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The Work Profiler: Revision and maintenance of a profiling tool for the recently unemployed in the Netherlands

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Abstract For the public employment services of many Member countries of the Organisation for Economic Co-operation and Development, the importance of using profiling tools for job seekers is increasing rapidly in importance. With this trend, there is also widening concern about the risks of an over reliance on such tools. Part of the concern lies with a lack of transparency concerning how such tools work. This article aims to address this by offering a detailed investigation of the Work Profiler – the instrument used in the Netherlands by the Institute for Employee Benefits (*Uitvoeringsinstituut Werknemersverzekeringen* – UWV) to predict re-employment success and provide a diagnosis of key factors hindering job seekers' return to work. Professionals use these insights to deepen their understanding of the situation of job seekers and decide together with job seekers how to support their return to work. UWV decided to maintain and revise the Work Profiler through a large-scale study involving a sample of 53,238 people. Work Profiler 1.0 was developed in 2007–2010 and has been in use on a regional basis since 2011

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and nationwide since 2015. This article explains how the new tool (version 2.0; implemented in 2018) works and, most importantly, demonstrates the choices made to ensure that it functions well and is used effectively by professionals. These latter two aspects are rarely discussed in the literature.

Keywords statistical method, job seeker, unemployment benefit, unemployed, the Netherlands

Introduction

For the public employment services (PES) of many Member countries of the Organisation for Economic Co-operation and Development (OECD), the importance of using profiling tools for the unemployed is increasing rapidly (Desiere, Langenbucher and Struyven, 2019). The use of a profiling tool offers job seekers several major advantages as it allows the PES to efficiently and fairly allocate resources to job seekers who need support and to support these job seekers with targeted services (O'Connell, McGuiness and Kelly, 2012). This makes job seekers less reliant upon the individual insights, preferences or capabilities of professionals (Bolhaar, Ketel and van der Klaauw, 2018; Desiere, Langenbucher and Struyven, 2019). Yet, profiling tools are not often implemented in practice for various reasons (Hasluck, 2008; Loxha and Morgandi, 2014). Such reasons may include the inaccuracy of results, lack of acceptance by caseworkers, or being perceived as impractical due to caseworkers not understanding the results (Desiere, Langenbucher and Struyven, 2019). The Dutch PES (*Uitvoeringsinstituut Werknemersverzekeringen* – UWV) uses a profiling instrument, the Work Profiler. The Work Profiler was developed in 2007–2010 and has been used on a regional basis since 2011 and nationwide since 2015 for all unemployed job seekers (Guiaux, Wijnhoven and Havinga, 2018; Wijnhoven and Havinga, 2014).[1] In this article, we describe how the UWV subsequently has maintained and revised the underlying predictive model with special attention being given to its generalized application using a more recent and extensive sample of unemployed people in the Netherlands.

Owing to the dynamic nature of labour markets, and of society more generally, prediction models should be revised regularly to maintain predictive accuracy and

1. In 2011, the first 11 UWV offices started working with the Work Profiler 1.0, but it was not until 2015 that it became the standard tool for all 35 offices and for all recently unemployed job seekers.

improve their quality (Black et al., 2003; Brouwer, Bakker and Schellekens, 2015; Caswell, Marston and Larsen, 2010; Frölich, 2006; O'Connell et al., 2009). For this current study, no publications could be identified that documented the maintenance or revision of predictive models in the field of unemployment. This article therefore seeks to make an important contribution to the body of literature on profiling tools. Specifically, it offers a transparent report of the revision and maintenance of a profiling tool, the Work Profiler used by the UWV in the Netherlands, and highlights several aspects related to the use of this tool to provide targeted services for job seekers as well as to its theoretical framework.

Work Profiler 1.0

The original version of the Work Profiler was based on a model with ten key factors which, at the start of unemployment period, predicted re-employment success within a year (Brouwer, Bakker and Schellekens, 2015). The aim was to create a parsimonious tool that could accurately predict reemployment success and identify factors amenable to change that could help shorten the duration of unemployment. In other words, with as few questions as possible, this sought a) to obtain a clear indication of which job seekers were in need of support, and b) to suitably tailor services to their personal needs. Consequently, the Work Profiler offers two outcomes for each individual job seeker. First, it indicates the probability of reemployment within one year, expressed as a percentage between zero and 100 per cent. Second, it shows which factors predict reemployment success and whether they hinder or promote the return to work. The latter information is obtained by comparing the factor scores of job seekers who returned to work within one year with those of the job seekers who did not return to work within one year. These two outcomes make it possible to decide which job seekers need help most urgently as well as offer a framework for the tailoring of services, because they show which factors to focus upon to enhance reemployment probabilities.

