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Statistical profiling in public employment services

AN INTERNATIONAL COMPARISON

Sam Desiere, Kristine Langenbucher, Ludo Struyven

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Statistical Profiling in Public Employment Services: An international comparison

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Authorised for publication by Stefano Scarpetta, Director, Directorate for Employment, Labour and Social Affairs

Sam Desiere – sam.desiere@kuleuven.be
Kristine Langenbucher, – Tel +33 1 45 24 18 37 – Kristine.Langenbucher@oecd.org
Ludo Struyven – ludo.struyven@kuleuven.be

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Summary

Profiling tools help to deliver employment services more efficiently. They can ensure that more costly, intensive services are targeted at jobseekers most at risk of becoming long-term unemployed. Moreover, the detailed information on the employment barriers facing jobseekers obtained through the profiling process can be used to tailor services more closely to their individual needs. While other forms of profiling exist, the focus here is on statistical profiling, which makes use of statistical models to predict jobseekers' likelihood of becoming long-term unemployed. New data sources such as "click data" on job searches, as well as advanced machine learning techniques are increasingly used in profiling tools in addition to administrative and survey data. Statistical profiling tools are more widespread now, due to progress in data management and analysis as well as greater pressure for improving the cost-effectiveness of public spending. Fiscal constraints, the rapid surge in jobseekers during the global financial crisis, a broadening of the target groups of employment services to the "inactive" and the continued focus on "activation" have also led to new interest in testing and introducing profiling tools.

Statistical profiling tools are not without limitations. It is not always possible to scrutinise the algorithm or statistical method underlying the profiling tool that is being used. The models might also lack accuracy such that some jobseekers will wrongly be classified as "high" or "low" risk individuals. However, tools based on comprehensive data will suffer less from it. These limitations can jeopardise the use and acceptance of statistical profiling tools amongst employment service staff, policy makers and the general public. Engaging all actors involved is key. The frontline staff of employment services should be involved in the development, testing and roll-out of a new profiling system to achieve full transparency. Furthermore, jobseekers should be involved more in the profiling process by informing them of the results and how services will be tailored to their needs. Post-implementation, continuous evaluation and updates of the system based on feedback from all stakeholders will improve the system and its accuracy and will also help to build trust in it.

Résumé

Les outils de profilage contribuent à améliorer l'efficience des services de l'emploi, en veillant notamment à ce que les services plus poussés et plus coûteux soient bien ciblés sur les demandeurs d'emploi les plus exposés au risque de chômage de longue durée. Par ailleurs, les informations détaillées obtenues à l'aide du profilage quant aux obstacles à l'emploi rencontrés par les chômeurs peuvent être utilisées pour assurer une meilleure adéquation entre les services fournis et les besoins individuels. S'il existe d'autres formes de profilage, ce document met l'accent sur le profilage statistique, qui s'appuie sur des modèles statistiques pour déterminer la probabilité des demandeurs d'emploi de se trouver en situation de chômage de longue durée. Outre les données administratives et celles qui sont issues d'enquêtes, les systèmes de profilage ont de plus en plus recours à de nouvelles sources de données, comme les « données de clic » liées aux recherches d'emploi, ainsi qu'aux technologies de pointe en matière d'apprentissage automatique. Les outils de profilage statistique sont aujourd'hui plus répandus, à la faveur des progrès accomplis dans la gestion et l'analyse des données mais aussi des pressions croissantes visant à améliorer le rapport coût-efficacité des dépenses publiques. Les contraintes budgétaires, la forte poussée du chômage pendant la crise financière mondiale, l'élargissement du périmètre d'action des services de l'emploi aux « inactifs » et le maintien de la priorité accordée aux mesures d'activation sont autant d'éléments qui ont eux aussi contribué à susciter un intérêt vis-à-vis des outils de profilage.

Les outils de profilage statistique présentent toutefois certaines limites. Ainsi, il n'est pas toujours possible d'examiner de près l'algorithme ou la méthode statistique qui sous-tend l'outil utilisé. Les modèles peuvent par ailleurs manquer de précision, ce qui conduit parfois à des erreurs dans l'établissement du profil de risque des demandeurs d'emploi. Les outils qui s'appuient sur des données exhaustives sont cependant plus épargnés. Ces limites peuvent compromettre l'utilisation et la reconnaissance des outils de profilage statistique par les agents des services de l'emploi, les décideurs politiques et le grand public. C'est pourquoi il est essentiel d'associer toutes les parties prenantes. Les équipes des services de l'emploi qui sont en contact direct avec les demandeurs d'emploi doivent participer à l'élaboration, à l'évaluation et au déploiement du nouveau système de profilage afin d'assurer une totale transparence. Il convient en outre d'impliquer davantage les demandeurs d'emploi dans l'établissement de leur profil, en les informant des résultats du processus et la façon dont les services fournis seront adaptés à leurs besoins. Une fois le système mis en place, un suivi continu et des mises à jour régulières en fonction du retour de toutes les parties prenantes contribueront à améliorer les outils et leur précision, ainsi qu'à instaurer la confiance à leur égard.

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Boxes

1. Profiling is a key tool in the provision of employment services

1. **Delivering services efficiently involves placing clients in different groups as a function of their needs.** It applies to all organisations that experience large inflows of clients with widely different needs and expectations, who cannot all be treated immediately, and who need different treatments. The Public Employment Service (PES) in each country is a case in point (or in countries like Australia the central body that decides on the level of provision that jobseekers can obtain from private providers of employment services). The PES continually processes new jobseekers, some of whom will easily transition to a new job without the need for intensive support, whereas others would benefit from more intensive counselling and guidance over a longer period. In this context, profiling is a useful tool to determine the type of intervention different jobseekers need.

2. **Profiling tools assess the prospects of jobseekers to find work**. These tools attempt to differentiate jobseekers likely to become long-term unemployed from jobseekers likely to find work quickly (Loxha and Morgandi, 2014). Profiling tools are typically implemented by the PES to support its work in reintegrating its clientele into the labour market. PES clients are usually the registered unemployed (with or without entitlement to unemployment benefits). In addition, recipients of other out-of-work benefits are also served by the PES in many countries. Typically, profiling tools are not used to assess the job-finding prospects of other groups with no or weak labour market attachment (e.g. underemployed, discouraged/inactive individuals) who are not registered with the PES. For a more "birds-eye" view, covering the entire working-age population, the OECD has developed a new tool as part of the *Faces of joblessness* project (Fernandez et al., 2016).

3. **Profiling tools help improve the cost-efficiency of the PES**. Accurate profiling tools improve the cost-efficiency of PES by reducing deadweight costs, i.e. the costs related to providing services to jobseekers who would have found a job in any case, and by targeting resources to jobseekers most in need of help. But profiling can also be used to guide planning and allocate budgets within the PES (e.g. Ireland and the Netherlands) or to determine payments to external service providers as in Australia and Sweden.

