning to enable a wider range of data to be included in the model, including information gathered through the individual's interaction with the PES and provision of services. In addition, the French PES has deployed AI to detect duplicate vacancies in its job mediation platform, as well as any illegal postings that are not compliant with French labour regulation (Section 3.3.2).

The PES in **Korea** has also been engaging in AI-based matching for several years. Using machine learning technology, enhanced with big data, the tool (*TheWork*) conducts two types of matching (Kim, 2023[76]; OECD, 2024[78]). First, job description-based matching, which creates matches using information from the jobseeker's profile and vacancy descriptions based on competencies (Figure 3.4, Panel A). Second, job-search behaviour-based matching identifies vacancies that similar jobseekers have looked at while browsing the vacancy site (Figure 3.4, Panel B). The result of the matching process then feeds into a job recommendation service accessible through *WorkNet*, the online portal of the Korean PES.

Figure 3.4. The job-matching tool of the Korean PES conducts matching across two dimensions



Source: Kim (2023[76]), *AI & Public Employment Services in Korea*, presented at International Conference on AI in Work, Innovation, Productivity and Skills, https://www.oecd-events.org/ai-wips-2023/session/8d837eb4-cbbc-ed11-9f73-6045bd8890e4/harnessing-ai-in-public-employment-services-to-connect-people-with-jobs

Since 2021, the PES in **Mexico** has been utilising AI to assist jobseekers in identifying suitable vacancies. Using supervised machine learning algorithms, the tool takes into account the interests of the jobseeker, including the occupation/sector of interest, their preferences regarding type of employment (e.g. full-time or part-time) and salary expectations. These preferences are then tallied with the profile of the jobseeker – including their career and education history – in order to make recommendations of suitable vacancies.

Job Market Finland, a digital platform for **Finnish** jobseekers and employers was launched in 2022. The new platform centres around an AI-enabled vacancy matching service. *Job Market Finland* utilises two matching methods concurrently in order to calculate a compatibility score between a candidate and a vacancy (Job Market Finland, 2023[86]; Hirsimäki, 2023[87]; Työmarkkinatori, 2023[88]). First, structural data matching takes place based on the jobseeker's work experience (i.e. job titles), skills, education, languages spoken and location (Räisänen, 2023[89]). Points are gained where professional history and skills are deemed relevant, meanwhile mismatches in language skills, education and geographic location can deduct points from the matching score. Second, natural language processing takes place on data from job postings on the platform, extracting important words using neural networks and word vectors. This measures the relevance between job postings and individual jobseeker profiles and was trained on vacancy postings in Finnish, Swedish and English. Based on this relevance model, jobseekers receive a list of most suitable jobs and employers receive a list of most suitable candidates among jobseekers. In anticipation of the development of *Job Market Finland*, an ex-ante evaluation was undertaken of the proposed reform (Räisänen, 2023[89]). This encompassed both a literature review and an analysis of Finnish PES vacancy microdata to examine the ways in which vacancies are filled. The study found that, among other things, vacancy filling efficiency (in terms of both vacancy duration and length of recruitment period) increases on average by 33 percent when web-based methods are used to facilitate the matching.

The **Israeli** Employment Service has deployed AI to assist with a number of activities, including vacancy matching since 2023. With labour shortages prevailing on the Israeli labour market, the PES is harnessing AI in the hopes of dramatically shrinking the time between a vacancy being notified and ultimately filled. As in several other countries, the Israeli job matching tool relies on the ESCO classification to facilitate competency-based matching. The tool extracts the skills of the jobseeker from their CV and translates all previous occupations into the ESCO taxonomy. The skills and competencies of the jobseeker are then compared to the pool of vacancies to identify potential vacancy matches. The end-user of this matching tool in the Israeli Employment Service is the PES counsellor, with the aim being to assist them in their support to jobseekers. For a given job offer, the matching tool generates a list of all potential matches and for each match the elements of the CV that meet the vacancy criteria, the distance between the person's home address and the workplace and the overall matching score (between 0 and 100 percent). Counsellors then make a decision informed by both their own judgment and the output of the matching application. Counsellors also have additional freedom to tweak the parameters of the matching tool if needed. In addition, in situations where a jobseeker is not the perfect match, the tool is helping counsellors identify gaps in their competencies – in turn informing the provision of suitable ALMPs (e.g. relevant training). Implementation of the matching system has assisted in the identification of priority areas for future iterations of the tool. One key area is that of performance, with the tool not yet being real-time and instead requiring its matching calculations to be run overnight.

Sweden has also been developing an AI-based matching tool, with the first iteration launched in early 2024. The tool combines various techniques (machine learning, deep learning, graph analytics and natural language processing), taking into account data on jobseekers and their characteristics from administrative data and vacancy information. This system also provides additional functionality to aid jobseekers on their broader career choice and orientation (as discussed in Section 3.2.3).

Several countries are also in the process of developing AI solutions to support labour market matching:

- In complementing and further enhancing the matching process, the PES in **Flanders, Belgium** is developing a new candidate outreach tool (*Kandidatenbereik*) for employers, which will use deep learning and graph analytics. This tool will aid employers by mapping those candidates who either fully or partially fit the profile of the vacancy posting.

- In **Luxembourg**, work is underway to lay the groundwork for several models that will feed into a number of AI projects – including a matching tool (ADEM, 2023[90]). The envisaged job matching tool, which is part of the larger digital PES project (*eADEM*), will build on this skills extraction work, likely using natural language processing to simultaneously analyse CVs and job vacancies to identify suitable matches. While the development for the matching tool is yet to get underway, machine learning is planned to be used for the system to learn from jobseeker browsing patterns when exploring vacancies.
- The PES in **Portugal** is also developing an AI-powered matching tool that will provide recommendations of both jobs to jobseekers and candidates to employers. The system will rely on the ESCO framework and will generate skills-based matches.
- In the **Netherlands**, the PES has recently embarked on a major IT project to modernise the current core IT system that supports its mediation services (*Sonar*). As part of this modernisation, a new matching solution will be introduced and will likely be supported by AI (Sanders, 2023[91]).
- The PES in **Estonia** is looking into the possibility of using ChatGPT to enrich and update the key words and synonyms for skills within ESCO taxonomy, and thus facilitate the use of ESCO to enhance skills-based matching in its matching tool.

3.3.2. Supporting employers

To further support employers in meeting their recruitment needs, several PES across OECD countries are using AI to help employers to correctly classify their vacancy postings in terms of occupations and skills, assist employers in designing their job advertisement, proactively identifying those vacancies that may be more difficult to fill and to predict hiring patterns of employers (Table 3.5). Some PES are also using AI to provide information to employers via chatbots, often in chatbots jointly available to both jobseekers and employers, these are discussed in Section 3.2.1.