Elaboration on the research steps and consequent considerations taken during the implementation of Work Profiler 1.0 is well documented (see Brouwer et al. 2011; Brouwer, Bakker and Schellekens, 2015; Wijnhoven and Havinga, 2014). An extensive literature review has identified a list of 550 items that could be predictive for reemployment success. These items corresponded with the variable groups in the Wanberg model (Kanfer, Wanberg and Kantrowitz, 2001; Wanberg, Song and Hough, 2002) and constructs of the Theory of Planned Behavior (TPB) (Ajzen, 1985; 1991) and the Valence-Instrumentality-Expectancy Model (VIE) (Vroom, 1964). In a series of cross-sectional and longitudinal research steps undertaken during 2007–2010, the list was reduced from 550 items (step 1) to 155 items (step 2) to 19 items (step 3) (Brouwer et al., 2011). These 19 items were further reduced into ten subscales by summing item scores that measured the same underlying construct (such as views on the return to work). The result produced a ten key factor model that proved predictive for reemployment success within one year. In the implementation step of the Work Profiler, UWV added an additional item, “physical work ability”, for the practical reason that professionals considered this item relevant for services (Wijnhoven and Havinga, 2014). Nineteen items were obtained through a digital questionnaire completed by all those who had recently become unemployed in the Netherlands. One item, “Age”, is taken from administrative data. Thus, Work Profiler 1.0 contains 11 key factors. Its accuracy to predict at the start of unemployment whether a job seeker will return to work within one year was 69 per cent (Brouwer, Bakker and Schellekens, 2015).

Job seekers may only benefit from a profiling tool if professionals understand and are able to explain its mechanisms to the job seeker. The theoretical context allows professional caseworkers to understand the mechanisms behind specific factors: how to influence the situation and why certain services may enhance the chance of reemployment. Taken together, the three theoretical models cited previously (Wanberg, TPB and VIE) incorporate non-amenable and amenable factors. Non-amenable factors, such as age, gender and education, are generally understood to influence reemployment. Amenable factors address a job seeker’s psychosocial situation, such as job search intention, job search behaviour, motivation and perceived health. Knowledge about these is necessary to tailor services, given that not all job seekers will likely benefit to the same extent from the same type of assistance. The theoretical fundament of the Work Profiler adds to a better understanding of the job search and reemployment process and contributes to the acceptance, trust and use of the tool by professionals. The validity of the three theoretical models was reaffirmed by the research underpinning Work Profiler 1.0.

Maintenance of predictive validity

Profiling models should be revised regularly to reflect the fact that labour market demands change as a result of economic and societal developments; in other words, labour markets and society are dynamic (e.g., Black et al., 2003; Caswell, Marston and Larsen, 2010; Frölich, 2006; O’Connell et al., 2009). Changing labour market demands affect job seekers who seek support from the PES; for example, in a recession more job seekers will call upon the PES, while opportunities on the labour market will be more limited. Changing labour market demands and other societal developments may also affect the services provided by the PES (e.g., across the last decade, the UWV has increasingly shifted to offering online services for job seekers). Due to these changes, profiling models require maintenance. It is to be underlined that revising the profiling model not only helps to maintain its predictive power, but also offers the possibility to take into account the evolving nature of the services provided by the PES and their fit with job seekers' needs.

Maintenance of predictive accuracy is also a factor that affects the acceptance and trust of profiling tools, since actual and perceived accuracy may differ. In Switzerland, for example, the development of a profiling model was cancelled because caseworkers did not accept and trust the profiling tool, which they perceived to lack in predictive accuracy (Arni and Schiprowsky, 2015). Only a few studies have compared the accuracy of profiling models with the accuracy of professionals' judgements. Case studies of the Swiss and Swedish PES (Arni and Schiprowski, 2015; Arbetsförmedlingen, 2014) show that their profiling models achieved a higher degree of accuracy than professional assessments. Regardless, professionals may still perceive their own assessment of a job seeker's situation to be more accurate. In the Swiss case, caseworkers perceived the prognosis as too low or not fitting special cases in 44 per cent of the cases. An explanation for this is that, in most of such cases, caseworkers had access to additional information that was not included in the profiling model (Arni and Schiprowsky, 2015). The Swiss study concluded that higher predictive accuracy may indeed increase trust and acceptance among caseworkers, but it remains important to also communicate how results of a profiling tool provide caseworkers with additional information to supplement their own assessment of the jobseeker's situation. In this vein, the PES in New Zealand consciously uses analytics to support caseworker decision making (Desiere, Langenbucher and Struyven, 2019). For job seekers, the question is not "who" or "what" performs more accurately, instead it is how caseworkers can complement the professional assessment with results provided by the tool, with the aim of providing job seekers with truly tailored services.

