Algorithm Profiling in Public Employment Services (PES)

Reporting Standards Policy Brief

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Hecat
Disruptive Technologies Supporting
Labour Market Decision Making

PES and Algorithm Profiling

Introduction to PES Algorithms

In an age where technology-first approaches are seen as increasingly viable, the datafication of public services is undertaken as a means of digitalising, modernising, and providing enhanced service efficiency (OECD, 2019). Governments, in particular, see the increased benefits and value of adopting such data-driven technologies as entities that possess large arrays of valuable historical and current datasets (Redden, 2018). Especially prevalent is the increased adoption of algorithms, here defined as an unambiguous procedure for solving a problem (Griffin et al., 2021). This is usually done via a computer system through mathematical modelling. Applications of algorithms are now visible across sectors, and with continued adoption, such modelling methods grow in both use and power.

The use of automated-decision systems in employment services isn't a new phenomenon. In many countries, datafied welfare provisions emerged during the Great Depression and World War Two (Dencik, 2022). Here, gathering information on citizens and monitoring their activities was an early function of resource allocation in a dawning welfare state. Thus, began a long-term reliance on citizen data collection, used to fuel public service allocation. The spread of digitalisation and the enhancement of technology, in particular, has played a key role in the adoption of advancing technologies such as algorithms in PES (OECD, 2019; 2022). As mass citizen data collection intensifies and we enter a "datafied state", profiling algorithms, such as those employed by PES, play a bigger role in social service provision globally (Dencik, 2022).

PES Profiling Algorithms

While most Public Employment Services (PES) adopt some basis of algorithmic system, recent advancements in data availability, the sophistication of Machine Learning (ML) techniques, and a new willingness to adopt automated technologies within public services have seen the rise in profiling tools. (Desiere et al., 2019). Here, profiling is described as the use of automated processes of personal data to predict or analyse individuals' characteristics (Data Protection Working Party, 2017). Algorithmic profiling is one of the most long-term adoptions of AI within PES, enacted in countries such as Australia, Canada, the US, and the UK since the late 1990s (McGuiness et al., 2022).

PES globally are increasingly adopting back-end algorithm functionality as 'value-added' information points to improve service provision. Automated statistical decision profiling algorithms (ASPAs) play an increasingly prevalent role in PES, providing automated categorisation of jobseekers. Here, job seekers are typically classified into either 'high-risk" or "low-risk" categories, based on their probability of entering Long Term Unemployment (LTU). Such tools are often additionally used to predict the likelihood of exiting the PES system over a given period, usually based on data given within entry to the PES system. Here, decision-making, based on machine discernment is replacing the judgment of PES employees and replacing both rule-based and case-worker-led profiling activities.

Adoption of Profiling Algorithms in PES

Today, a range of research notes a growing reliance on algorithm-based decision-making across governmental entities, including PES (OECD, 2022). The role of automated decision systems within public services is increasingly recognised; enacted to provide advanced effectiveness in terms of time and cost saving while complimenting human-centric activities (Desiere et al., 2019). The Covid-19 Pandemic has been a particularly rife breathing ground for the digitalisation of PES, with algorithm-powered functions moving to a more widespread role in employment services globally (Dencik, 2022). Such digital enactment became increasingly essential to maintain service provision while global lockdowns limited public mobilisation. Thus, the Pandemic has provided optimum conditions for accelerating such modelling capabilities within PES (OECD, 2022).

Profiling algorithm efficiencies are primarily contingent on statistical accuracy and the ability to correctly recognise those at risk of LTU, without bias, which needs advanced exploration in practice (Gallagher and Griffin, 2022; Desiere and Struven, 2021). Increasingly, calls for advanced transparency and openness regarding PES' increased use of algorithms recognise the potential social and ethical issues associated with these tools. Indeed, as algorithm profiling becomes a new norm within PES, there is an expanding need to examine the ramifications of such technologies in front-facing public services. An increased need to balance efficiency with equality becomes apparent for PES as further examination of statistical profiling tools emerges (Desiere and Struyven, 2020).

Though efforts have been made to provide standardisation recommendations in pursuit of worthy AI use, little has been explored in relation to Public Employment Systems (PES). While the OECD has made some effort in offering considerations here, much more work is needed to avoid potential risks and misuse of these technologies in PES. Utilising available research, previous standardising efforts and knowledge from case examples, this policy brief seek to present recommendations for reporting standards in regard to profiling algorithm used in PES.