Table 3.5. Several PES are using additional AI tools for employers to further support job matching

Key features of the AI solution, by type and country

Category	PES location	Details	Type of AI
Aiding the design of job postings, including through occupational classification	Flanders, Belgium	Extracts skills or competencies from vacancy postings and provides employer with suggestions of those missing from posting	Deep learning
	Flanders, Belgium	Classify occupation of job posting	Deep learning
	Wallonia, Belgium	Classify occupation of job posting	Natural language processing
	Canada	Assists employer to draft job vacancy using historical job description text from similar occupations	Expert system
	Finland	Extracts skills or competencies from vacancy postings and provides suggestions for occupation (including job title)	Natural language processing
	Germany	Turning vacancy information received by employers into standardised job vacancy proposals, alleviating manual processing of staff	Machine learning
	Luxembourg	Classify occupation of job posting and identify misclassified vacancies	Natural language processing
	Norway	Provides suggestions to employers when drafting job vacancy postings	Large language model
	Spain	Classify occupation of job posting	Machine learning
Detecting any illegalities in vacancy postings	Canada	Detect if vacancies include any illegal, discriminatory or erroneous elements	Expert system

Category	PES location	Details	Type of AI
	France	Detect if vacancies include any illegal or discriminatory elements	Deep learning and machine learning
	Sweden	Detect if vacancies include any illegal or discriminatory elements	Deep learning and natural language processing
Diagnosis of hard to fill vacancies	France	Estimates time it will take to fill a vacancy	Not specified
	France	Estimates attractiveness of a vacancy according to a number of factors	Not specified
Predicting recruitment likelihood	France	Identifies companies with a high recruitment likelihood, based on historical trends	Machine learning

Note: Not specified refers to cases where the type of AI model was not provided by the responding authority.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

Aiding the design of job postings, including through occupational classification

Monitoring and checking the quality of information in the vacancies posted by employers on PES job portals can require significant time and resources from PES. In the same vein as competence mapping tools for jobseekers (discussed in Section 3.2.3), AI tools can help PES to systematically identify and classify the occupation of a job offer and the associated competencies and skills required by the employer. This creates greater consistency between the title and content of a job description, increasing the likelihood it will be viewed by relevant jobseekers. In some cases, such AI tools can act as inputs to other systems, including vacancy matching tools.

Several countries are engaging in AI-assisted vacancy classification including:

- **Finland's** matching platform, *Job Market Finland* has an in-built *Skills Suggester* tool, which takes input text from users (both jobseekers and employers) and uses natural language processing to suggest the appropriate occupations and skills according to the ESCO classification (Job Market Finland, 2023[86]). For example, from job description text input by an employer, *Skills Suggester* can formulate suggestions for potential job titles.
- The PES in **Flanders, Belgium** has two relevant AI initiatives in this space. First, the Competency Extractor (as mentioned in Section 3.2.3), identifies the competencies or skills included in vacancy postings drafted by employer and provides suggestions for those missing from the description. Second, the Occupation Finder (*Beroepzoeker*) analyses the same vacancy descriptions, but this time identifies the most appropriate occupation title for each vacancy according to VDAB's occupational taxonomy. More precisely, the tool estimates the vacancy's distance from each of the 600 occupations included in the taxonomy in order to (re)label the job advertisement with the "closest" matching occupation. This assists employers in creating the most accurate job advertisements and aids jobseekers in their job search, thanks to enhanced consistency across job postings.
- Since 2023, the PES in the **Walloon region of Belgium** has been utilising natural language processing to propose the appropriate occupational classification for job offers published by employers on the PES website.
- The **Spanish** PES is employing machine learning to classify job vacancies using the National Classification of Occupations (CNO-11).
- In **Luxembourg**, the PES has recently deployed an AI-powered tool to classify job vacancies and to identify those vacancies that have been misclassified by the employer. This tool relies on natural language processing methods, allowing the PES staff to view the outcomes of two AI models (by job titles and by job descriptions) in dashboards. The system uses the ROME classification and has been trained on English, French and German. Eventually, the aim is for this model, along with the skills extractor model also in development, to act as inputs to a matching tool.

- Other countries are developing such solutions, including **Portugal**. Here, the PES plans to use generative AI to provide skills and occupation suggestions to employers when drafting vacancies, based on the ESCO taxonomy. The same tool will likely also be available for jobseekers, to better capture their skills and occupation profiles.

Outside of recommending the most relevant occupation and skills to include in a job posting, PES can use AI tools to assist employers more generally in drafting their job advertisements. This is done in **Canada** on the job vacancy portal of the PES (*Job Bank*). When filing a vacancy posting, an employer receives suggestions on how to draft the job description from an expert system which uses text from historical job vacancy descriptions in similar occupations. Similarly, **Norway** has since 2023 implemented a large language model to provide suggestions to employers when creating their vacancy postings.

In cases where PES staff are required to validate and create job vacancy postings based on submissions from employers, AI can assist with this process and alleviate some of the associated workload. For example, the PES in **Germany** previously relied on staff to manually process job vacancies received from employers. Often, job descriptions are not standardised, requiring a lot of effort to manually input this information into the PES system. A recent innovation now sees implementation of an AI solution to overhaul this process, with the aim of relieving staff of these manual tasks and freeing up more time for placement and counselling services. Employers submit potential vacancies either directly through the PES portal or by email, in the case of the latter PES staff can trigger the transfer of the data to the vacancy system using a newly integrated button in their email inbox. Once in the system, machine learning is then used to generate a job vacancy proposal based on the data provided (including any ancillary links or attachments included in email requests). PES staff in the employer service area of the PES can then check and amend the offer before publishing.

Detecting any illegalities in vacancy postings

AI presents opportunities for PES to engage in further quality assurance of vacancy postings including to identify illegal or discriminatory content contained within job descriptions. Three PES are using AI for this purpose.

In **France**, deep and machine learning are used to identify vacancies that contain problematic or discriminatory components. This includes detecting vacancies that are in breach of the French Labour Code (*Code du Travail*), which prohibits discrimination towards candidates on a number of grounds, including age, gender and disability status. Caseworkers are then alerted to flagged vacancy postings and can take steps to address the problem, including contacting the employers to find a solution. The French PES also use AI to detect and withdraw fraudulent job advertisements from its vacancy portal.

Similarly, **Sweden** has been using AI to identify cases of discrimination in job vacancies submitted to the PES since 2023. Here the tool utilises deep learning and natural language processing, aiding case managers in their work to review job advertisements published on the PES' vacancy portal.

Canada also has a tool to detect illegal vacancy postings built into its PES vacancy portal *Job Bank*. This operates as an automated flagging system, powered by an expert system, which alerts PES agents of any potential errors or discrepancies found within job ads and the estimated integrity risk.

Diagnosis of hard to fill vacancy postings

By identifying vacancies that – according to various criteria – may be more difficult to fill, AI tools can help employers to make these vacancies more attractive to jobseekers.

In 2020, the **French** PES established an initiative (*Action Recrut*) to assist employers facing difficulties in filling vacancies. This programme sees PES advisors reaching out to employers with unfilled vacancies after 30 days in order to diagnose any issues and propose solutions. Two AI tools have been developed to help this initiative:

- First, a predictive model estimates the time it will take to fill a vacancy. In the context of the *Action Recrut* initiative, this facilitates the proactive identification of those positions that will likely be more difficult to fill, allowing an advisor to reach out and provide recommendations to the employer to increase the vacancy attractiveness.
- Second, an AI-powered tool analyses a vacancy to assign it an attractiveness score based on a number of criteria, including the region's labour market context. The score facilitates the PES advisor in the assistance they gives to employers to enhance a vacancy's appeal. The initiative has been positively received by employers; contributing to accelerated recruitment and a reduction in the number of vacancies abandoned by employers (Pôle Emploi, 2023[92]).

Predicting recruitment likelihood

AI methods can also enable PES to estimate the hiring potential of companies. To date, the **French** PES is the only known example where a dedicated tool using AI has been implemented for this purpose. *La Bonne Boîte*, implemented in 2018, identifies companies with a high recruitment likelihood, even before a vacancy has been officially advertised (OECD, 2021[85]; World Bank, 2023[81]). The tool has a dedicated website and aims to assist more efficient job-search among jobseekers by allowing them to focus their efforts on those companies most likely to hire within the next six months. The tool relies on machine learning to forecast future hiring likelihoods based on past recruitment trends. The platform allows jobseekers to search for jobs they are interested in in a given location, select a company based on their hiring potential (rated out of five stars) and send an unsolicited application (La Bonne Boîte, n.d.[93]). An evaluation of the *La Bonne Boîte* found that the tool contributes to enhanced job-finding rates among users and can be beneficial in reducing mismatch, by guiding job search towards tight occupations (i.e. where labour demand exceeds supply) (Behaghel et al., 2022[94]).