Model quality and accuracy depend partly upon the type of data and research methods used to develop the profiling model. Richer and more recent data will likely improve the accuracy of the model. However, the increasing body of profiling tools within OECD Member countries also demonstrates that adding behavioural factors to the prediction model will not necessarily significantly improve its overall accuracy (Desiere, Langenbucher and Struyven, 2019). The added value of these factors lies more in the insights they offer to the PES.

When using profiling models, it is not only the accuracy of the model that matters. Also important is the extent to which the decision rule[2] correctly classifies job seekers into different groups (van Landeghem, Desiere and

2. Policy makers or researchers use a decision rule, or cut-off point, to define who belongs to the risk groups under scrutiny. For example, for the Work Profiler, the decision rule is the cut-off point of 0.5 probability of returning to work within one year. Job seekers with a lower probability are defined as belonging to the at-risk group of becoming long-term unemployed.

Struyven, 2021). Typically, two types of errors may occur. First, a misclassification of job seekers as short-term unemployed, but who eventually will become long-term unemployed. Second, a misclassification of job seekers as long-term unemployed, but who eventually will not be. Related to these errors, consideration must be given to the sensitivity and specificity of the model. These two terms pertain to the percentage of those who are correctly classified as a low-risk group (in this case, job seekers) who will return to work in a relatively short term (sensitivity), and those correctly classified as a high-risk group of not returning to work and thus becoming long term unemployed (specificity).[3] There is a trade-off between levels of sensitivity and specificity. Specifically, increasing sensitivity decreases specificity, and vice versa. Policy makers should take this into account when deciding upon a specific decision rule.

All the above observations apply to the Work Profiler tool. The model underpinning version 1.0 predicted accurately for 69 per cent of cases whether a person entering unemployment would obtain paid work within one year or not, but it was suspected that the model's accuracy had dropped in 2014–2015. One option to improve the model's accuracy was simply to adjust the values of the factors based upon a more recent population sample to re-calibrate the Work Profiler 1.0.

Nevertheless, there were several important reasons why the UWV opted for a more thorough revision of the design of Work Profiler tool. First, there were doubts about the generalizability of the Work Profiler. The longitudinal research underpinning the first version was conducted only in the Province of North Holland, and not across the entirety of the Netherlands. It was therefore important to ensure that the instrument worked well nationwide (see also the section on Method). The response rate to the questionnaire used to develop Work Profiler 1.0 was low (27 per cent), a rate that the UWV wished to increase substantially to support the development of the new version.

Second, there were concerns about the method used for analysing the data obtained during the research. The dataset used to develop Work Profiler 1.0 was not large enough to immediately apply a multivariate logistical regression analysis. To remedy this, first a univariate analysis was undertaken to reduce the number of factors. Only significant factors were then used for the multivariate analysis (Brouwer, Bakker and Schellekens, 2015). However, this solution increased the risk of excluding important predictors. For the development of Work Profiler 2.0, the UWV wished to substantially increase the dataset, an

3. Specificity (i.e., correctly predicted negatives) is defined as the proportion of respondents who did not return to work within one year and who are correctly classified by the model as not returning to work. Sensitivity (i.e. correctly predicted positives) is defined as the proportion of respondents who resumed work within one year and who are correctly classified as "resuming work within one year".

outcome which would remove the need to apply the unsatisfactory remedy used for the small dataset for Work Profiler 1.0.

Third, there was a question about the outcome variable. During the development of Work Profiler 1.0, the ability to see what might happen with a recently unemployed person over time was limited. This meant that the most suitable outcome variable at the time was whether a person after a year was still in receipt of unemployment benefit (i.e., unemployed), or not (i.e., reemployed). Of course, in addition to return to work, there are other reasons why the receipt of benefit may cease, such as an extended period of ill health, migration or death. Access to additional information made available during the development of the new Work Profiler permitted to change the outcome variable to work resumption, independently of whether the benefit had ceased or not, which is better suited than the prior outcome variable.

In 2014, the UWV commenced the research that led to the development of Work Profiler 2.0 (Dusseldorp, Hofstetter and Sonke, 2018). The next section outlines the research steps in this process.