HECAT and Profiling Algorithms in PES

The aim of the HECAT project is to expand thinking beyond black-boxed, profiling algorithms in PES. Work within this project has brought a range of minds together to consider how such tools can be used to work with PES stakeholders. To date, HECAT deliverables have explored topics such as; "state of the art" first generation PES algorithms adopted in Ireland, Austria, Croatia, France and Australia, data sources and data protection for algorithm development and selecting the suitable job quality items in profiling and job matching algorithms. Findings of such studies inspire the need for advanced considered of reporting standards for profiling algorithms in PES as examined here. HECAT is funded under the European Union's Horizon 2020 research and innovation program under grant No. 870702.

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Case Examples

In evaluating current adoption, we first explore active examples of algorithm-based tools used in global PES as a means of noting best practises and key oppertunities.

Ireland

The Irish PEX model is used to predict the risk of LTU and apply support to those profiled within the highest risk categories. Data comes from a demographic-based survey issued to all who register for PES. While admirable, PEX's data input leaves little room for personalisation based on individual cases. Additionally, in a 2014 review conducted by ERSI, the model's developers found that the score produced by PEX was unlikely to predict the probability of LTU. Rather, it measures relative labour market disadvantage. This model has recently been updated to reduce the number of variables used in modelling.

Estonia

Estonian PES utilise an algorithm profiling tool, similar to Ireland's PEX, capable of segmenting job seekers based on their capabilities to re-integrate into the labour market (OECD, 2022). Here, full discretion is given to caseworkers, who are trained appropriately to advance their service offerings (Desiere et al., 2019). Algorithms are additionally adopted by Estonia's Unemployment Insurance Fund (EUIF) in offering automated functionality capable of authenticating jobseekers' welfare applications via various databases (Dembla, 2020). Automated decisions on job seeker entitlements include the rate of unemployment pay and length of payment (Raudla, 2020). This example highlights the benefits of a combined approach; using caseworker intercession as a means of evaluating algorithm categorisation.

Belgium

Similar systems have been adopted in the Flanders region of Belgium, where VDAB, local PES, adopt a statistical approach to predict job proximity and assist intervention (OECD, 2022). The job seeker is first assigned a profiling score based on their likelihood of gaining employment in the next six months by Next Steps, the current model. This is assigned after 35 days of registering with PES (McGuiness et al., 2022). Jobseekers are assigned into one of four groups, similar to Irish PEX, with those at the highest risk of LTU met first by PES. (PES Network, 2018). Data used within this modelling is from several sources; this includes socio-economic characteristics, job history, caseworker interaction insights, and, most interestingly, click data accessed from VDAB's job posting website (McGuiness et al., 2022). Further, this algorithm is designed in a manner where regular updating and iteration are encouraged, and recalibration of the model is automated (Desiere et al., 2018).

Poland

The Polish Government's Publiczne Służby Zatrudnienia (PSZ) is one example of an unsuccessful deployment. Enacted in 2014, the PSZ was a national scoring and profiling system for the unemployed, determining assistance based on three assigned categories (Redden et al., 2022). Following such enactment, major criticism was received from civil society, national data protection authorities, and the Human Rights Commissioner concerning the lack of transparency, oversight, and alleged unregulated decision-making of this system. In addition, data protection infringements were also noted. Following an official review, the PSZ was deemed to breach Poland's constitution, and its use was ended in 2019. Such an example proves that data transparency should not be an oversight in PES algorithms and must be a key factor in reporting standards.

Sweden

The Swedish Public Employment Services were also forced to abandon their automated welfare payment system, which was used to ensure those benefiting from unemployment payments were reaching their obligations. An internal report noted that between 10-15% of decisions made by this system needed to be revised, failing to generate key actions as required (Redden et al., 2022). As such, the system was retired in 2018. This case highlights the importance of regular audits on such systems, which should be factored into PES algorithm adoption. Further, the need for more oversight regarding such automation is noted in reporting on this Swedish application. In many reported systems that had limited longevity, there are similar cases of push-back against the removal of human-centred decision-making as a cause for their removal.