3.4. AI tools to assist PES administrative activities and knowledge generation

Most PES have digitalised their back-office processes to increase the speed and efficiency of administrative activities, as well as enable knowledge generation, particularly making the data available monitor and evaluate ALMP provision. While most back-office innovations fall into the category of more traditional digitalisation or automation, a few OECD PES have developed AI initiatives – particularly in the areas of fraud detection, impact evaluation and generating labour market information.

3.4.1. Administering benefits and detecting fraud

Upon registering with the PES, newly unemployed jobseekers will often simultaneously file their application for unemployment benefits. For PES, the administrative burden associated with benefit administration is significant, requiring large amounts of staff time. With eligibility for benefits largely relying on a strict set of rules, the potential for automation and assistance from algorithms (both AI and non-AI) to aid benefit management and assistance is high (Verhagen, forthcoming[95]).

In practice within PES, many countries have elements of the benefit administration process digitalised or automated to some degree, including for example in Estonia where the whole process is automated (Box 3.2). However, applications of AI largely remain to be seen. In the context of this study, use cases of AI to assist the benefit administration process have been identified in two countries: in Sweden to detect fraud (discussed further below) and in Germany to assist the processing of supporting documents. In the case of **Germany**, the PES (the Federal Employment Agency) has responsibility for various benefits, including the non-employment related child benefit (*Kindergeld*). After the age of 18, eligibility for child benefit can be extended up to age 25 in cases where the child is still in education or training. For this, the PES is using a support vector machine (a type of machine learning) to recognise and extract information from documents received as proof of continuing studies.

Box 3.2. Estonia's automated benefit system has provided efficiencies for both staff and clients

The Estonian PES, the Estonian Unemployment Insurance Fund (EUIF), has implemented automated decision-making (ADM) to process jobseekers' registration with the PES and subsequent applications for unemployment benefits for several years now. ADM is used to evaluate a client's eligibility for unemployment insurance benefit, which sees the system automatically checking the relevant registers and, provided no supplementary information is needed, will automatically issue a decision. In addition to automating the eligibility for benefits, the system also calculates the benefit amount and duration of eligibility. An update to the system in 2022 now sees an automatic check of registers prior to a client's counselling session, in order to verify the continued eligibility of the client for both services and benefits. For the EUIF, the automated system has greatly contributed to the saving of staff time, where previously a significant amount was spent doing manual data entry and verifying the contents of application forms. In addition, for clients, the automated system has materially sped up the waiting time for a decision and avoids human error and any other disruptions associated with the original manual process.

The right of the EUIF to make automated decisions to fulfil its legally established organisational objectives is set out in the Unemployment Insurance Act. Furthermore, transparency is embedded into the process. Clients are advised at the time of the application of the automated nature of the process and again upon receipt of the decision. Clients also have the right to request further explanatory information or appeal the decision.

Source: Responses to OECD questionnaire on digitalisation and AI use in PES; Estonian Unemployment Insurance Fund (n.d.[96]), *Data Protection Terms: When does the Unemployment Insurance Fund make an automatic decision regarding you*, https://www.tootukassa.ee/en/data-protection-terms/data-protection-estonian-unemployment-insurance-fund/when-does-unemployment; Raudla (2020[97]), *Töötukassa automatiseeritud infosüsteem otsustab raha jagamise sekunditega*, https://virumaateataja.postimees.ee/6904529/tootukassa-automatiseeritud-infosusteem-otsustab-raha-jagamise-sekunditega; Riigi Teataja (2023[98]), *Töötuskindlustuse seadus (lühend – TKindlS)*, https://www.riigiteataja.ee/akt/TKindlS.

In addition to aiding the process of administering benefits, AI also has the potential to assist PES to detect fraud in this domain. This refers to situations in which individuals are purposefully claiming benefits, despite having no eligibility or entitlement. However, as outlined in Section 2.1.4, the use of AI in fraud detection also comes with significant risks. The misidentification of fraud by these systems can lead to the issuance of requests for corrective action (repayment of benefits, sometimes with added fines and/or interest) to those who are genuinely eligible for benefits. Across OECD PES, one PES currently has a solution for fraud detection in place. The PES in **Sweden** has developed a largescale fraud detection system, rolling out in early 2024. This system combines several techniques (machine learning, deep learning, social network analysis and knowledge graphs) and encompasses a wide pool of data, including information on jobseekers, employees and employers (i.e. labour market contracts data), and suppliers (partners or service providers of the Swedish PES).

The lack of adoption of AI in the area of benefit administration may be driven by a number of factors, including the high-risk nature of this work and its impact on citizens, ethical concerns, regulatory and legislative barriers and high-profile cases where such systems were abandoned due to poor results. In addition, AI systems may have limited added-value in the area of benefit administration over simpler rule-based systems that could conduct these activities as effectively. Similarly, in social protection systems more widely, AI use to aid the provision of social benefits also remains limited (OECD, 2024[99]).

3.4.2. Generating knowledge on PES and ALMPs

Enhanced possibilities for data analytics present a major opportunity for PES to harness AI for knowledge generation, both in terms of ex-post analysis and forecasting labour market trends. While only a few PES are using AI for this purpose at the time of writing, this is an area where AI will likely be harnessed more extensively in the coming years.

Generating labour market information

Labour market information is needed by labour authorities and PES to design ALMPs that meet the labour market needs, as well as other policymakers to design services, measures and benefits in related areas, such as in the fields of education, social services and social security. Reliable and up-to-date labour market information is also needed to aid counsellors to target ALMPs to jobseekers, enable jobseekers and workers make career choices and support employers with staff planning. So far, AI has been harnessed to generate a better understanding of skill needs and enhance the production of labour market information by four PES.

In **Luxembourg**, the PES has developed an AI-based model to classify occupations linked to vacancies according to the ROME classification system. In addition, the PES has launched a new skills extraction model, powered by natural language processing, to identify skills from job descriptions using the ESCO framework. At present, these two AI applications are solely used for statistical and labour market monitoring purposes, some of which has been made publicly available through an online dashboard (ADEM, 2024[100]). However, the PES aims to gain further operational utility from these models, including by using them as inputs into a planned job-matching system and to aid the work of counsellors in the job-search support and guidance they provide to jobseekers.

The PES in **Flanders, Belgium** is also engaging in AI-supported labour market monitoring. Here the PES is utilising autoregressive neural network models to both measure and forecast the demand for occupations and the associated skills. It does so using data from job vacancy postings.

Similarly, the PES in **Sweden** employs AI to analyse the labour market situation. Natural language processing is used to analyse job postings from the previous two years, to better understand the skills needs, educational requirements and task composition of occupations. This is part of wider work in the Swedish PES to develop AI solutions to monitor and analyse labour market trends, including changes in labour demand regarding occupations and competencies, with the aim of contributing to a better understanding of the needs of both jobseekers and employers. Furthermore, this use of AI to generate labour market information also acts as an input to the career orientation and matching tools of the PES.

AI can also be a useful tool in the data preparation stage of research and analysis of PES. For example, in **Germany**, AI methods have been used for several years to produce anonymised research data from high volume structured and unstructured data sources, that adhere to data quality and privacy standards. The exact type(s) of AI used depends on the individual project and data used. These data can then be used for various research projects, including for example to examine the development of competence requirements for occupations across regions (Stops, 2021[101]), and as input to ALMP monitoring and evaluation activities.