Method

Participants

The participants were recently unemployed job seekers who had applied for an unemployment benefit at the Dutch PES. Included were all job seekers from 11 PES offices, geographically spread throughout the country, across the period 1 March 2014 to 28 February 2015. Participants were selected if they were entitled to unemployment benefits for more than 3 months, were still receiving benefits 10 weeks after their application, had access to the Internet, and lived in the Netherlands. The sample contained 76,817 job seekers, who received a digital questionnaire containing a list of relevant items.[4] A total of 53,238 job seekers responded (total response rate of 69.3 per cent; 50.9 per cent women, 49.1 per cent men; mean age of 42.1 years; level of education: 20 per cent primary school/lower vocational training, 51.4 per cent middle education, 28.6 per cent higher education). At the time of data collection, the number of Dutch PES offices was reduced from 50 to 35, but the 11 participating locations all continued to operate during the entire period of data collection. Of the collected data, 0.3 per cent of the sample was not used in the analysis because of missing values in some of the measurements, mainly from the administrative data. Finally, complete data were available for 53,079 job seekers. A comparison of respondents

4. This article is supplemented by an extensive online Appendix developed by the authors and made available to readers (see Supporting Information). See Appendix A, Table A.1.

and non-respondents revealed only marginal differences between both groups regarding their gender, education, nationality and pre-benefit employment. The effect sizes of these differences were small (Cramer's $V < .2$). The largest difference between respondents and non-respondents was a moderate difference in age ($M = 42.1$ vs. $M = 38.4$; $p < 0.001$; Cohen's $d = .32$). It was concluded that the respondents formed a representative sample for Dutch job seekers receiving unemployment benefits. Moreover, the study's participants represented 25 per cent of the total population of recently unemployed people registered with the Dutch PES during that period. To ensure that the sample was representative of the entire population with unemployment benefits, the 25 per cent participating sample was compared with the remaining 75 per cent of job seekers at the other PES offices regarding several key characteristics, such as reemployment, age, gender and education. The analysis confirmed that the participating job seekers were representative of the entire population (Dusseldorp, Hofstetter and Sonke, 2018).

Questionnaire and procedure

To operationalize the factors from the three theoretical models into concrete questions (i.e., items) we used various validated questionnaires (e.g., Blau, 1994; Schellekens, Langkamp and De Vries, 2005; Vinokur and Caplan, 1987; Wanberg, Song and Hough, 2002). This resulted in a list of 550 items, most of which were phrased in English with fewer in Dutch. All items were subsequently translated into Dutch. An elaborate description of the items and the response scales is found in Schellekens et al. (2007); Brouwer et al. (2011); and Brouwer, Bakker and Schellekens (2015).

In this prospective cohort study, a questionnaire was administered to a one-year cohort of unemployment benefit recipients.[5] Participants received the online questionnaire between the sixth and tenth week after making their application to receive unemployment benefits. The questionnaire was made available to participants on the PES online platform, by means of which the PES delivers all online services (e.g., online coaching, webinars, online workshops) and communicates with clients. Participants received a digital message requesting them to complete the online questionnaire and for which they were given two weeks to respond. After one week, the participants received a reminder message.

5. The job seekers in this study concerned the recently unemployed who have just lost their work as an employee and who are entitled to unemployment benefit provided by the Dutch PES. Job seekers that have become unemployed through other circumstances (e.g., never having had a job, wanting to change work, or have been jobless for a long period) represent a different category, the responsibility for whom lies with Dutch municipalities that may provide social assistance and offer support in job searches.

Questionnaire items

The questionnaire for the current study was specifically developed to revise and maintain the earlier predictive model of the Work Profiler 1.0 (Brouwer et al., 2011). It comprised all 20 items of Work Profiler 1.0, and also new and re-inserted items from the earlier set of 155 items (see section on Work Profiler 1.0). The questionnaire items reflected elements from the three theoretical models (Wanberg, TPB and VIE), but not every element of the three theoretical models was included in the questionnaire.

The new and re-inserted items were added only after several exploratory analyses. First, cluster analyses were used to obtain sets of related predictors for reemployment (Romesburg, 2004). In addition, the data used for the analyses of the original model were updated with more detailed employment data. Also added was additional reemployment data from a new set of PES administrative data. Using these data, the reemployment status of more participants was available (the original dataset contained complete data for 3,618 participants, the new dataset contained complete data for 4,849 participants). With these data, multivariate logistic regression analyses checked whether the extra items had a statistical relationship with reemployment status in the total sample. If so, these items were selected as potential predictors that should be reconsidered when updating the original model. In addition, two expert group meetings were held with professionals from the PES to review the selection of potential predictors. Based on their feedback the sequence of items in the final revised questionnaire was determined and some items were reformulated in simpler Dutch. Items from validated questionnaires were not reformulated. The final questionnaire contained 45 items and a further ten items were acquired through administrative data.[6]