4. **Profiling is an input into targeting and tailoring to jobseekers' needs.** Profiling is sometimes described as covering both a systematic approach to identify jobseekers at risk (i.e. profiling in a narrow sense) and a way of allocating or adapting employment services and programmes to jobseekers (i.e. targeting and tailoring). However, the process of profiling to assess the job-finding prospects of jobseekers should be distinguished from its use for targeting and tailoring. This paper focuses on profiling in a narrow sense. However, it is important to highlight that countries, which apply profiling, use the results to target services to certain customers groups. Furthermore, the detailed results of profiling often support caseworkers in tailoring services to the jobseekers they serve.

5. **The design and implementation of profiling tools is not a new endeavour.** The OECD, for instance, published a report in 1998 entitled "Early identification of jobseekers at risk of long-term unemployment", which identified a few countries – Australia, Canada, the UK and the US – which had already introduced more

formal methods of identifying at-risk jobseekers (OECD, 1998). Many of the key issues raised in 1998 are still relevant today such as the choice of a profiling approach, the accuracy of profiling tools, the link with service delivery and ensuring buy-in by caseworkers.[1]

6. **The use of statistical profiling tools is now more widespread.** What has changed since 1998 is that many more countries have been experimenting with various profiling tools in the last two decades and these experiences can provide useful lessons for best practice. Statistical profiling models, which were still in an early phase at the end of the 1990s, are now more widely used because real-time data availability has increased and complex statistical models and the required computing power are now widely available (Pieterson, 2017). Furthermore, the PES in each country often had to rethink its approach to identifying jobseekers at risk, against a backdrop of:

- Budgetary pressures or increased inflows of jobseekers following the global financial crisis;
- Changes in the composition of jobseekers and a greater diversity of client groups;
- A stronger focus on activation (i.e. motivating and encouraging jobseekers to find work in exchange for benefits); and
- A greater diversity of employment forms and shorter job tenures (at least for some groups).

7. The US and Australia introduced fully operational profiling systems based on statistical prediction for customer segmentation already in 1996, respectively 1998. Over the past decade, the approach has gained prominence in Europe and more countries have introduced profiling systems. The topic has also been discussed by the European Commission’s Mutual Learning Programme for Public Employment Services (e.g. Weber, 2011, Konle-Seidl, 2011, Barnes et al., 2015, Pieterson, 2017) and continues to receive attention from policymakers.

[1] For an overview of the debate in the 1990s, see Eberts, O’Leary and Wandner (2002).

2. Countries use a variety of profiling tools

8. Taking into account the proliferation of profiling approaches, three types of profiling are distinguished here[2]: rule-based profiling, caseworker-based profiling and statistical profiling. Figure 1 provides an overview of the different types of profiling systems with examples from across the OECD. The online Annex Characteristics of statistical profiling models across the OECD provides an overview of profiling systems currently used or under development throughout the OECD. While all three types are presented here, this paper mainly focuses on statistical profiling.

9. **Rule-based profiling** is a widely applied method to place clients in different groups. This method uses administrative eligibility criteria, such as jobseekers' age, educational level, or unemployment duration to classify jobseekers into client groups. It is easy to understand, implement and adapt to changing policy environments. For instance, the profiling system in Flanders in place until October 2018 aimed to serve young jobseekers (<25 years old) within four months after registration at the PES, while it aimed to reach jobseekers aged 25 and above within twelve months. Eligibility criteria often target groups with a higher risk of becoming long-term unemployed, although this is not necessarily always the case. For instance, given the same educational background, a young jobseeker in Flanders is more likely to find a job than a jobseeker aged 55. Nevertheless, the former was more likely to be supported by a caseworker than the latter. This illustrates that eligibility criteria are not only selected to focus on vulnerable groups, but are also determined by political realities and policy priorities (e.g. the Youth Guarantee in the EU). While simple rules are easy to understand, most employment services combine them with caseworkers' discretion and with a battery of assessment tools that may be used to detect specific needs. Poland also applies rule-based profiling, but uses a more complex system. The assignment to different client groups is based on a point-based system, which uses socio-economic characteristics as well as factors of job readiness and motivation gathered through an online questionnaire. When such complex rules are used, the results may be difficult to understand for caseworkers and jobseekers alike.

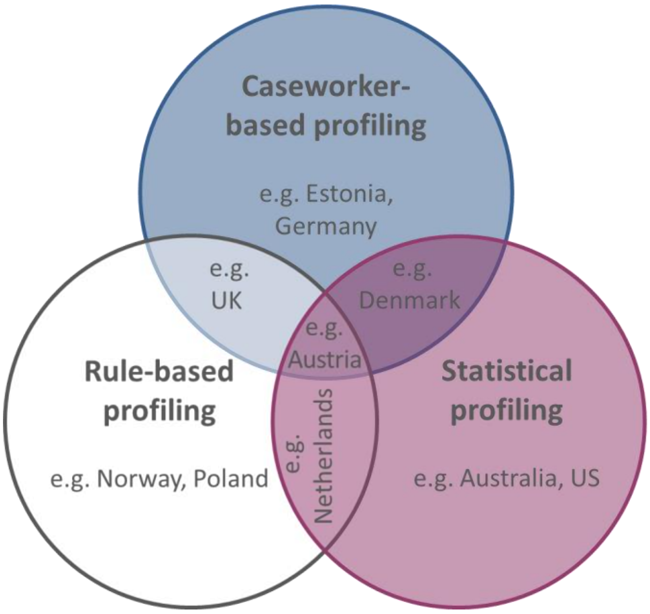
10. **Caseworker-based profiling** relies on caseworkers' judgement to profile jobseekers and is used, for example, by Estonia, Germany, Greece, Luxembourg, Slovenia and Switzerland. Although caseworkers have full discretion, they are frequently supported by quantitative or qualitative tools to assess jobseekers' skills and needs. In Germany, for instance, caseworkers categorise jobseekers as "easy" or "hard-to-integrate" in the labour market after a one-hour long interview at the start of the unemployment spell. Greece just rolled out a data-assisted system to provide its caseworkers with support to profile caseworkers as high, medium or low risk. Estonia's PES gives full discretion to

[2] Barnes et al. (2015) distinguish a fourth type, "soft-profiling", which is a combination of rule-based and caseworker based profiling. Loxha and Morgandi (2014) further distinguish between "rules-based profiling with time-based segmentation" and "rules-based profiling with demographic segmentation". Hasluck (2008) also has differentiates four types of profiling and refers to "screening", as a combination of rule-based and caseworker-based profiling.

caseworkers and invests in training caseworkers in order to improve the quality of their assessments.