Monitoring and evaluating ALMPs

AI, in particular machine learning, can be used to enhance counterfactual impact evaluations, with particular benefits gained in understanding the impacts of interventions on specific sub-groups of people (Athey, 2019[25]; Lechner, 2023[26]; Cockx, Lechner and Bollens, 2023[27]). By better estimating the heterogeneity of effects, AI can help PES to use the evidence to better target ALMPs. For example, **Canada** has begun experimenting with these recent methodological developments, particularly in order to enhance its gender-based evaluation work (Employment and Social Development Canada, 2023[102];

Handouyahia, 2023[103]; OECD, 2022[104]). Through this experimentation, the modified causal forest methodology has enabled the generation of robust results at a level of granularity not previously possible. In addition, it has been possible to more accurately identify the sub-groups that benefit more from interventions than others (and vice versa), which is particularly important in informing the policy design and provision for vulnerable or marginalised groups.

AI can also be used to enhance evidence generation within PES through designing and implementing AI-driven systems to facilitate more systematic and regular evaluation of policies. The one country with such an initiative in place is **Estonia**, where the PES has developed the *MALLE* tool (Printsmann, 2023[105]; OECD, 2022[1]). The purpose of this tool is to conduct regular automated counterfactual impact evaluations of key ALMP measures, including labour market training, work experience programmes (internships), wage subsidies and labour market rehabilitation measures. These evaluations are conducted using both propensity score and exact matching, with the matching and evaluation processes being automated. The main outcome variables explored are employment status and earnings, with results visualised in interactive end-user dashboards. Currently, MALLE could be classified as an expert system, however in collaboration with researchers at the University of Tartu, the PES plans to further develop *MALLE* by testing machine learning methods, such as causal random forest and regularisation techniques, and by integrating cost-benefit analysis into the system.

4 Impact of AI adoption on PES staff

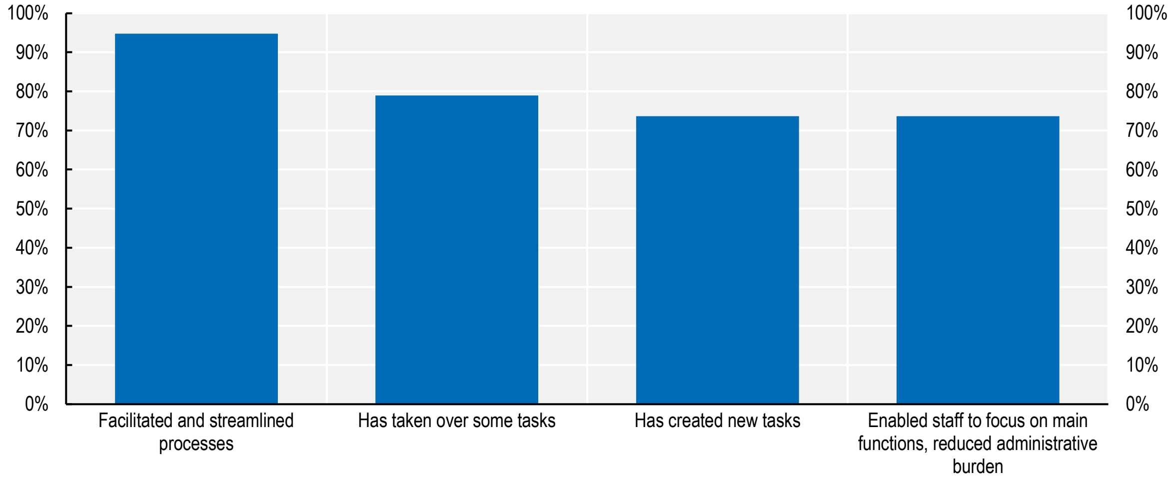
The introduction of AI to PES activities, while often initiated in order to improve the services and measures it provides to clients, also has significant implications for PES staff. This section explores the impact of AI adoption PES staff and their work, the workforce needs of the PES more generally and what measures can be taken by PES to support staff on this journey. For a more in-depth exploration of both the positive and negative effects of AI use and digitalisation more generally on PES staff, further work aided by dedicated surveys among PES staff would be beneficial in generating additional insights.

4.1. AI adoption can significantly impact the day-to-day work of staff and PES workforce needs

While the exact impact of AI on PES staff depends on the specific tool(s) or system(s) implemented by PES in a given case and the exact role of the individual (some are more impacted than others), some overarching impacts are commonly seen. Figure 4.2 presents the main effects of technological change more widely as reported by PES, many of which are also relevant in the case of AI adoption.[7]

Figure 4.1. More widely, technological adoption has significantly impacted PES staff

Share of responding countries that report each type of impact



Note: This figure is based on responses from 38 PES (including two sub-national responses from Belgium) to a question on a number of pre-defined impacts of digitalisation on PES staff.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

[7] The information presented in Figures 4.1 and 4.2 reflects the views of respondents to the OECD questionnaire on PES digitalisation and AI, which in most cases were PES management or teams working on topics related to digitalisation (including IT departments).

One of the avenues through which AI can have the greatest impact on PES staff is through changes to the task composition of their jobs. This change in the selection of tasks that make up the day-to-day work of a staff member can occur across two dimensions. First, AI can entirely take over some tasks previously done by PES staff. This is most likely to occur in areas where tasks are repetitive, routine and tedious in nature (OECD, 2023[37]). Second, AI adoption can also create new tasks for PES staff, due to the changes to business processes and activities brought about by the implementation of an AI tool or system. These new tasks can occur along the entire lifecycle of the AI tool, from development to post-implementation. The balance between the two effects, automation or creation of tasks, depends on the individual context – both avenues seem to be widely experienced by PES as a result of technological change (Figure 4.2).

AI can improve the working experience of PES staff by facilitating the streamlining of PES processes. This can be achieved through the aforementioned automation of manual processes, a reduction in the completion times for certain tasks, mitigating the risk of human errors and the simplification of more complex or lengthy processes (Mikalef et al., 2023[106]).

In addition, AI can complement the human resource capacity of PES. This can occur in instances where PES staff and AI tools and systems are working side-by-side (e.g. profiling or matching tools), enabling PES workers to conduct certain tasks and activities more quickly and efficiently. This can lead to the potential for productivity gains for PES.

Overall, AI can contribute in various ways to reducing the administrative burden on PES staff and in turn free up staff time for use in more high-value tasks. This can allow PES staff to focus on their core functions and those tasks that require cognitive skills (such as problem solving, creativity and empathy) and transversal skills (such as management, social skills and communication), which are more difficult to replicate using AI (OECD, 2023[37]; Lassébie and Quintini, 2022[107]). For PES, AI may enable staff to increase the time spent on high value and high impact tasks, including the provision of support to and engagement with clients, both jobseekers and employers.

As PES engage in the development and deployment of AI solutions, this has implications for both the occupations and skills they demand in their workforce. AI can impact demand for PES staff through three main channels (Acemoglu and Restrepo, 2018[108]; OECD, 2023[37]):

- *Displacement effect*: this refers to AI replacing humans in the performance of certain tasks and processes, which decreases the demand for labour. This is most likely to occur where tasks are largely repetitive and routine.
- *Productivity effect*: this refers to an increased demand for labour for tasks or jobs that have not been replaced by AI, thanks to the enhanced productivity and cost savings brought about through automation.
- *Reinstatement effect*: the introduction of AI brings with it the creation of new tasks, which can result in increased demand for labour for entirely new jobs – particularly in areas which human labour has a comparative advantage. These jobs will most commonly be linked to the AI itself – generating demand for workers with skills to be able to develop, maintain and interact with AI solutions.