Measurements

Measurement of the outcome variable

The outcome variable "Reemployment status after one year" was determined in the following manner. Respondents were defined as reemployed (=1) when their benefit had completely ceased and they had returned to work, according to administrative data, within one year after the start of receiving the benefit; otherwise, they were defined as not reemployed (=0). To assess whether claims to benefits were valid, the PES has a reliable administrative record of benefit use

6. This article is supplemented by an extensive online Appendix developed by the authors and made available to readers (see Supporting Information). See full list of items in Appendix A, Table A.1.

and employment status for all Dutch citizens. The study followed up on the reemployment status of all participants until 30 April 2016. Depending upon the duration of their previous employment, job seekers may be eligible for a maximum benefit entitlement period of up to three years.

It should be noted that, in the Dutch benefit system, it is possible to become partly reemployed while still receiving unemployment benefits. In that case, income from the part-time job will be partly deducted from the benefit amount. For this study, this situation was not counted as reemployment.

Measurement of predictors

For the analyses, 37 factors (i.e., predictors) were constructed based on the 45 questionnaire items and ten administration items. Some of these items were considered as separate factors (e.g., "Age"). Other items could be combined straightforwardly to construct one factor, for example, the factor "Number of hours per week available for work" was calculated with the answers to the following two questions: "How many days per week are you available for work" multiplied by the answer for "How many hours per day are you available for work". For the remaining 27 items that were assumed to measure ten factors, confirmatory factor analysis was performed. This analysis showed a good fit ($CFI \geq .95$, $NFI \geq .95$, $TLI \geq .95$, and $RMSEA < .05$), implying that the assumed structure was appropriate. Based on this analysis, sum scores were computed for the items that loaded on the same factor. These sum scores were used as predictors in the next step of the analysis.

All predictors are presented in the online Appendix,[7] including corresponding items, answer possibilities and corresponding literature. For the administrative data the relevant categories are also included. As mentioned previously, the predictors mainly reflect the three theoretical models. For ease of understanding, the items have all been translated in this article from Dutch to English, except for those that come from already validated English questionnaires.

Analysis and results

The aim of the analysis was to obtain a parsimonious, understandable model with as high as possible predictive accuracy. For the development of this predictive model, the research sample was randomly divided into three subsamples (Table 1). A training sample (n = 26,541; 50 per cent), a validation sample (n = 13,269; 25 per cent) and a test sample (n = 13,269; 25 per cent). The

7. This article is supplemented by an extensive online Appendix developed by the authors and made available to readers (see Supporting Information). See full list of items in Appendix A, Table A.1.

Table 1. *Reemployment within one year in the total sample and subsamples*

	Reemployment within one year*n* (%)	Total *n* (%)
Total sample of job seekers	27,670 (52%)	53,079 (100%)
Training sample	13,857 (52%)	26,541 (100%)
Validation sample	6,945 (52%)	13,269 (100%)
Test sample	6,868 (52%)	13,269 (100%)

Source: Authors' elaboration.

training sample was used to estimate the univariate and multivariate logistic regression models (the latter using all available predictors). The validation set was used for model selection, and the test set was used to estimate the out-of-sample predictive accuracy; that is, the accuracy of the prediction for future respondents (Hastie, Tibshirani and Friedman, 2001). Model selection was based on statistical criteria (see below) as well as theoretical criteria. The theoretical criterion to drop a predictor from the model was that its relationship with reemployment status was not in line with the expectations of any of the aforementioned three theories.

Several criteria were applied to assess the goodness-of-fit of the models: The Nagelkerke R^2, the AUC (area-under-the curve), and the Brier score. The Nagelkerke R^2 for logistic regression is comparable to the multiple R^2 for multiple regression, and a value of equal to or more than .3 is generally accepted as a good fit in the social sciences (Cohen, 1992a). We consider an AUC between .7 and .8 as moderately predictive, and values above .8 as very good (Weinstein and Fineberg, 1980). A Brier score lower than .2 is regarded as good (van Houwelingen and Putter, 2011). Effect sizes of predictors were computed as follows: the difference in the variance-accounted-for of the regression model with the predictor compared to the variance-accounted for of the regression model without the predictor (f^2; Cohen, 1992b). The analysis strategy followed the following five steps:

Step 1

During the first step of model building, a training sample was used to analyse the data and estimate which variables predicted reemployment. First, a univariate logistic regression was used to verify whether the relationship with reemployment lay in the theoretically expected direction.[8] Also verified was whether the

8. This article is supplemented by an extensive online Appendix developed by the authors and made available to readers (see Supporting Information). See Appendix A, Table A.2.

relationship was linear, and when it was not, a categorical variant of the variable was used in further analyses. For this purpose, it was necessary to identify which univariate model, either the one with a continuous predictor or that with a categorical version of the same predictor, fitted the data best based on Nagelkerke R^2. The assumption of a linear relationship between the log odds of reemployment and specific predictors was visually checked. This was done by looking at the marginal model plots. The univariate analyses showed that all 37 predictors were related with reemployment as theoretically expected, and that the categorical variant of "Years employed in the last job" fitted the data best.