11. **Statistical profiling** uses a statistical model to predict labour market disadvantage. It is the main focus of this paper and is discussed in more depth in the following sections. PES increasingly apply statistical profiling to replace rigid eligibility criteria and streamline PES processes, as statistical profiling is less time-consuming and, thus, less expensive, than caseworker based profiling. In comparison to rule-based profiling statistical profiling has the advantage of considering all jobseekers as individuals and not simply as members of a particular group. As a result, services can be tailored to specific needs of the individual, not to the average needs of the group. This, of course, requires that caseworkers make full use of the information collected as part of the profiling in order to look beyond "group" characteristics. Most statistical profiling tools predict the likelihood of becoming long-term unemployed[3], but other "outcomes" are also possible. For example, Austria assess the likelihood of labour market integration in the short and long term (Box 3.2). The most well-known statistical profiling models are those developed under the *Worker Profiling and Reemployment Services* (WPRS) initiative in the US, the *Job Seeker Classification Instrument* (*JSCI*) in Australia and the *Work Profiler* in the Netherlands, but a number of other OECD countries also use statistical profiling (Table 1).

Figure 1. Different types of profiling are used across the OECD



Source: Authors.

12. **In practice, different types of profiling are often combined.** In the Netherlands, for instance, statistical profiling determines when jobseekers are invited for a first interview with a caseworker. But a rule stipulates that all jobseekers, regardless of their initial profiling score, are invited after six months. Denmark (*profilafklaringsværktøjet;*

[3] The definition of long-term unemployment is country specific. Most countries use either 6 months or 12 months as threshold (Table 1).

"the profiling tool") and New Zealand (Service Effectiveness Model, SEM) combine statistical profiling with caseworker based profiling. In Austria, the profiling tool segments jobseekers into three service streams. However, the profiling results are overridden for jobseekers under 25 years, which are assigned to the middle service stream even if they have a low score. Also for other jobseekers, PES caseworkers have the possibility to override the results of the profiling tool and assign them to a service stream they consider more appropriate. Thus, in these countries statistical profiling tools support, but do not replace the caseworker's judgement.

3. How to design a statistical profiling model and what to watch out for

13. Most statistical profiling models predict the probability that a jobseeker will become long-term unemployed. For this purpose, countries collect different types of data through administrative records, questionnaires or personal interviews. The usefulness and legitimacy of statistical profiling models hinge on model accuracy, which can only be achieved with rich datasets and through regular updates of the models. A number of countries explore both new methods such as advanced machine learning techniques and make use of innovative data sources (e.g. "click behaviour"). For countries with statistical profiling systems, Table 1 provides an overview of the outcome variable, data collection method, type of data used (beyond socio-economic information, which is used by most countries), the statistical model, whether the participation in profiling is compulsory for jobseekers and whether caseworkers must use the results. Additional information is available in the online Annex Characteristics of statistical profiling models across the OECD.

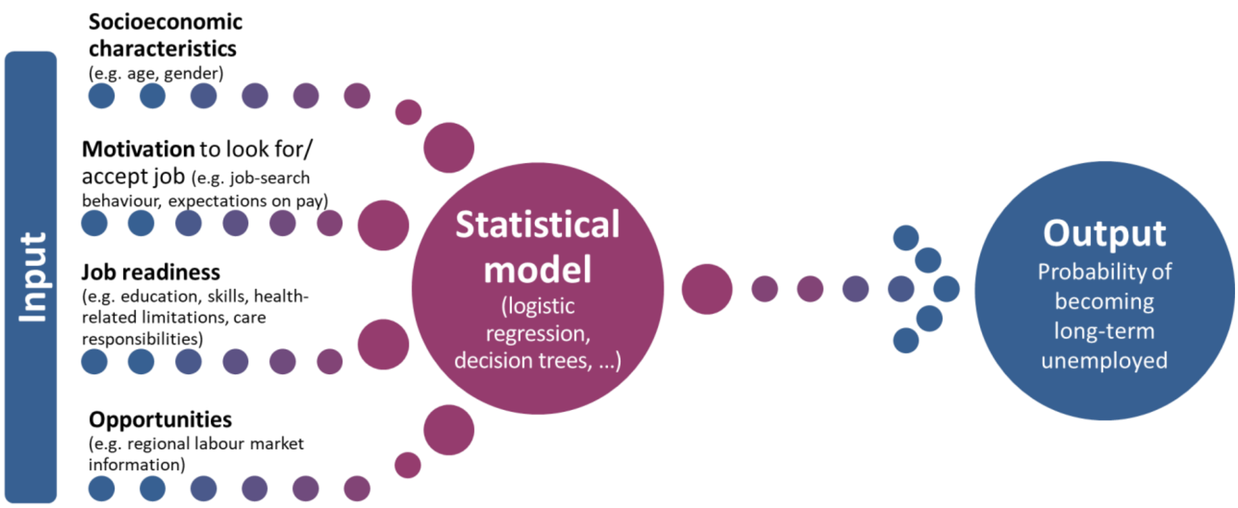
Table 1. Characteristics of statistical profiling models across the OECD

	Outcome (probability of)	Data derived from	Type of data sources (in addition to socioeconomic info)					Statistical model	Accuracy	Compulsory/voluntary use by	
			Job readiness			Motivation	Opportunities				
			Labour market history[a]	Hard skills	Soft skills	Jobseekers' behaviour	Regional labour market info			Jobseekers	Caseworkers
Australia	Long-term unemployed (12 months)	Personal interview; online trial ongoing	Yes	Yes	No	No	No	Logistic regression		Compulsory	Compulsory
Austria	Labour market integration probability[b]	Administrative data	Yes	Yes	No	No	Yes	Logistic regression	80%-85%	Compulsory	
Belgium (Flanders)	Long-term (>6 months) unemployed	Administrative data; "click" data	Yes	Yes	No	Yes	No	Random forest model	67% (AUC ~0.76)	Compulsory	Compulsory
Denmark	Long-term (>26 weeks) unemployed	Online questionnaire; Administrative data	Yes	Yes	Yes	Yes	No	Big data model	>60%	Voluntary	Voluntary
Ireland	Probability of exit to employment within 12 months	Questionnaire as part of benefit claim process, administrative data	Yes	Yes	No	Yes	Yes	Probit regression	70% - 86%	Compulsory	Compulsory
Italy	Long-term unemployed (12 months)	Administrative data	Yes	Yes	No	No	Yes	Logistic regression		Compulsory	Compulsory
Latvia	Long term unemployed (12 month)	Personal (individual) interview, questionnaire, administrative data	Yes	Yes	Yes	Yes	Yes	Factor analysis	No data yet	Compulsory at PES & voluntary online	Compulsory (advisory for now)
Netherlands	Long-term unemployed (12 months)	Online questionnaire		Yes	Yes	Yes		Logistic regression	70%	Voluntary	Compulsory
New Zealand	Lifetime income support costs (LET), change in lifetime income support and staff costs from receiving a case management service (SEM)	SEM/LET are based on administrative data	Yes	Yes	No	No	No	Random forest (LET), Gradient boosting (SEM)	AUC: 0.63 - 0.83	Compulsory for jobseekers; opt-in for other PES clients	Compulsory
Sweden	LTU (6 months)	Administrative data	Yes	Yes	No	No	Yes	Logistic regression			Voluntary
US	Exhausting the 26-week entitlement to UI benefits	Online questionnaire; Administrative data		Yes	No	No	Yes	Logistic regression		Compulsory	Compulsory

Notes: a. Input data includes information on prior periods of employment, unemployment, inactivity; occupation(s) held; sector(s) worked in.
b. Outcome variable in Austria: Labour market integration probability measured in short and long term (short term: 3 months of unsubsidised employment within 7 months; long term: 6 months of unsubsidised employment within 24 months).
Source: Authors' compilation.