Austria

The Arbeitsmarktchancen-Assistenz-System (AMAS) was a program developed to assist caseworkers in assessing jobseekers' claims. Using a predictive system based on rules, statistics, and caseworker-based profiling, jobseekers were categorised based on the similarity of characteristics (Desiere et al., 2019). This system worked on assumptive principles, assuming similarities among those who shared characteristics. Following testing, the Austrian Data Protection Authority blocked the country-wide rollout of this tool (Szigetvari 2020). Publicly, this algorithm has received major criticism for its lack of transparency, with the Austrian Government only publishing a minute part of the overall algorithms' makeup (Allhutter et al., 2020). In addition, this system has been criticised for gendered biases, the use of sensitive information, and the potential for amplifying inequalities in the labour market (Allhutter et al., 2020). The danger of assumptive practices within PES profiling algorithms is recognised within this Austrian example.

The Need For a Reporting Standard

Data-driven AI systems, including profiling algorithms, are often shrouded as black box and esoteric (IBM, 2020; Gasser and Almeida, 2017). In this, the processes and complexities of such models often hold much contention for the general public. While regulations such as GDPR have increased public conversations on personal data and its ethics, significant public unease and miseducation regarding data and its use within public services have become increasingly apparent. As digitalisation is expected to produce actively informed “digital citizens”, there is a worry that such a concept has not fully translated into everyday life (Dencik, 2019). This has particular ramifications for people engaged in PES systems who may not be actively aware of the effects of their personal data being processed through such autonomous and algorithm-powered functionalities.

The Human Factor of Profiling Algorithms

While digitalisation champions the adoption of new and advancing technologies, the person's role beyond the statistical model still needs to be highly prioritised in system design and deployment. To ensure that profiling algorithms benefit all, design protocols should be human-centric and “ethically aligned” (IEEE, 2020). In this, human well-being needs to be the priority of all system design decisions, and technology choices should be made with the ethics of the end subjects in mind. For profiling algorithms to be meaningful in PES, systems must offer more significant benefits than costs to stakeholders and, to be justifiable in application, should benefit as many service users as possible (Dawson et al., 2019). Human welfare and the empowerment of the end user need to be a clear goal of such PES systems, providing a compliment to the work of case workers for the betterment of PES offerings.

Additionally, the voices of all stakeholders must be heard where profiling algorithms are concerned. This should include a range of interests from the end user, i.e. the jobseeker to the technically proficient algorithm expert. While algorithms can be programmed and adapted to a certain extent, a further core problem exists in encompassing the "human-ness" where such machines are involved in decision-making (Redden, 2018). When developing algorithms for PES, the dehumanisation of the service must, as such, be factored in and considered in all aspects of service provision.

Low Trust and the Data Subject

GDPR’s enactment has not been the sole cause of growing awareness of data privacy. For evidence of this, one must look at recent news stories featuring rising evidence of data breaches and similar scandals daily. For the first time, the extent of big data systems and their application in citizens' daily lives has become a public talking point, spurred by mainstream media reporting in a post-Cambridge Analytica Scandal era (Dencik et al., 2018). Combined with an increased public awareness of the power of data and privacy, trust in data-driven systems is a contentious subject within the public sphere (Dencik et al., 2018).

Trust in such technology is further affected by a need for more transparency and/or open communication about the nature of the technology at hand. Where automated decision-making systems are deployed, there is rarely a clear distinction regarding related processes and resulting cause and effect (Alan Turing Institute, 2021). This is especially clear in PES, where the general public, who are users of such systems, are rarely aware of the use of algorithms in decision-making (Desiere et al., 2019). In this regard, it is imperative to advocate for clear and open communication regarding profiling algorithm enactment in maintaining public trust in PES.

Risk of Data Misuse

With the extended use of such systems, there is increased precedence for misuse. This should not be taken lightly. When misuse occurs, there is a potentially potent effect on individuals, groups, and their communities. Individual effects can negatively impact a person's ability to participate in society and go so far as to cause massive detriment to personal lives.

To date, little regulation exists regarding data used within such PES systems, and no clear reporting standards provide best practice guidelines in this regard. Such unregulated profiling allows the margin of potential misuse to grow substantially. For example, research recognises an over-reliance on data from particular parts of populations, allowing for a disproportioned representation of groups already at risk within these systems (Dencik et al., 2019). Additionally, data is often aggravated from multiple unsuited sources, and these incremental approaches allow for a "people like you" classification instigating increased stigmatisation and stereotyping while labelling citizens based on incomplete views of their social context (Big Brother Watch, 2018).