Step 2

This step involved using a multivariate logistic regression model with all 37 predictors. A check was made for linearity and multicollinearity and whether the Variance Inflation Factor (VIF) did not exceed 5 (Rogerson, 2001). The multivariate analyses showed multicollinearity ($r > .8$) for two pairs of variables. One pair was "Average number of hours worked per week prior to unemployment", and "Number of hours per week unemployed" ($r = .91$); the other pair was "Maximum duration of unemployment benefits", and "Age" ($r = .87$). From the first pair, the "Number of hours per week unemployed" was dropped from the analysis. A marginal model plot showed a non-linear relationship between "Average number of hours worked per week" and "Reemployment status", therefore the "Average number of hours worked per week" was categorized in terms of 24 hours or less, between 25 hours and 32 hours, and more than 33 hours. From the other pair, the study dichotomized the "Maximum duration of unemployment benefits" (0 = less than 12 months and 1 = more than 12 months) and kept "Age" as a continuous variable. After these alterations, all VIFs were below 5.

Next, it was assessed whether all the relationships in the multivariate model were still in line with theoretical expectations. For seven variables, the relationship with reemployment was not as expected theoretically. In addition, the effect sizes for these seven variables were very low ($f^2 < .003$). Given that the aim was to obtain a predictive model that fits with theoretical expectations (i.e., to obtain a profiling tool that can be explained to the professional practitioners who work with it), the following variables were dropped from further analyses: "Job search attitude regarding advantageousness/pleasantness", "Subjective norm family and partner", "Job search attitude regarding usefulness and necessity", "External variable attribution", "Readiness to accept work with undesirable characteristics", "Self-efficacy (preparation)", and "Average number of hours worked per week prior to unemployment").

Step 3

This step saw the selection of the best fitting and most parsimonious model using the validation sample. The number of predictors was reduced by performing three stepwise selection methods (i.e., backward and forward selection, and a combination of both). As is recommended, model selection was based on AIC (Akaike Information Criterion) as well as BIC (Bayesian Information Criterion), with smaller values of AIC and BIC indicating better fit (Kuha, 2004). In total, six stepwise logistic regressions (three selection methods times two criteria) were run to choose the model with the best fit, the smallest number of predictors and the highest predictive accuracy in the validation sample. In general, the BIC resulted in more parsimonious models (i.e., the smallest number of predictor variables). All three selection methods with the BIC criterion resulted in the same model. The most parsimonious model contained 18 predictors,[9] named Work Profiler 2.0, fit well ($R^2 > .30$, AUC =.77), had a low Brier score (.19). Of the 11 factors of Work Profiler 1.0, nine are still present in Work Profiler 2.0. Three factors from version 1.0 were combined into one single factor ("Perceived health"), which means that the nine recurring factors were reduced to seven in Work Profiler 2.0. Furthermore, Work Profiler 2.0 includes 11 new factors, such as the "Position within a household", the "Industry prior to unemployment", and "Income besides the unemployment benefit". The five most important factors for predicting reemployment were "Age", "Years employed in last job", "Views on return to work", "Desired profession", and "Position within the household".

Step 4

This step used the test sample to estimate the predictive accuracy of the final model. This involved assessing the quality of the final prediction model, the predictive validity, with the AUC. For use in practice, also assessed were the specificity and sensitivity of the model in the test sample at different cut-off points. As discussed previously, specificity (i.e., correctly predicted negatives) is defined as the proportion of respondents who did not return to work within one year who are correctly classified by the model as "not returning to work". Sensitivity (i.e., correctly predicted positives) is defined as the proportion of respondents who resumed work within one year who are correctly classified as "resuming work within one year". Table 2 shows how there is a trade-off between specificity and sensitivity at different cut-off points: the model with a set value for sensitivity of 95 per cent has a specificity of 34 per cent, and the model with specificity

9. This article is supplemented by an extensive online Appendix developed by the authors and made available to readers (see Supporting Information). See Appendix B, Table B.1.