14. **Various statistical approaches can be used to build profiling tools, but accuracy is not very sensitive to the choice of model** (Desiere et al., 2019). Figure 2 shows how statistical profiling models work. Information about jobseekers, i.e. the data input, is translated through a statistical model into a probability of becoming long-term unemployed. Logistic regression is the most commonly used technique to build statistical profiling models. Logistic regression is currently used in Australia, the Netherlands, the United States, Austria, Sweden, and Italy, while Ireland uses a probit model. Denmark, Belgium (Flanders) and New Zealand use advanced machine learning techniques (Box 3.2 for details on Denmark and Flanders). Empirical research by the Department of Work and Pensions in the UK and the Flemish PES, however, has shown that model accuracy is not very sensitive to the choice of the statistical model (Matty, 2013 and VDAB, 2018). In other words, traditional statistical methods like logistic regressions can be as accurate as machine learning.

Figure 2. The building blocks of statistical profiling models



Source: Authors.

15. **What determines the accuracy of profiling models is the quality and type of the data input**. Four types of input variables can be distinguished. These include i) socio-economic characteristics of the jobseeker (e.g. age and gender) on the one hand, and the three employment barriers motivation, job readiness (or capability) and opportunities on the other hand (based on Immervoll and Scarpetta, 2012): ii) motivation to look for or accept a new job can be included through data on job-search behaviour, expectations on pay, amount of out-of-work benefits received; iii) job readiness is captured through education, skills, detailed work experience, care responsibilities, health-related limitations etc.; and iv) opportunities are reflected in regional labour market information like unemployment rates and available vacancies. Hence, both “hard” factors such as age and educational level and “soft” factors such as motivation and job aspirations can be included in statistical profiling models (Box 3.1). Several PES are exploring new types of data. The Flemish PES registers the job-search activity of jobseekers on their website and includes this “click data” in the profiling model. Even though it does not currently have a statistical profiling tool, the UK Department for Work and Pensions explores many new

data sources to explain clients' contact reasons and behaviour, amongst them: i) speech analytics (e.g. emotion scores); and ii) information on contact channels (e.g. personal, telephony, online; length of phone calls). The example of Austria (Box 3.2) shows that statistical profiling tools can also obtain high accuracy with existing administrative data only, provided that they are of high quality.

16. **Both administrative and survey data are used in statistical profiling models.** Administrative data contain a wealth of information on jobseekers' socio-economic characteristics and labour market history, but require data integration from different sources within the government. This is often a complex and lengthy process (Pieterson, 2017). Surveys provide behavioural information about jobseekers' expectations, motivation and job search behaviour. It requires, however, that jobseekers complete (lengthy) surveys. Completing the underlying survey is mandatory in Ireland, as it is part of the process for claiming benefits. In Australia, jobseekers can skip some sensitive questions, however they are advised to disclose as much as possible in order to be accurately assessed and to receive the appropriate level of services. In the Netherlands, completing the survey underlying the profiling tool Work Profiler is voluntary. Jobseekers need to respond to twenty statements ranging from their vision on return to work to their job search intentions and the response rate is around 70%. Both approaches to data collection pose privacy issues and require standardised processes and dedicated IT-systems that can safely store and handle data, while making it easily accessible within the organization.

Box 3.1. How important is behavioural information for statistical profiling models?

A vast academic literature has examined the influence of socio-emotional factors on job prospects, including: how personal adaptability, career identity and human and social capital shape employability (e.g. Fugate et al., 2004); how different job search strategies and job expectations affect the likelihood of resuming work (e.g. Weber and Mahringer, 2008); and how the five big personality traits influence labour market performance (e.g. Judge et al., 1999). What these factors have in common is that they are typically not captured in administrative data and are, generally, more difficult to measure than "hard" skills such as education.

For this reason, only a few statistical profiling models account for these behavioural factors, most notably the Dutch Work Profiler. The question is whether including behavioural variables – in addition to hard skills – would substantially improve the accuracy of profiling models (Caliendo et al., 2017). This is not necessarily the case because behavioural factors might be strongly correlated with other factors such as jobseekers' labour market history. In this case, adding behavioural factors to profiling models would not increase model accuracy. In this respect, it is interesting to note that the Dutch Work Profiler, which relies on self-reported (behavioural) information, and the Flemish profiling model, which relies on administrative data, are equally accurate (Table 1). The accuracy of the Danish profiling model did not improve substantially when administrative data were complemented with survey data.

So far, the question of whether adding behavioural information to statistical profiling models improves model accuracy has only been studied empirically in Germany by Arni et al. (2014). The authors build a profiling model using a unique dataset that includes traditional administrative data including jobseekers' labour market history as well as a set of behavioural variables. They show that the addition of information on individual expectations, family background, job search behaviour, personality traits and life satisfaction significantly improves model fit. Yet the full model's accuracy is still only about 65%, similar to the profiling models used in Denmark, Belgium (Flanders) and the Netherlands (Table 1).

Source: Arni, P., M. Caliendo, S. Künn, and R. Mahlstedt (2014), "Predicting the Risk of Long-Term Unemployment: What can we learn from Personality Traits, Beliefs and other Behavioral Variables", Working Paper; Caliendo, M., R. Mahlstedt, and O.A. Mitnik (2017), "Unobservable, but unimportant? The relevance of usually unobserved variables for the evaluation of labor market policies", Labour Economics, Vol. 46, pp. 14-25; Fugate, M., A. Kinicki, and B. Ashforth (2004), "Employability: A psycho-social construct, its dimensions, and applications", Journal of Vocational Behavior, Vol. 65/1, pp. 14-38; Judge, T. A., C. A. Higgins, C. J. Thoresen, and M.R. Barrick (1999), "The big five personality traits, general mental ability, and career success across the life span", Personnel psychology, Vol. 52/3, pp. 621-652; and Weber, A. and H. Mahringer (2008), "Choice and success of job search methods." Empirical Economics, Vol. 35/1, pp. 153-178.