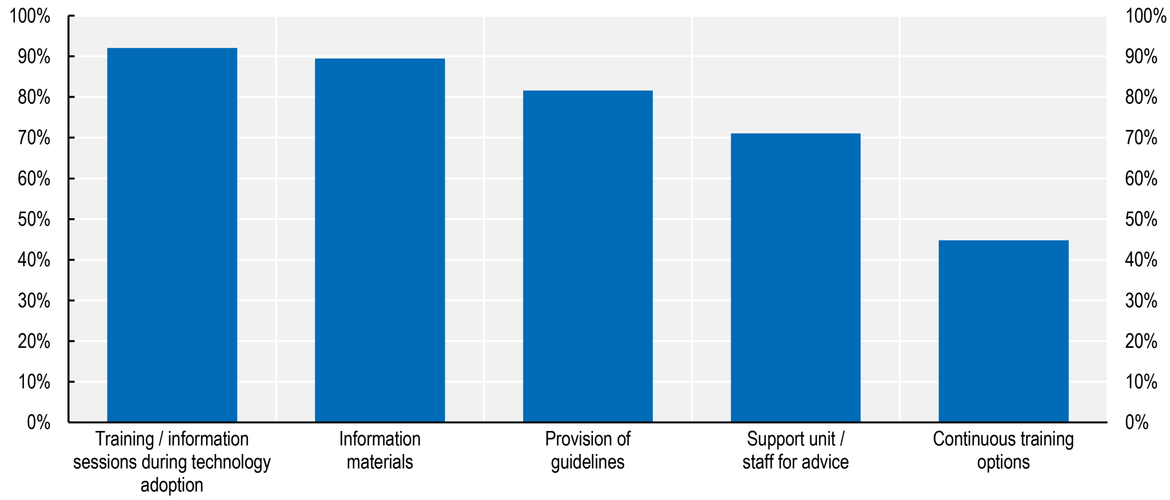
Which channel will dominate, and in turn whether PES' staff needs will increase or decrease as they adopt AI solutions remains to be seen and is a central question in respect to the future of work and AI. However, aside from the impact on aggregate employment, it is clear that AI adoption will have implications for the skills needed by PES staff. In particular, this includes increased demand for complementary skills to AI. This will require PES to adapt its hiring and training to ensure that both prospective and existing staff are equipped with the necessary skills to adapt to and take full advantage of AI solutions.

4.2. PES must be proactive in addressing the challenges AI adoption may bring for staff, including resistance and lack of trust

The PES modernisation journey, as with other forms of organisational change, can be met with resistance and lack of trust among PES staff. In the case of AI adoption, these reactions among PES staff may be exacerbated due to scepticism or lack of understanding of these technologies and fears related to the impacts on their job – both their job content and security – due to displacement and reinstatement effects. This sentiment, if not adequately addressed, can present numerous risks for PES, including rejection and low take-up rates which can undermine AI investments. In addition, a lack of appropriate skills among PES staff is also a risk to successful AI adoption and has the potential to intensify the aforementioned feelings of resistance and fear of these new developments. In order to seize the opportunities of AI, PES must take proactive steps to support staff in adapting to new trustworthy AI technologies and solutions and their impacts.

Figure 4.2. Most PES take steps to support staff in adapting to new technologies

Share of responding countries engaging in each type of support



Note: This figure is based on responses from 38 PES (including two sub-national responses from Belgium) to a question on a number of pre-defined impacts of digitalisation on PES staff.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

In the PES modernisation journey more generally, the vast majority of PES across OECD countries are engaging in efforts to aid their staff (Figure 4.2), most commonly through:

- ***Guidelines and informational materials***: PES in 82% and 89% of countries are providing staff with guidelines and informational materials respectively. PES guidelines can assist staff to use AI systems and tools properly, responsibly and ethically. Similarly, informational resources aim to increase staff members' understanding of the AI solution and should assist them in getting started or if they encounter any problems. Where appropriate, these resources should be non-technical in nature, as most of the users of AI-enabled PES tools will most likely be non-experts. An interactive approach to help PES staff learn how to use new digital tools is seen in the German PES, where they use "click dummies". Similar to a sandbox, a click dummy is essentially a workable mock-up which allows staff to familiarise themselves with a tool in a testing environment, without using the online or live version. Some PES are also taking steps to enhance staff familiarity with digital and AI topics through informal approaches, including in Flanders, Belgium where the PES organises information sessions over lunch or coffee to encourage open dialogue between caseworkers and IT staff.

- ***Training opportunities***: Training is crucial to ensure that PES staff are AI-ready and to promote proper and trustworthy usage of AI tools. 92% of countries provide training or information sessions during the initial roll out phase of new technologies. While this is a positive trend, opportunities for continuous training are available in less than half of countries. PES should endeavour to provide training on an ongoing basis, including as AI tools are modified and evolve over time, to ensure that staff stay up-to-speed. This can assist in increasing staff's familiarity and comfortability levels with the new AI solutions and can promote effective use of the systems or tools (Lanteri et al., 2023[109]; Gillepie, Lockey and Mabbott, n.d.[110]). Interesting initiatives in digitalisation-focussed training include the "train the trainer" approach in Switzerland. In such approaches, training is designed to both teach staff the content and to equip them with the knowledge and skills needed to teach it to others. This allows for the information to flow quickly through the organisation, as staff can train and help their colleagues. In addition, such initiatives could be expanded to train PES staff in helping clients with utilising AI and other digital tools, which can also contribute greater transparency and explainability.
- ***Dedicated contact points for support and advice***: 71% of OECD PES have put in place dedicated support staff or teams who can provide assistance to staff as needed. Such initiatives are beneficial to staff, thanks to the presence of a clear and constant route to seek help.

However, in the case of AI adoption, support to PES staff should go further in order to foster a successful adoption and to promote greater trust in these advanced solutions, including by:

- ***Involving staff in decision-making*** – engaging and including staff, especially those who will be directly impacted by new AI systems and tools, in the decision-making process can foster a more collaborative culture (Gillepie, Lockey and Mabbott, n.d.[110]). This can assist in generating buy-in and acceptance among staff, by increasing their understanding of the AI solution and its purpose and providing them with an opportunity to be a part of the process (Campion et al., 2020[111]). This can be done in various ways, including through staff involvement in the bodies or teams within PES responsible for designing and implementing AI solutions in the PES, involving staff in the testing phase of tools where relevant and actively consulting staff along the entire lifecycle, from development to post-implementation. This involvement of staff can also contribute to improved design and user-friendliness of AI tools, particularly where staff are the intended end-user.
- ***Promoting transparency and open communication*** – PES and its management should prioritise fostering transparency within the organisation, including in its use of AI. Transparency, combined with open and regular dialogue with staff, can help boost overall understanding and awareness of why AI is being implemented and its likely impact and intended benefits (Lanteri et al., 2023[109]). Staff members should also be given the opportunity to ask questions and raise any concerns. Given the complexity of AI solutions, PES should endeavour to demystify the use of AI for PES staff members and support a white box, rather than black box, approach to its use. In the same vein, this approach to promoting to transparent use of AI should also be extended to PES clients.
- ***Leading by example*** – Sponsorship of AI initiatives from leadership can provide legitimacy to AI projects (EsadeGov, 2021[112]). As in change management more widely, successful adoption and acceptance of AI by PES staff will require leadership and management to lead by example and set the precedent for the organisation as a whole. In the case of PES, this could include managers in PES offices being first adopters of new AI systems and showcasing to their staff, through their actions, how to adapt and benefit from these new tools and processes.