Further, where no clear digital reporting standards are available, there is a risk that datasets used in modelling are incomplete, mismanaged or error-prone (Allhutter et al., 2020). Data scoring is used to predict behaviour, with the incorrect assumption that objective data flows through such systems (Van Dijck, 2014). This, however, is only sometimes the case as much data used to train algorithms have not been collected for this purpose, Often, these data are incorrect or unsuitable to act as training data in such applications (Allhutter et al., 2020).

> **Public service algorithms should not be allowed to become a vessel of social exclusion (AI for Humanity, 2018).**

Consideration for Accuracy

For algorithms to have their desired benefit within PES, accuracy must be a key component of their design and usage. However, significant work on labour market discrimination and studies focusing on AI and ML technology within employment systems recognise an “inherent tension between model accuracy and discrimination” (Kern et al., 2021; Desiere et al., 2019, p. 7).

Accuracy

the proportion of individuals out of the full data set who are correctly predicted based on a statistical measure (Allhutter et al., 2020).

While a range of accuracy rates are reported across the OECD region, few fully detail methodology in reporting. In providing full transparency, this should include a detailed method statement and a significant effort to explain what such accuracy scoring actually means (Griffin et al., 2021). Without these, such reported ‘accuracy figures’ are unsubstantiated; to date, many such examples are often 'forecast accuracy'. Such figures may not fully capture all variables required for substantial accuracy figures (Gallagher and Griffin, 2022).

In aptly reporting accuracy, data science concepts need to be adopted. This includes considerations for error, sensitivity, specificity, and, indeed, accuracy. There are additionally false positives and false negatives to contend with, which affect such modelling based on variable sensitivities and specifies of the model. Much current reporting of accuracy figures does not capture the extent to which models fail to identify those at high risk (Griffin et al., 2021). Such misclassification has the potential to cause real-world harm for jobseekers, particularly for those needed additional assistance who receive a lower-risk score in error.

Potential for Biases

Research to date dictates that at-risk communities are the prime victims of inherited biases based on skewed data and understandings enveloped in profiling models (Gandy, 2010). Algorithmic profiling inherently damages such groups when unregulated and unchecked. In a prime example of the dangers of algorithm biases, the Universal Social Credit (USC) system in the UK is often noted. This program provided a single system capable of processing unemployment claims via entirely digital means (Dencik, 2022). Such a system was expected to revolutionise and reform traditional social welfare processes through digitalisation. However, the reality was highly different and, indeed, has extreme effects on 'at-risk' communities and individuals across its catchment area. Under investigation by UN Special Rapporteur on extreme poverty and human rights Philip Alston, USC was recognized as having contributed to a range of inequalities and infringements on human and civil rights and has had particularly negative effects on social protection (OHCHR, 2018).

The USC has particularly been critiqued for violating lone mothers and those already living below the poverty line, enhancing pre-existing stereotypes and deepening the social divide even further (Carey and Bell, 2022). Further effects of similar profiling efforts include financial and societal harms, through which an individual’s ability to participate in society can be greatly harmed by the outcome of skewed profiling (Dencik, 2022). Indeed, this calls for further regulation of algorithmic systems within PES, with reporting standards that openly account for bias potential and mitigation. Additional biases need to be accounted for in algorithm design as well as consideration for human biases that can occur in algorithm deployment.

Towards a Reporting Standard

Although algorithms are at a stage of rapid development, this technology is still emergent (Gasser and Almeida, 2017). Breakthroughs are often uncovered, and systems must be designed flexibly to ensure they can develop with the times (IBM, 2020). Looking towards expert voices to guide profiling algorithm design and deployment is vital. In this, leading reporting standards in the technical development of AI which should influence PES profiling algorithm development are explored.

The Institute of Electronic and Electrical Engineers (IEEE)

The IEEE produces the IEEE P7000 series, the first global standardisation process for addressing ethical concerns in system design. These cover the development of autonomous technologies (7001), data privacy processes (7002), and algorithmic bias considerations (7003). The IEEE, in particular, advocates for the involvement of those with technical expertise in AI and algorithm rollout and "ethically aligned design", which prioritises human well-being where autonomous technology are concerned

For PES, aligning with the IEEE P7000 series would mean a degree of standardisation with global, ethically aligned best practices. It would also allow for increased transparency and the collobration of a range of stakeholder voices