17. **The usefulness and legitimacy of statistical profiling models hinge on model accuracy.** Statistical profiling models rank jobseekers according to their risk of becoming long-term unemployed. Using this ranking, jobseekers can be classified in two (or more) groups, the "low-risk" and "high-risk" jobseekers. Statistical models are never perfectly accurate. Some jobseekers will be wrongly classified in the high-risk group and nevertheless quickly resume work, whereas other will be classified as low-risk and become long-term unemployed. Both errors reduce the cost-efficiency of service delivery and, perhaps more importantly, jeopardise confidence and trust in the use of profiling. A number of countries achieve high accuracy for some client groups (Table 1). This suggests that there is still room for improvement for some of the profiling tools currently in use.

18. **Few empirical studies have compared the accuracy of profiling models with caseworkers' judgement.** Exceptions are two studies by the Swiss and Swedish PES (Arni and Schiprowski, 2015, and Arbetsförmedlingen, 2014). Both studies show that profiling models achieve higher accuracy than caseworkers.[4] Both studies, however, suffer from some set-up drawbacks. The Swiss PES piloted a profiling tool, the *job chances barometer* (JCB), in the Fribourg Canton between 2002 and 2014, without, however, later continuing to use it or rolling it out nationally. In the pilot, set-up as a randomised control trial (RCT), caseworkers were asked for an assessment of jobseekers' expected unemployment duration following the initial interview. As part of the initial interview, caseworkers also asked jobseekers an additional set of questions covering motivation, self-confidence, health, wage expectations and job-search behaviour. The profiling model used this additional information and existing administrative data to predict the unemployment duration in days and produced a "risk profile", which visualised jobseekers' risk of long-term unemployment in comparison to the total jobseeker population. However, only half of the caseworkers saw the results of the profiling tool, while the remaining caseworkers did not. A comparison of the profiling tool results and the caseworkers assessment with the actual duration showed that caseworkers, on average, underestimated the unemployment duration and differentiated the expected durations too little (i.e. too many "medium" durations of

[4] Another exception is a study of Lechner and Smith (2007) who compare caseworkers' efficacy in allocating jobseekers to ALMPs to allocation based on statistical treatment rules, and conclude that statistical treatment rules improve efficiency in terms of allocating jobseekers to the most cost-effective programmes given their specific needs.

150 to 200 days). The profiling tool's predictions suffered from similar problems, but to a lesser extent, making an accurate prediction in about 60% of cases. A major drawback of the Swiss pilot, however, was that actual unemployment durations were censored at 150 days and longer durations had to be imputed for the calibration of the model. This imputation is likely to have reduced the accuracy of the profiling tool (Arni and Schiprowski, 2015). In Sweden, the profiling model *assessment support* has been developed to target early intervention at jobseekers considered to be at greatest risk of long-term unemployment. In a study, the Swedish PES, compared caseworkers' judgement on which jobseekers are likely to become long-term unemployed and the profiling model's predictions with jobseekers' actual unemployment durations (Arbetsförmedlingen, 2014). The results showed that the profiling model correctly identified more jobseekers at a risk of becoming long-term unemployed than the caseworkers. However, considering all wrong decision together – i.e. jobseekers wrongly identified as at risk of long-term unemployment and jobseekers wrongly identified as not at risk of long-term unemployed – shows little difference between caseworkers' and the profiling tool's performance. In fact, the profiling tool identified a particularly high number of jobseekers wrongly as at-risk of becoming long-term unemployed. This could result in high deadweight costs, if all wrongly identified jobseekers benefit from early intervention. The results from the Swedish study have, however, to be interpreted with caution. The comparison between caseworkers' judgement and the profiling tool was carried out following the national roll-out of the profiling tool. In fact, the profiling tool may have influenced caseworkers' predictions.[5]

19. **Cost-benefit analysis should accompany the introduction of profiling tools**. The overall cost savings that can be achieved through the use of profiling not only depend on its accuracy relative to caseworkers but also on the potential reductions in the number of caseworkers involved in the early registration process. However, profiling tools are not costless to design or maintain and decisions based on wrong predictions could result in increased costs rather than improving cost efficiency. Countries using such tools, consequently, should not only consider the accuracy of these tools, but also assess costs and benefits of decisions based on them. Again, few empirical studies cover this topic.

20. **Regular updates of profiling models are important to ensure accuracy.** As statistical profiling models are developed using historical data, the models need to be updated regularly to remain accurate. With the structure of the economy changing, certain characteristics of jobseekers (e.g. experience in a now declining sector) that in the past strongly contributed to quickly resuming work are not necessarily still good predictors today. The same is true for regional labour market information, which also needs to be updated regularly. When the profiling model is based on administrative data, it is straightforward to recalibrate the model using the most recent datasets. In Belgium (Flanders), for instance, recalibration of the model is fully automated. However, updating profiling models based on survey data might require more time. If existing instruments do

[5] Whether caseworkers have or have not used the tool cannot be determined. This is because the profiling tool is an independent web application caseworkers use on a voluntary basis, but no information is saved from it. Moreover, unemployment durations of those deemed to be in need of early intervention are affected by the fact that the PES has actually intervened early, thereby potentially shorting unemployment durations. Hence, for jobseekers assessed to be in need of early intervention by the profiling tool or the caseworker and who did not become long-term unemployed, it is unclear whether the assessment was wrong or the early intervention successful (Arbetsförmedlingen, 2014).

not any longer predict work resumption, new survey instruments and questions have to be tested, which takes time. For instance, it took several years to develop the first Dutch *Worker Profiler* and the ongoing development of an updated *Work Profiler* remains a lengthy process. In Australia, new factors or sub-factors can also be included into the existing model. New factors are generally based on expert advice, consultation and academic research.

Box 3.2. Statistical profiling in Belgium (Flanders), Denmark, Austria and the US

Several OECD countries have developed and implemented statistical profiling models since the 1990s. The most well-known and well-documented examples are the *Work Profiler* in the Netherlands (Wijnhoven, 2014), the *Job Seeker Classification Instrument* in Australia (OECD, 2012) and the *Worker Profiling and Reemployment Services* (WPRS) initiative in the US (Black, 2003). Presented here are lesser-known examples of statistical profiling tools, including the recent experiments with machine learning techniques in Flanders (Belgium), the implementation of a sophisticated profiling tool in Denmark, the introduction of a highly accurate profiling tool based exclusively on administrative data in Austria, and recent innovations in the well-established profiling tools in the US.