5 Conclusion and key considerations

For PES, advances in the field of AI present various opportunities and potential for application across all aspects of activity – from aiding service provision to assisting back-office processes. Several countries are already seeking these benefits, with half of PES covered in this paper having AI initiatives in place at the time of writing – most commonly to assist matching jobseekers with vacancies, aid the design of job postings, profile jobseekers, provide information to clients (commonly via chatbots) and support the career management and job-search orientation of jobseekers. As PES seize the opportunities of AI, steps must be taken to simultaneously mitigate associated risks, both for those already on this journey and those soon to embark. Some of the key considerations for PES on this journey include:

- ***Ensuring a sufficient level of expertise, even when solutions are outsourced*** – In some cases, commonly due to lack of necessary expertise available internally, PES opt to outsource the development of AI solutions to external contractors. In these cases, PES should still have some expert staff within their IT department available to successfully manage the development process and work closely with the contractor to ensure solutions meet the needs of both the PES and end-users and include the necessary measures to mitigate risks required by the PES. For example, in Norway this is achieved through housing external consultants working on AI development in house within the relevant PES departments. Without such engagement with contractors and a minimum level of internal expertise, PES may face difficulties in implementing, monitoring and evaluating outsourced AI systems due to insufficient understanding and knowledge.
- ***Establishing frameworks to guide and govern AI use*** – The establishment of guardrails is an essential step in the promotion accountable and trustworthy AI use in the public sector (OECD, forthcoming[33]). For PES, this should see the development of frameworks and mechanisms to oversee and govern AI use in PES, including in assigning responsibility for AI systems and their outputs. This can take the form of two main categories of measures. First, PES should consider developing agreed strategies to set the high-level vision for their modernisation journey, including the use of AI. Across countries covered in this paper, only about one-in-four PES have a dedicated digitalisation strategy in place, with another quarter seeing it included in the overall PES strategy to some degree. The remaining half of countries do not feature topics related to digitalisation in their PES strategies. Second, PES should develop and implement principles and associated structures to govern and oversee AI use. Some promising initiatives in this domain are seen in both France and the Flanders region of Belgium, where the PES have established an Ethics Board or Committee to advise the respective PES on their AI use. In the case of the French PES, this has resulted in the agreement of a "Charter for Ethical AI", drafted by a working group that featured PES counsellors and jobseekers in its membership.
- ***Putting transparency and explainability at the centre of AI initiatives*** – PES should avoid the development of opaque AI solutions, instead prioritising transparent and even white box approaches to AI. Such transparent approaches to AI by PES foster enhanced explainability and better facilitates auditing and evaluating AI systems and their outcomes. In addition, transparency and interpretability is important in fostering trust in AI systems among both PES staff and clients. For example, in the Netherlands, the PES has established a dedicated webpage to provide information on algorithms used, including what data are involved, how discrimination is prevented and what supervisory and risk management practices are implemented (UWV, n.d.[113]). However,

efforts to promote transparency and explainability need to be balanced against intellectual property rights and the risk of facilitating fraud.

- ***Ensuring that AI systems do not perpetuate biases or distort the functioning of labour market*** – AI-powered tools that make personalised recommendations for jobs, career pathways or services based on learnings from historical data may be prone to generating and amplifying biases (OECD, forthcoming[114]). Distortionary effects can additionally arise even from the design of the user interface, such as how the recommendations are displayed to (the different) users. Poorly designed AI recommender tools could lock some groups into lower quality jobs and career tracks, penalising those who are already experiencing discrimination in their working lives, such as mothers or people with migratory backgrounds. In addition, tools to recommend alternative job search pathways and occupations should direct jobseekers to occupations in demand on the labour market without overly distorting competition between jobseekers and generating new bottleneck vacancies. These potential negative effects should be proactively addressed in the design and development phase and should be subject to ongoing auditing during testing and after rollout to avoid their development over time.
- ***Including and supporting staff in the AI journey*** – The introduction of AI tools and systems by PES often can have significant implications for PES staff, particularly in changing the task make-up of their jobs. Such changes to business processes may be met with resistance and, if left unmitigated, have the potential to undermine AI investments, including through low usage rates. Therefore, PES must prioritise the inclusion and supporting of staff through this transition – including by involving them along the entire process (from design to adoption), prioritising open dialogue and transparency and providing adequate support and training.
- ***Guaranteeing the facility for human determination*** – Due to the nature of the work of PES and its impact on clients, including their labour market prospects, mechanisms to facilitate human oversight and possible intervention in AI systems should be established as a priority (OECD, 2023[37]). Such safeguards may be required by law. For example, for PES in the EU, GDPR establishes that individuals should not be subject to decision-making conducted on a solely automated process. This is also in line with OECD AI Principles and can foster the values of human-centredness and fairness in PES AI systems. Knowledge of human input and oversight into PES AI systems may also contribute to greater trust and acceptance in these tools by clients.
- ***Involving end-users in the development of AI tools*** – End-users and those impacted by the results of PES AI systems and tools, both PES staff and clients, should be involved in the AI development process (including design and testing). This can generate added value for PES, including in enabling the development of AI systems that are more user-friendly and better meet the needs and expectations of its users. In addition, involvement in the development process can also contribute to enhancing buy-in among end-users. End-user involvement is also crucial post-implementation, particularly in receiving feedback on the ongoing performance of AI tools and systems rolled out by PES.
- ***Ensuring ongoing and rigorous monitoring and evaluation of AI solutions*** – AI solutions, just like other digital or policy initiatives introduced by PES, should be closely monitored and evaluated along their entire lifecycle in order to ensure they are performing as intended (OECD, 2022[1]). This includes exercises such as counterfactual impact evaluations, process evaluations and cost-benefit analyses, as well as monitoring to ensure quality of outputs and to detect any potential drift or degradation in the AI model. Equally as important as the monitoring and evaluation itself, is the establishment of a feedback loop, so that corrective action can be taken as needed.

The world of AI is rapidly evolving, with new methods and applications emerging on a regular basis. Alongside these technological advancements is an evolving regulatory and legislative landscape. This includes the EU's Artificial Intelligence Act, which is the world's first comprehensive AI act (European Commission, 2021[115]). This Act could have significant implications for EU PES given the classification of

AI use in certain areas relevant to PES activities, including to aid recruitment and assessing eligibility for public services, as high-risk and will likely be accompanied by a set of obligations.

As PES across OECD countries continue to engage in using AI to enhance their activities and processes, further work should be done to examine their impacts, including to better understand how such tools impact the efficiency and effectiveness of PES provision and to have a deeper look at the implications for PES staff, for example, through PES staff surveys. In addition, latest innovations in the areas of generative AI and large language models have the potential to further transform the AI use by PES, through enhancing existing AI tools and developing new ones and using AI in different ways and for different functions. Furthermore, as AI adoption rates in PES and other organisations continue to grow, this may contribute to these technologies becoming less costly over time – underpinning the need for ongoing monitoring and evaluations of such tools to understand their impacts on PES effectiveness and efficiency. Increased AI adoption across PES may also be facilitated by an increased prevalence of AI algorithms in off-the-shelf software and technologies. This creates increased opportunities for PES to take advantage of these emerging AI capabilities, but still requires vigilance regarding associated risks. As more PES embark on the AI journey, there will also be even more scope for peer learning and identifying good practices in the design, use and governance of AI tools by PES. Here the OECD can play a key role in developing cross-country insights and creating fora for knowledge exchange. Future work should also examine how PES develop digital and AI tools by exploring decision-making processes, stakeholder involvement, development processes, oversight and governance mechanisms and associated monitoring and evaluation activities.