European Commission’s High-Level Expert Group

The Assessment List for Trustworthy AI (ALTAI) is an important tool for the self-assessment of automated systems and, as such, provides insights for algorithm reporting standards for PES. This tool, designed by the High-Level Expert Group on AI, is intended to provide a flexible assessment of an AI system’s trustworthiness, considering the sector of operation (ALTAI, 2020). Using a series of questions, this tool facilitates the consideration of risks an AI system could generate and the best practices in mitigating such potential risks while still using the system for benefit. The key benefits of using this tool lie in the engagement it gives multiple stakeholders in evaluating such AI systems' organisational, ethical, societal, and political impact. Therefore, the ALTAI should be deployed as a questioning exercise for all entities considering implementing algorithms, guiding internal guidelines, and system governance processes. It can additionally be used as an auditing tool by PES already using such tools.

The Organisation for Economic Co-Operation and Development (OECD)

The Organisation for Economic Co-Operation and Development (OECD) is similarly invested in enacting transparent and ethical AI. Adopting a council on AI, the OECD has, in particular, made considerable leeway in classifying AI systems.

The OECD's consideration for digitalisation in PES is of particular interest in this context, publishing a recent policy brief on the use of digital services to connect people with jobs (OECD, 2022). This brief note the benefits of algorithm adoption in PES while further recognising the need for awareness of potential limitations and risks associated with such technologies. The OECD calls for active monitoring and evaluation activities for such technologies in PES to maintain ethical use of these tools for all involved. Of high importance in this report is consideration for the range of digital skills recognised within PES users. Allowances must be made for those lacking digital prowess, including vulnerable groups who may have considerable access issues where digital technology is concerned. Again, this feeds into reporting standards through the recognition that the needs and voices of all stakeholders need to be aligned in utilisation of algorithmic processes in PES. Further, it highlights a clear need for open and accessible education that reaches multiple stakeholder groups and levels, intending to increase knowledge and awareness of these digital technologies and how they affect PES decision-making.

Additional Standards and Regulations of Note:

GDPR

The General Data Protection Regulations (GDPR) gives everyday citizens a basis to challenge decisions related to their own lives based on personal data. GDPR has also enacted a range of restrictions that may benefit an individual's personal data rights where profiling Algorithms are concerned. Articles 13-15 and 22 are especially of note.

European Statistical Code of Practise

These standards ensure that "Procedures are in place to ensure that standard concepts, definitions, classifications and other types of standards are consistently applied throughout the statistical authority" (EU, p. 13.) This is led by 15 core principals, including; a mandate for data collection and access to data, commitment to quality, sound methodology, appropriate statistical procedures and accuracy and reliability.

The Algorithm Transparency Reporting Standard Hub - UK Example

This information point provides knowledge for public sector organisations on remaining clear and open about their use of algorithm tools. This includes a template for Algorithm Transparency Recording Standard which includes consideration for metadata and title information.

Requirements for PES Profiling Algorithm Reporting Standards

Based on research from the HECAT project, additional exploration of the current state of profiling algorithms in PES, case examples, and currently available standards, the following should be included in PES Profiling Algortihim Reporting Standards

Design and Deployment of PES Profiling

- Documentation of potential for biases within:
  - Model
  - Dataset
  - Training Data
- Preparation of risk statement evaluating the risk of algorithm modelling for data subjects
- Outline of risk mitigation process
- Outline of bias mitigation process

Accuracy of PES Profiling Algorithms

- Outline of process for maintaining accuracy
- Naming of accuracy measure
- Outline standards of statistical accuracy reporting
- Outline process for reporting accuracy publicly

Transparency of PES Profiling Algorithms

- Contingency for transparent reporting
- Recognition of “non-informed” end use

Bias and Risk Mitigation in PES Profiling Algorithms

- Consideration for stakeholder engagement, pre-deployment and continuously
- Consideration for expert engagement, pre-deployment, and continuously
- Consideration for de-humanisation of PES services in algorithm design and development

Processes

- Plans for:
  - Internal audits
  - External Audits

- Plans for:
  - algorithm training
  - algorithm maintenance
  - algorithm updates/iteration
  - auditing (both internal and external)

- Complaints and redress procedures

- Process for FOI and data-requests

- Accessibility statement

- Outline of any further safeguarding procedures

Data Used in PES Profiling Algorithms

- Methodology statements on
  - Precision on variables used and weighting
  - Precision on training data and revision/learning approach
  - Precision on imposed capacity constraints
  - Reporting on disaggregated false positive and false negative data
  - Formal post-hoc/outrun accuracy