New techniques and data in Flanders (Belgium). Applications of artificial intelligence for use in profiling have not been widely applied. One notable exception is the application of machine learning algorithms at the VDAB, the Flemish PES (Desiere et al., 2019). The Flemish PES founded an innovation lab in 2014 that focuses on developing new apps and "big data" analytics. Using a random forest model with hundreds of variables (called features), this lab has developed a statistical profiling model, called "Next Steps", that estimates the probability of becoming long-term (>6 months) unemployed. The model is built in a flexible way so that it can be updated regularly in order to remain accurate. The underlying data are collected and stored in a data warehouse and contain detailed information on jobseekers' socio-economic characteristics as well as some information on jobseekers' labour market history. Information collected by caseworkers during previous and current unemployment spells is also used in the model. An additional innovation is the use of "click data", which monitors jobseekers' activity on the website of the PES, including clicking on job vacancies. This is considered a proxy for job search behaviour and motivation. The statistical profiling model is part of a new contact strategy that has been rolled out in October 2018. The strategy aims to reach and screen all new jobseekers within six weeks after registration at the PES, but priority will be given to high-risk jobseekers as predicted by the profiling model. The model is meant to assist caseworkers in decision-making, not to impose it. Three further innovations are currently being examined: i) adding more behavioural information to the model using a short online questionnaire to capture jobseekers' motivation and self-reliance; ii) developing a tool that visualises barriers to employment; and iii) developing a tool that suggests specific (online) programmes to a jobseeker and caseworkers based on the jobseeker's profile and the experiences of other jobseekers with a similar profile.

Machine learning techniques in Denmark. Just like the Flemish PES, the Danish Agency for Labour Market and Recruitment (STAR) developed a profiling model (*profilafklaringsværktøjet*) using machine learning techniques, more specifically decision tree classification. The decision tree identifies nine paths that predict the likelihood of becoming long-term (>26 weeks) unemployed. The model combines data from administrative records and an online survey that gathers behavioural information. In collaboration with the University of Copenhagen, a new survey instrument is currently being developed that aims to capture structural personality traits such as time and risk preferences. The system is voluntary to use for jobseeker but, if they use it, they get full access to the model's results. The system does not automatically refer jobseekers to active labour market programmes (ALMPs), but only supports caseworkers who keep full discretionary responsibility.

A new profiling tool in Austria. The Austrian PES introduced its first statistical profiling model in November 2018 and will test its performance and evaluate the acceptance by its caseworkers in 2019. The model achieves a very high level of accuracy (Table 1), using existing administrative data sources only (i.e. there is no additional data collected) in a logistic regression model. The profiling model consists of two functions, which assess clients' likelihood of reintegration into the labour market in the short term and long term. The short-term function assesses the probability of moving into unsubsidised employment for at least three months in the first seven months after the start of unemployment. The long-term function estimates the probability of moving into unsubsidised employment for at least six months over 24 months. Clients are then assigned to three different client segments: clients with a high chance of labour market reintegration have a likelihood above 66% of achieving a three-month outcome; clients with a low chance of labour market reintegration have a likelihood of achieving a long-term outcome of less than 25%; and all remaining clients are classified to the medium segment, which is the largest segment and the focus of the PES. The model makes use of socio-economic variables (gender, age, nationality), information on job readiness (education, health limitations, care responsibilities), and opportunities (regional labour market development). A clear strength is the use of all available labour market history information, including detailed information on prior work experience (type and intensity), frequency and duration of unemployment, and participation in active labour market programmes. The full labour market history is available for about two thirds of all new client inflows. The history is typically incomplete for youth, individuals with longer periods outside the labour market and migrants. The varying availability of labour market history information requires different models to be estimated for various subgroups. Regional labour market data is captured through segmenting regional PES offices into five clusters, based on supply and demand for labour in each region.

Rethinking a long-standing model in the US. Together with Australia (see Box 4.1), the US was a pioneer in the use of statistical profiling tools. In 1993, the Clinton administration required states to identify unemployment insurance (UI) claimants who are most likely to exhaust their benefits and to refer these clients to compulsory reemployment services. This is known as the Worker Profiling and Reemployment Services (WPRS) initiative. It was the start of the development and implementation of profiling models (Black et al., 2003). Profiling models greatly differ across states, but most models are relatively simple and only include a limited number of variables such as the claimant's occupation, education, benefit history and county. As a result, model accuracy is relatively low. In addition, a report published in 2007 by the US Government Accountability Office pointed out that most states did not regularly update their models, further reducing model accuracy. Profiling models are used to rank UI claimants in descending order of the likelihood of exhausting UI benefits. Claimants most likely to exhaust their benefits are then referred to reemployment services until all available slots are filled. In this sense, the profiling model is also a rationing tool. This approach did not change markedly until 2016 when the Reemployment and Eligibility Assessment (REA) was introduced. Rather than focusing exclusively on the claimants most likely to exhaust their benefits, states can now serve jobseekers within a range of scores and align the services to the claimants' characteristics. Evaluations of REA are currently ongoing.

Source: Black, D. A. et al. (2003), "Profiling UI claimants to allocate reemployment services: evidence and recommendations for States", Final Report to United States Department of Labour; Holl, J., G. Kernbeiß and M. Wagner-Pinter (2018), "Das AMS-Arbeitsmarktchancen-Modell", Arbeitsmarktservice Österreich, Wien; OECD (2012), *Activating Jobseekers: How Australia Does It*, OECD Publishing, Paris; STAR (2018), "Profilafklaringsværktøj til dagpengemodtagere ("Profiling tool for unemployment benefit recipients")"; Wijnhoven, M., and Havinga, H. (2014), "The Work Profiler: A digital instrument for selection and diagnosis of the unemployed", *Local Economy*, Vol. 29(6-7), pp. 740-749.

4. How is profiling used?

21. Profiling serves primarily to: i) determine the timing and frequency of contacts with caseworkers; and ii) refer jobseekers to different service streams. In most OECD countries, basic employment services are provided by the PES. Australia is an exception, where the delivery of employment services are fully contracted out to external service providers.

22. **Profiling is frequently used to determine the timing and intensity of the support for jobseekers identified as at-risk of becoming long-term unemployed.** In the Netherlands, for instance, only jobseekers with a profiling score lower than 50 (out of a maximum score of 100) are invited for a face-to-face interview with a caseworker early on. Jobseekers with a score higher than 50 are initially referred to digital services only, but will also be invited for a face-to-face interview, at the latest after six months of unemployment. In Germany, caseworkers categorise jobseekers as "easy" or "hard-to-integrate" in the labour market, referring the latter group to more intensive support, often in collaboration with the local administration. Using the results of the *Probability of Exit* (PEX) model, the Irish PES differentiates between jobseekers who have a "low", "medium" or "high" likelihood of exiting to employment within 12 months. A combination of this classification and eligibility criteria determines the timing and frequency of the services. All jobseekers, regardless of profiling score are called in for a group information session within the first three weeks of their claim. Jobseekers aged 25 and above with a low or medium PEX score have a one-to-one meeting with a caseworker and commit to a Personal Progression Plan shortly after registration at the PES. In contrast, jobseekers with a high score are only expected to agree on a Personal Progression Plan after six months. Finally, newly registered jobseekers under 25 years receive the most intensive engagement (i.e. every month), regardless of their PEX score. Most countries emphasise the fact that more resources per person are being devoted to high-risk jobseekers. Such allocations might sometimes need to change. For example, at the onset of a recession, when the inflow of jobseekers is high, relatively more resources might be devoted to low-risk jobseekers to contain the caseload increase. The decisions made on the basis of the profiling results (i.e. on targeting and tailoring of services) are usually driven by budget considerations. What, however, is often missing is testing of "what works for whom", supported through impact evaluations.