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Annex A. Overview of AI use by PES

Table A A.1. AI use by PES by country/region and area of PES activity

	Understanding jobseeker needs & providing targeted support				Labour market matching & employer services					Administrative activities & knowledge generation		
	Providing information to clients via chatbots	Identifying jobseeker needs via profiling tools	Career management & job-search orientation	Targeting ALMPs	Matching jobseekers with vacancies	Aiding the design of job postings	Detecting any illegalities in vacancy postings	Diagnosis of hard to fill vacancies	Predicting recruitment likelihood	Benefit administration, including fraud detection	Generating labour market information	Monitoring & evaluating ALMPS
Austria			X									
Belgium, Flanders		X	X		X	X					X	
Belgium, Wallonia		X				X						
Canada					X	X	X					X
Denmark			X									
Estonia		X										X
Finland	X				X	X						
France	X	X	X	X	X		X	X	X			
Germany										X	X	
Greece	X											
Iceland	X											
Israel					X							
Korea			X		X							
Lithuania	X	X										
Luxembourg						X					X	
Mexico					X							
Norway	X					X						
Portugal	X	X										
Spain						X						
Sweden			X		X		X			X	X	
Türkiye		X										

Note: PES locations not using AI are not included in the table. PES tools planned or under development are not counted in these statistics, only solutions live or implemented at the time of writing.
Source: Responses to OECD questionnaire on digitalisation and AI use in PES.

Annex B. Technical Annex

The impact of AI on Natural Language Processing techniques

Natural language processing (NLP) aims at enabling computers to understand human language (i.e. natural language) and to generate human-like text. NLP has various practical applications, making it possible to automate certain tasks such as: extracting relevant information from documents; summarising, classifying, and clustering documents; answering end-user questions; and translating documents (Lauriola, Lavelli and Aiolli, 2022[116]; Zhang, Zhao and Wang, 2020[117]). In the context of public employment services, NLP is employed for two main purposes:

- To improve information exchanges with jobseekers and employers, by using smart virtual assistants that, on the one hand, help PES customers find the information they need regarding their rights and obligations vis-à-vis the PES (question-answering tools), and on the other hand, help PES agents collect the information they need to best serve their customers (i.e. information-retrieval tools)
- To support and enhance the matching process between jobseekers and job vacancies, by identifying similarities between CVs and vacancy descriptions (i.e. document-classification and document-clustering tools)

NLP uses methods from various disciplines, such as linguistics, computer science, data science and artificial intelligence (Kavlakoglu, 2020[118]). Although NLP largely predates the development of AI, recent advances in Deep Learning models (notably, Deep Neural Network models) have considerably boost the performance of existing applications, while also paving the way for new types of NLP applications (Lauriola, Lavelli and Aiolli, 2022[116]). In its early stages, NLP was primary used to develop translation tools and chatbots, drawing on hand-written rules to establish links between words in different languages or between questions and answers. To take an example, one the first chat bot (called ELIZA) was developed in the mid-1960s' by MIT researcher J. Weizenbaum, who summarised its functioning as:

> *"The central issue is clearly one of text manipulation, and at the heart of that issue is the concept of the transformation rule […] associated with certain keywords. The mechanisms subsumed under the slogan "transformation rule" are a number of SPLIT functions which serve to (1) decompose a data string according to certain criteria, hence to test the string as to whether it satisfies these criteria or not, and (2) to reassemble a decomposed string according to certain assembly specifications" (Weizenbaum, 1966[119]).*

While the basic mechanisms have not changed much, Deep Neural Network (DNN) models make it possible to generate transformation rules automatically and to refine them substantially, thereby enabling computers to read and comprehend whole documents, not just keywords. Like with their predecessors, advanced NLP techniques consists of two distinct but closely related subfields (Kavlakoglu, 2020[118]): Natural language understanding (NLU) that focuses on computer reading comprehension, and Natural Language Generation (NLG) that enables computers to write human-like text.

Broadly speaking, NLU analyses the meaning of words, their frequency of occurrence, and the structure of sentences to determine the general subject-matter of a text. The most advanced NLU techniques – known as Contextualised Word Embedding (CWE) techniques – identify a complex set of relationships between all words in a given text (Selva Birunda and Kanniga Devi, 2021[120]). This allows for taking into account the context in which individual words appear in order to get a better sense of their intended meaning. The basic premise of this approach is that words with similar or related meanings are grouped together within the text (Wollacott, 2023[121]). This hypothesis was first suggested by British linguist J.R. Firth in a seminal paper published in 1957, where the author summarised the idea as: "You shall know a word by the company it keeps." (Firth, 1957[122]).

Following this approach, CWE models analyse the distribution of words throughout texts to produce a mathematical representation of each word, which consists of their distributional properties (Selva Birunda and Kanniga Devi, 2021[120]).[8] In this way, unstructured data (i.e. words, sentences, paragraphs and, ultimately, whole documents) are converted into structured data that a computer can "understand". Since these structured data are produced based on both semantical and contextual analyses of words and sentences, the same word used in two different contexts will have two different mathematical representations. This also means that two texts dealing with the same topic – therefore having many words in common – will have two different mathematical representations if they convey different ideas or express different views about that topic.

For its part, NLG is the process of producing a human-like text that answers a specific user's query. NLG comprises four main steps:

- Building a so-called knowledge database that contains the information needed to answer various queries. This database consists of structured data, which have been produced using NLU techniques to encode the information contained in various documents.
- Converting user queries into structured data, using NLU techniques.
- Building a matching algorithm that selects the right answer to a given query. In cases where several potential answers are found, this step may require an iterative process, whereby the algorithm asks the user to better specify his/her query. This process enables the algorithm to gather the contextual information needed for selecting the most relevant answer.
- Converting the selected subset of structured data into a human-like text. The complexity of this task varies greatly according to the intended purpose of the NLG application. For example, the task will be relatively simple in the case of smart bots designed to provide information about the range of services or products an organisation offers to its customers. But in the case of applications that aim to address a wide range of questions, touching upon a variety of topics and issues, it becomes much more complex to formulate a relevant answer. For example, this may require summarising the different stances and ideas that emerge from various sources/documents on a given issue.

Summing up, NLG applications heavily rely on NLU techniques, which are used to feed their knowledge database and to process (e.g. analyse, compare) the structured information this database contains. Above and beyond technical considerations, the quality (e.g. accuracy, relevance, fairness) of the outputs produced by NLG applications strongly depend on the quality of the information sources that were selected for the computer to read, comprehend, and process.

While DNN models have considerably boosted the performance of NLP applications and expand their functionalities, these models are also bringing about a number of issues that need to be addressed. In particular, Lauriola et al. (2022[116]) underline two major areas of concern:

- New NLP applications are black-box tools since the way they operate to generate outputs is hardly interpretable. This lack of interpretability is probably the most visible and newsworthy issue, which researchers in the field of AI are starting to investigate. For example, it has been the main topic of

[8] The mathematical representation of a given word is a set of numerical values, namely a vector, measuring the "distance" between that word and the other words used in the text. It follows that the mathematical representation of the corresponding text is a complex combination of vectors.

several recent workshops aiming to better understand the inner workings of DNN models, by taking inspirations from linguistics, neuroscience, psychology, and machine learning.

- DNN models that fuel new NLP applications have high computational costs and require specialised and expensive hardware. Moreover, the computational costs of DNN models grow rapidly as more information is encoded and added to their knowledge database. As they are becoming increasingly used, the carbon footprint of training such models is also growing exponentially. Consequently, a considerable body of research is now exploring ways to reduce the computational costs of advanced NLP applications.