Table 2. *Predictive characteristics of the most parsimonious, interpretable model for the prediction of reemployment status within 12 months on the test data set (n = 13,269)*

SN	SP	Cut-off value	% correctly predicted	SN + SP	AUC	Brier
25.7	95.0	0.80	59.1	120.7	0.78	0.19
40.1	90.0	0.72	64.2	130.1		
49.2	85.0	0.66	66.5	134.2		
57.3	80.0	0.61	68.3	137.3		
63.7	75.0	0.57	69.1	138.7		
69.1	70.0	0.53	69.5	139.1		
70.0	69.2	0.52	69.6	139.2		
75.0	64.7	0.49	70.0	139.7		
80.0	**59.9**	**0.45**	**70.3**	**139.9**		
85.0	53.7	0.40	69.9	138.7		
90.0	46.1	0.34	68.8	136.1		
95.0	34.3	0.27	65.7	129.3		

Note: SN = Sensitivity; SP = Specificity; AUC = Area-under-the-curve; row with highest predictive accuracy is shown in bold.

Source: Authors' elaboration.

of 95 per cent has a sensitivity of 26 per cent. At a cut-off value of 0.45, the highest correct test-set classification was obtained (70.3 per cent) with a sensitivity of 80 per cent and a specificity of 60 per cent. Thus, at the cut-off value of 0.45, the highest predictive accuracy of Work Profiler 2.0 was 70.3 per cent.

To show the increase in predictive accuracy of this final model compared with Work Profiler 1.0, the predictive accuracy of the Work Profiler 1.0 model was estimated using the test sample. Table 3 shows a similar trade-off between sensitivity and specificity at different cut-off points and that the Work Profiler 1.0 model obtains a lower accuracy than the Work Profiler 2.0 model at all levels. The highest accuracy of the Work Profiler 1.0 model has dropped to 66.8 per cent at the cut-off value of 0.57. This confirms that although the Work Profiler 1.0 is quite robust, accuracy drops in the long term from 69 per cent to 66.8 per cent. As stated above, the Work Profiler 2.0 model has a substantially higher accuracy of 70.3 per cent.

Step 5

In the final step, the norms for diagnostic purposes were determined. These norms are created to show professionals which factors (out of the 18 factors) hinder or

Table 3. *Predictive characteristics of Work Profiler 1.0 on the same test data set (n = 13,269)*

SN	SP	Cut-off value	% correctly predicted	SN + SP	AUC	Brier
22.4	95.0	0.82	57.4	117.4	0.74	0.21
35.5	90.0	0.77	61.8	125.5		
44.3	85.0	0.72	63.9	129.3		
51.5	80.0	0.69	65.3	131.5		
58.1	75.0	0.65	66.2	133.1		
62.8	70.0	0.61	66.3	132.8		
70.0	63.4	0.57	66.8	133.4		
75.0	58.0	0.53	66.8	133.0		
80.0	52.5	0.49	66.7	132.5		
85.0	46.1	0.44	66.2	131.1		
90.0	38.0	0.38	64.9	128.0		
95.0	28.7	0.31	63.0	123.7		

Note: SN = Sensitivity; SP = Specificity; AUC = Area-under-the-curve; row with highest predictive accuracy is shown in bold.

Source: Authors' elaboration.

facilitate a specific job seeker to return to work. A different approach for numeric factors was used compared to categorical factors. For the numeric factors, the norms were created using the scores of the group of job seekers in the sample who returned to work within one year. The first task was to convert these job seekers' raw scores for each factor into *T*-scores (Eggen and Sanders, 1993),[10,11] using the following equation: standardized *z*-score*10 + 50, resulting in scores with a mean of 50 and standard deviation (SD) of 10. Then these scores were split into five categories based on the SD: -1.5 SD, - 0.5 SD, + 0.5 SD and + 1.5 SD; thus, the boundary values of the categories were 35, 45, 55 and 65, respectively. Table 4 offers an example for the factor "Age".

10. The numerical factors are: "Age", "Views on return to work", "Job search behaviour regarding contact with employers", "Perceived health", "Readiness to accept a fulltime job", "General work ability", "Number of hours per week available for work", and "Readiness to accept work with irregular working hours".

11. Alternative approaches (percentiles and stanine) were also tried, but the analyses showed that *T*-scores worked best for caseworkers.