- Documentation of data source
  - Initially
  - Continuously

- Detailing for the process for ensuring data is representative

- Documentation of data aggravation and data minimisation

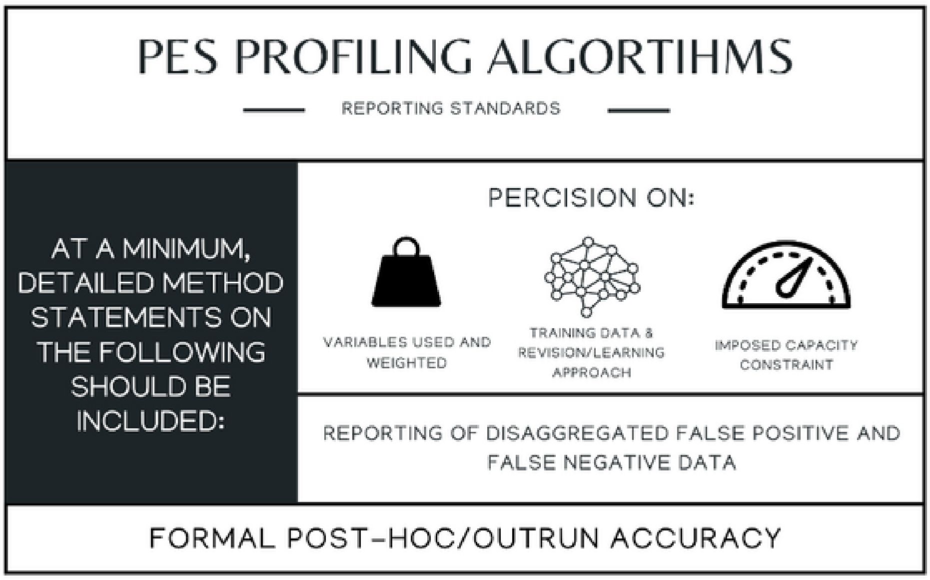
- Outline of data management practices

- Outline of alignment with data regulations

Minimum Reporting Standard

In summating the above considerations on reporting standards that are necessary for PES profiling algorithms, a minimum standard is additionally presented as an alternative here. It is recognised that in providing transparency, all reporting may not be readily available initially. However, efforts should also be made to include the recommended elements across reporting efforts at all times.

Though the ideal scenario would see extensively transparent and open reporting on such modelling via the elements mentioned previously, below are the very minimum elements that should be made visible to all stakeholders where profiling algorithms are concerned. They are summarised within a PES Profiling Algorithm Reporting Label.



Towards an IOS Standard

Though there is great merit in aligning automated systems with current best practices and industry guidelines, there is also remit for the development of an ISO standard in regards PES enactment of algorithm profiling. ISO standards are globally aligned best practices, agreed upon by leading experts and followed internationally (ISO, 2022). There are over 24,000 standards across sectors, with an array covering AI and automated technologies introduced in the past years. The most recently applicable ISO/IEC TR 24028:2020 provides "practical solutions to improve the trustworthiness of systems providing or using artificial intelligence: (ISO, 2020). Especially viable here and fitting with this report to date is consideration for stakeholder engagement, platform auditing, and addressing common AI and algorithm issues including bias mitigation (ISO, 2020). However, despite its usefulness in exacting standards for PES applications, it is not enacted with situational and variable considerations that are public-sector specific. As such, evidence exists for such a PES-focused standard through the examination of current automated system applications, guiding principles, legislative and industrial standards, and the exploration of the need for reporting standards.

ISO standards are unique in that their very users create them. As such, to propose an automated system proposal with a PES focus, there is a need to convene an expert group with a range of skills and knowledge on the varying encompassing elements of profiling algorithms within PES. Based on this report, there is enough evidence for the need for such a standard with a specific PES focus.

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About HECAT

HECAT is a research consortium carefully brought together to achieve the mammoth task of developing an ethical algorithmic based platform to assist Public Employment Services (PES) and Unemployed people in making informed, transparent and integrated decisions.

The research aims to use sociologically and anthropological insight into unemployment and the labour market to guide technical developers of the back-end algorithms and front-end user interface with the objective of creating an ethical and equal platform. Consortium partners are drawn from AHSS and STEM disciplines, academics, NGOs and PES.

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