Measuring the performance of profiling models

Profiling tools aim to categorise jobseekers according to their employment prospects, with the goal of setting priorities for caseworkers' interventions. These tools rely on two building blocks:

- A prediction model, which estimates the employability of jobseekers. Based on historical data (i.e. training data), the modelling exercise involves identifying both, a relevant set of predictor variables, and a relevant functional form that best approximates the true relationship between those variables and the outcome variable of interest (Traverso et al., 2019[58]; Dankers et al., 2019[59]). This requires rich datasets that contain a wealth of information on jobseekers' characteristics, behaviours, and labour market outcomes. Both data quality and modelling choices determine the performance of a prediction model, whether AI-augmented or not.
- A set of thresholds, which classify jobseekers in groups according to estimated employability. Groups with lowest employment probabilities are contacted first and are offered more intensive support. Hence, the choice of thresholds is a policy choice, not a modelling one, but it can affect the performance of the overall profiling approach (cf. infra).

The performance of a profiling tool can be assessed using various metrics. As underlined by Dankers et al. (2019[59]), there is no general best performance metric for model evaluation. This strongly depends on the underlying data, as well as on the intended application of the model. For the sake of simplicity, the remainder of this discussion will focus on a simplified profiling tool, which uses a single threshold to classify jobseekers in two groups: those at risk of long-term unemployment (LTU), on the one hand, and job-ready individuals, on the other. The performance metrics for assessing this tool are described in Table A B.1.

Table A B.1. Performance metrics of profiling tools

	Predictions		**Performance metrics**
Observations	*High risk (HR)*	*Low risk (LR)*	Accuracy = (True HR + True LR) / N
High risk (p)	True HR	**False** LR	Precision = True HR / (True HR + False HR)
Low risk (1-p)	**False** HR	True LR	Sensitivity (or Recall) = True HR / (True HR + False LR)
N= total number of observations			Specificity = True LR / (True LR + False HR)
p = observed proportion of high-risk jobseekers			It follows that: Accuracy = p x Sensitivity + (1-p) x Specificity

Source: Dankers et al. (2019[59]), Table 8.4.

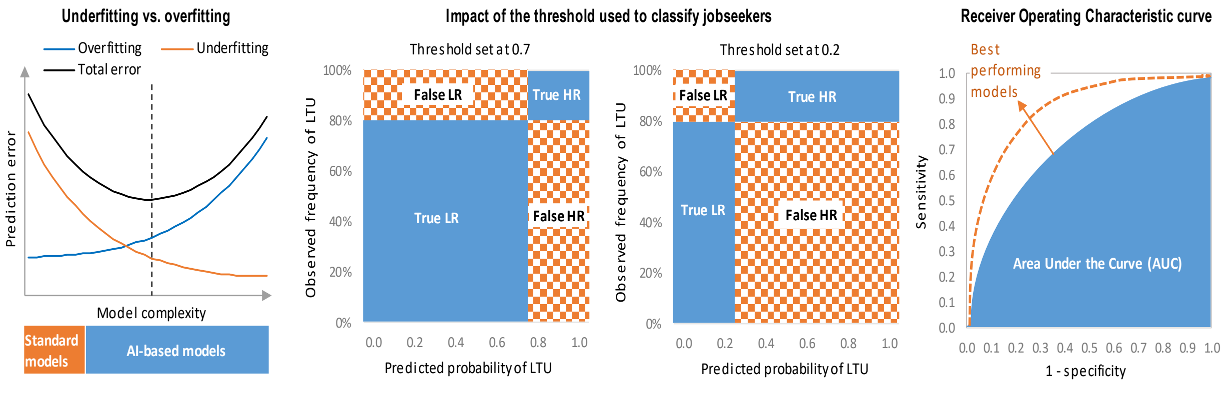
These metrics can be divided into two main categories according to their level of generality:

- Model accuracy and model precision. The former refers to the proportion of individuals correctly labelled as high- or low-risk jobseekers amongst all jobseekers, whereas the latter refers to the proportion of jobseekers correctly labelled as being at high risk of LTU amongst all high-risk predictions made by the model. Model accuracy is the broadest and most widely used metric in the literature, as it provides an overall assessment of the model's predictive power. However, this performance metric lacks reliability when the target group represents a small share of the total population. For example, if only 10% of jobseekers are facing a high risk of LTU, a profiling model that would fail to identify any of them will still achieve an accuracy level of 90% whereas the precision level will be close to zero. In that case, the relevant metric for assessing the overall predictive power of the model is the precision level.

- Model sensitivity and model specificity. The former measures the proportion of high-risk jobseekers that the model successfully identifies, while the later provides the same kind of information for low-risk jobseekers. Model sensitivity is a key determinant of policy inclusiveness: the higher the model sensitivity, the less likely it is for hard-to-employ people to be left without adequate reemployment support. Model specificity is an indicator of cost-effectiveness: the higher the model specificity, the less likely it is for job-ready individuals to receive support that they do not need.

AI algorithms have the potential to improve the overall predictive power of profiling models, as they draw on more advanced optimisation techniques to make predictions (Dankers et al., 2019[59]). Profiling tools based on standard regression techniques have limited degrees of freedom, which tends to limit their ability to closely follow the underlying patterns in the training dataset. This in turn reduces their predictive power (underfitting). Since AI-based tools are much more flexible, they can capture complex relationships between variables and tend to fit the training data much better. But in doing so, the model may also start to follow the noise in the data, thereby accounting for too much variance in the training dataset. As a result, the model will achieve very good performance on the training dataset, but its predictive power could be much lower for subsequent datasets that include more recent data, even if the latter show slightly different patterns. As sketched out in Figure A B.1, model complexity tends to reduce underfitting but has the opposite effect on overfitting. Therefore, finding the optimal trade-off between the two is a key factor to achieve higher levels of accuracy or precision (i.e. to minimise prediction errors). AI algorithms could get closer to this optimal solution since they have more degrees of freedom to do this. Yet, this requires careful adjustment and calibration (to avoid overfitting issues).

Figure A B.1. Key determinants of model performance



Note: HR (resp. LR) refers to jobseekers at high risk (resp. low risk) of LTU.
Source: Dankers et al. (2019[59]), Figures 8.3, 8.4 and 8.5.

Figure A B.1 also illustrates (in a very simplistic way) the influence of the threshold used to classify jobseekers on model accuracy, which is represented by the blue areas. Setting up a very low threshold for labelling jobseekers as being at high risk of LTU makes it easier for the model to identify those effectively facing strong labour market difficulties (true HR). However, this also increases the proportion of job-ready individuals who are wrongly labelled as high-risk jobseekers (false HR), thereby affecting negatively the overall predictive power of the model (accuracy and precision). But first and foremost, the threshold used to round model predictions to 0 (low risk) or 1 (high risk) is a strong determinant of model sensitivity and model specificity. A trade-off exists between these two metrics: lowering the threshold used to define the high-risk group(s) increases the model sensitivity but decrease its specificity (and vice versa). The choice of thresholds therefore reflects a policy trade-off between inclusiveness and cost-effectiveness, at least to some extent. For a given threshold, the only way to improve both metrics is to increase the overall predictive power of the model. And for a given accuracy or precision level, there are multiple combinations of sensitivity and specificity.

The so-called Receiver Operating Characteristic (ROC) curve enables to visualise the impact of different thresholds on model sensitivity and model specificity (Figure 2). The curve displays the rate of true “high-risk” predictions (i.e. sensitivity) versus the rate of false “high-risk” predictions (i.e. 1-specificity) for all thresholds that can be used to classify jobseekers in two groups according to predicted risk of LTU. The ROC curve therefore allows for setting up the threshold that corresponds to the chosen trade-off between policy inclusiveness and cost-efficiency. Moreover, the Area Under the Curve (AUC) is a widely used metric for assessing the overall performance of a prediction model and to compare different models (Dankers et al., 2019[59]). Powerful models have higher ROC curves (that approach the upper left corner of the chart), indicating that they can achieve high sensitivity and high specificity simultaneously, and therefore have larger AUC values.