23. **While profiling is typically used to focus on jobseekers most at-risk of becoming long-term unemployed, some countries are shifting towards identifying jobseekers with a medium risk.** Under the WPRS initiative in the US, for instance, the most vulnerable jobseekers are automatically referred to reemployment services. Recently, both the US and Austria have shifted to providing more support to jobseekers in the "middle" of the distribution (see Box 3.2). One reason is that ALMPs may be more effective for these jobseekers. Using statistical profiling, Austria segments jobseekers into three service streams, "service clients" (low risk of becoming long-term unemployed), "counselling clients" (medium risk) and "support clients" (high risk), and is now providing support to the "counselling clients" earlier in the unemployment spell than before.

24. **Statistical profiling can complement caseworkers or support them.** In some countries, statistical profiling automatically determines the frequency and timing of contacts or assignment to different service streams. In other countries, statistical profiling can be overruled by caseworkers and is only used to support them (see Table 1). The first approach is followed in Ireland and the US and aims to allocate resources most efficiently and effectively. Ireland introduced its statistical profiling tool – the *PEX model* – during times of high unemployment. PES staff regarded the profiling support positively as an aid to help cope with increased inflows and a means of delivering better client services. In the Netherlands, jobseekers with a low score must be invited to an interview early on. Also jobseekers with a high score can receive extra services if deemed necessary by the caseworkers. A fully voluntary approach has been adopted by Sweden and Denmark. If caseworkers' use of statistical profiling is voluntary, efforts are needed to understand why caseworkers might sometimes not use these tools or not as intended and address those reasons accordingly. For example, a study for Sweden shows that caseworkers with a higher tenure tend to make use of the voluntary profiling tool less often (Assadi and Lundin, 2015). Acceptance and use of profiling tools might also take time for both caseworkers and jobseekers. In Denmark, less than a third of jobseekers have been assessed with help of the profiling tool in 2015. In 2017, already over half had been assessed with help of the profiling tool.

25. **Profiling supports coordinating with external service providers.** The outcomes of profiling tools can support decisions on which jobseekers should be referred to contracted-out labour market services or programmes. The results of the profiling then also determine payments to external providers. Far-reaching examples in this respect are the *Work Programme* in the United Kingdom and *jobactive* in Australia. Between 2011 and 2018, the *Work Programme* applied rule-based profiling to refer jobseekers already long-term unemployed or at-risk of becoming long-term unemployed to a network of external service providers. There are nine different payment groups. The jobseekers' age, benefit claimed and other "risk" factors (e.g. repeated benefit claims, ex-offender status, disability, homelessness), determine the payments providers receive for successful and sustained employment outcomes. Australia has fully contracted out its employment services to external providers since 1998. Since then, a statistical profiling tool – the *Job Seeker Classification Instrument* (*JSCI*) – assesses jobseekers' level of labour market disadvantage. The results of the JSCI determine different service streams jobseekers are assigned to and outcome payments providers receive (Box 4.1).

Box 4.1. The Job Seeker Classification Instrument in Australia

In Australia, employment services are delivered by external employment service providers since 1998. The largest of these employment services programmes is now called *jobactive*, for the contract period of 2015-2020. Although Australia has outsourced its employment services, the Government still needs a way to identify jobseekers' barriers to employment so that providers receive appropriate resources in helping jobseekers find work. *Centrelink*, the benefit administration body, therefore profiles all jobseekers using the *Job Seeker Classification Instrument* (JSCI).

How does the JSCI work and what is it used for?

The JSCI calculates a score, which reflects a jobseeker's relative difficulty in gaining and maintaining employment, and helps to assign jobseekers to different levels of servicing. Based on the JSCI score jobseekers are either directly assigned to two different *jobactive* service streams or are referred for further assessment.

The JSCI combines a questionnaire and existing data about the jobseeker (e.g. age, gender, location, claim history). The questionnaire consists of up to 49 questions. The minimum number of questions jobseekers answer is 18. Jobseekers with a higher level of disadvantage will usually answer more questions. Since the JSCI predominantly relies on the self-disclosure of personal information, the quality of the data is in part dependent on jobseekers' honesty and readiness for full disclosure (jobseekers can decline to answer certain questions e.g. about refugee status, disability/medical conditions, criminal convictions). Centrelink provides guidance for interviewers to encourage full disclosure.

Jobseekers with the least barriers to employment and a low to moderate risk of becoming long-term unemployed are referred to jobactive Stream A. Jobseekers with a moderate to high risk of becoming long-term unemployed and a need for extra help go to jobactive Stream B. The JSCI may also indicate the need for an additional Employment Services Assessment (ESAt). The ESAt reviews jobseekers' barriers to finding and maintaining employment and work capacity more closely to determine if they are better suited to jobactive Stream C (jobseekers with a high risk of becoming long-term unemployed due to a combination of vocational and non-vocational barriers to employment) or Disability Employment Services. To ensure that a jobseeker's JSCI score remains accurate, jobactive employment service providers and Centrelink can update the JSCI through a "Change of Circumstances" reassessment.

The JSCI going forward

Up to now, the JSCI has been administered by telephone or face-to-face interview. In 2018, Australia trialled a digital service delivery of the JSCI through an online interface, informed by behavioural economics techniques and user centred design of the questions. Early findings of the trial reveal that many jobseekers are comfortable with managing their personal information and engaging with the government online.

5. Overcoming the limitations of (statistical) profiling

26. The most important objective of profiling tools usually is improving the cost-efficiency of service delivery by PES. However, profiling tools have a number of inherent limitations. Transparency and involving all stakeholders in the implementation of these tools is therefore crucial. In addition, jobseekers could be involved more in the process of profiling and the decisions based on its results.

27. **Statistical profiling systems have a number of inherent limitations, including data lags, a lack of accuracy and a lack of transparency.** First, automated decisions are as good as the data used to inform them. These data are representative of the past but not necessarily of the present or the future. Systematic biases can remain unnoticed and amplify over time (Pope and Sydnor, 2011). Second, even in systems based on many factors, some jobseekers will wrongly be classified as high or low risk individuals and this will inevitably entail statistical discrimination. Jobseekers that do not score well still have a chance of quickly resuming work, while jobseekers that score well might still become long-term unemployed (Box 5.1). Third, difficulties in scrutinising or understanding the algorithm or statistical method used can result in a lack of transparency. For example, the *JSCI* in Australia was subject to some criticism from caseworkers, because the government chose not to publish the statistical model. The lack of transparency is even more apparent when machine learning techniques are used. Machine learning risks being a black box, making it hard to understand which characteristics of the jobseeker actually determine the profiling score. All of these limitations are endemic to statistical profiling systems, and it is therefore important to continuously improve the design of these systems (Berger et al., 2001). Improving model accuracy requires richer data. Data on labour market history as well as soft skills may improve model accuracy. As labour markets change continuously, the profiling models need to be updated regularly to remain relevant. Some countries choose to mitigate the drawbacks of statistical profiling by using the tools as only one of the components in the decision making process, rather than automating decisions based on – sometimes wrong – outcomes of a statistical model. This is the case, for example in Austria and the Netherlands, where caseworkers are allowed to overrule the "judgement" of the statistical model. However, caseworkers may also incorrectly assess a jobseeker's risk of long-term unemployment. As has been argued before, evaluations should therefore be carried out on whether this is cost-effective in terms of the benefits achieved, i.e. aligning better the support jobseekers receive relative to their needs, and the extra costs incurred with respect to additional caseworker resources required.

Box 5.1. Will statistical discrimination jeopardise the legitimacy of statistical profiling models?

Statistical models developed to predict individual behaviour have been criticised on the grounds that they discriminate against disadvantaged groups (Williams et al., 2018). An example is COMPAS, a model used in the US to predict the likelihood of the defendant's likelihood to becoming a recidivist, which misclassifies black defendants more often than white defendants (Dressel and Farid, 2018). This jeopardizes the fairness and legitimacy of statistical profiling models (Desiere et al., 2019).

Unfortunately, statistical discrimination is an inherent feature of statistical profiling models. Within the framework of a PES, profiling models estimate the probability of work resumption for an individual by relying on average probabilities of the group to which the individual belongs. For instance, if migrants are *on average* less likely to resume work, than *each individual* migrant will be assigned a lower probability. In other words, average group characteristics are assigned to an individual. That is exactly the definition of statistical discrimination. As a result, migrants who find a job ex-post are more likely to have been wrongly classified ex-ante as "high-risk" individuals compared to non-migrants. The other side of the coin is that non-migrants are more likely to be wrongly classified as "low-risk" individuals than migrants. This not only holds for migrants, but for all individual jobseekers belonging to a vulnerable group such as older or low-educated jobseekers.

Statistical discrimination cannot be avoided completely, but more accurate models will suffer less from it. However, other types of profiling, particularly caseworker-based profiling, but also rule-based profiling, are also prone to (statistical) discrimination. In Sweden, for legal reasons information on gender cannot be included in profiling models. In the US, including sensitive variables like age, gender and race in statistical models is prohibited by law in order to reduce statistical discrimination. Excluding these variables only partially helps, because variables like race are often strongly correlated with other variables like education or postal code (Žliobaitė and Custers, 2016). The challenge of not making use of these variables could, however, be overcome if the employment barriers could be measured more directly. Another important element is emphasizing the positive aspects of statistical discrimination. Classification as high-risk jobseekers could be considered advantageous if it offers access to services that are denied to low-risk jobseekers. In this sense, statistical profiling can be considered "positive" rather than "negative" discrimination. The characteristics of jobseekers that contribute to raising or lowering their assessed job-finding prospects by the profiling tool can and should be explicitly identified. In contrast, it may be harder to detect any inherent bias or discrimination by caseworkers in the services they provide to different jobseekers.

Source: Desiere, S., Van Landeghem, B. and L. Struyven (2019), "Wat het beleid aanbiedt aan wie: een onderzoek bij Vlaamse werkzoekenden naar vraag en aanbod van activering", HIVA KU Leuven; Dressel, J., and H. Farid (2018), "The accuracy, fairness, and limits of predicting recidivism", *Science Advances*, Vol. 4(1); Williams, B.A., C.F. Brooks, and Y. Shmargad (2018), "How algorithms discriminate based on data they lack: Challenges, solutions, and policy implications", *Journal of Information Policy*, Vol. 8, pp. 78-115; and Žliobaitė, I. and B. Custers (2016), "Using sensitive personal data may be necessary for avoiding discrimination in data-driven decision models", *Artificial Intelligence and Law*, Vol. 24(2), pp. 183-201.

28. **Involving all stakeholders in the implementation of any type of profiling early on is crucial.** In the past, several countries have developed a profiling system without it being implemented. For example, Switzerland has tested and evaluated several statistical

profiling tools in pilot projects, most recently in 2015. Even though the tool supported earlier labour market integration for some jobseekers, it was not further developed nor rolled out nationally due to an insufficient accuracy and the resulting lack of acceptance by caseworkers (Arni and Schiprowski, 2015). In other countries, profiling tools were scaled back after being implemented because caseworkers did not consider the tools useful and did not trust the results from the tools. Even in some countries where it features prominently, its use has been questioned (Caswell et al., 2010). Supporting and fostering a data-driven and innovation oriented culture, rolling out pilot projects in order to learn by trial and error and involving caseworkers, frontline staff and jobseekers when testing the new systems and procedures help to build support for new tools and facilitates the transition to a new system. Once implemented, continuous evaluation and updating of the system based on feedback from all stakeholders will improve the system and will help to build trust in the system. For example, before the national rollout in November 2018, Greece piloted its new profiling tool first and prepared the national implementation with training for both front office and back office staff. Moreover, workshops with coaches are used to gather feedback and suggestions for improvements. In New Zealand, the focus is on caseworkers' needs and how analytics can support their decision-making. The PES therefore takes a co-design approach and small, multi-disciplinary teams – involving analysts, IT experts and service delivery staff – to develop employment assistance applications for front-line services. In the Netherlands, the development of the *Work Profiler* and other digital services was also influenced by the fact that customers demand high-level (intelligent) e-services (Heijnen and Dekenga, 2017). However, not all jobseekers participate in the profiling (the response rate is around 70%), as participation is voluntary. Active engagement with the jobseekers through sending messages and reminders to answer the questionnaire are important to keep the response rate up (Meeldijk et al., 2016).

29. **Developing a positive narrative for profiling.** Critics dispute that it is in the jobseeker's favour to be identified as someone with a high risk of becoming long-term unemployed, because then the jobseeker is more easily exposed to follow-up and job search control compared to a jobseeker who is identified as a low-risk individual. In order to ensure the legitimacy and fairness of profiling models, it is important to frame profiling and the services provided as a result of it in a positive narrative and use it to support rather than punish jobseekers (Desiere et al., 2019).

30. **Stronger involvement of jobseekers in the profiling process.** Finally, even though it is not common practice now, there may be a case for involving jobseekers to a greater extent in profiling. Denmark is an exception, and already does this. All results of the profiling are shared with both caseworkers and jobseekers to achieve full transparency. Beyond the results of the profiling, it is, of course, also important to explain to jobseekers how profiling impacts on decisions of caseworkers and the allocation or tailoring of services. In contrast, some might argue that not sharing the profiling outcome avoids discouraging jobseekers. Different considerations might apply when profiling is used to determine payments to private providers as e.g. in Australia. Sharing detailed results then carries the risk of manipulation by providers to achieve higher payments. Whatever the choice, without the involvement of jobseekers in the actions taken based on the profiling model, no system will deliver effective employment services.

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