Table 4. *Norms for the factor "Age"*

Age	Hindering	Somewhat hindering	Neither hindering, nor promoting	Somewhat promoting	Promoting
T-score	≥ 65.01	55.01–65.00	45.01–55.00	35.01–45.00	≤ 35.00
Observed score	≥ 55	44–54	33–43	22–32	≤ 21
Norm group (row%)	8.6%	25.7%	28.9%	34.7%	2.1%
Not-reemployed (row%)	22.2%	32.9%	25.6%	13.0%	0.2%

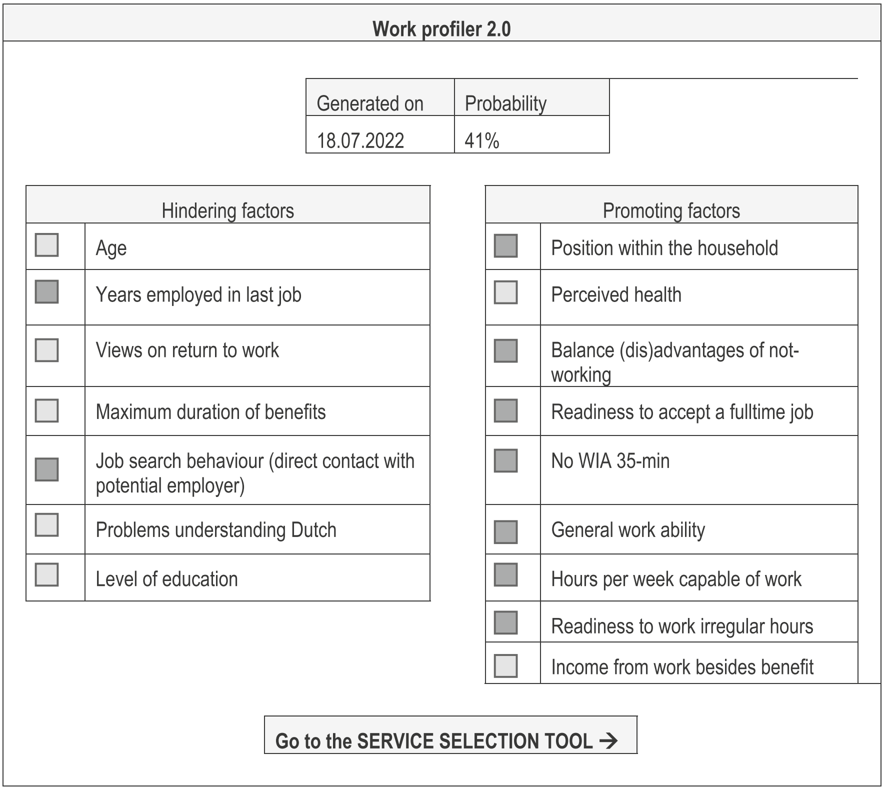
Source: Authors' elaboration.

A three-step approach was developed for the categorical factors.[12] The goal of the approach was to convert each factor (with more than two categories) into five categories in such a way that they were discriminating between those who returned to work within one year and those who did not. The first step was to fit the final logistic regression model multiple times. Each time, the reference category of the factor was changed until all categories served once as the reference category. The second step was to determine which categories could be combined. This was deemed to be the case when two categories did not differ significantly from each other, which in the large sample meant that the odds ratio (OR) was around 1. The third step reran the logistic regression model, with the adjusted categorical factor, and determined the order of the categories: the most hindering category of the scale is always the reference category; if the OR of another category is less than 1.5, this category is placed in the next part of the scale; if the OR is greater than 1.5, the category is placed in the subsequent part of the scale, and so on.

The norms are used to convert the scores of an (new) individual on each factor into a norm score of 1 to 5. In the final Work Profiler 2.0 dashboard, these norm scores are coloured from red (very hindering) to dark green (very promoting). Figure 1 displays them here in black and white meaning that the darker shades in the left column denote factors with a higher level of hinderance; while the darker shades in the right column denote factors with a higher ability to promote. For

12. The categorical factors are: "Years employed in last job", "Position with the household", "Maximum duration of unemployment benefit", "Balance of the advantages and disadvantages of not-working", "WIA 35-min", "Problems understanding Dutch", "Level of education", "Income from work besides the unemployment benefit". Two factors ("Industry prior to unemployment benefit", and "Desired profession") are only used for the prediction for work resumption within one year. The categories within these factors produced results for the caseworkers that were too aggregated to be useful in deciding which services to offer. Instead of this, they use local labour market information, which is available for each region, sector and even for most professions.

Figure 1. *The Work Profiler as a seen by professionals, which includes the probability of work resumption and the scores on each of the factors.*



Source: Authors' elaboration using the Work Profiler 2.0 dashboard.

example, the greatly hindering factors of the job seeker displayed in Figure 1 are "Years in last job" and "Job seeking behaviour". For this latter numeric factor, this job seeker has a norm score of 1, meaning that he or she scored less than -1.5 standard deviation below the mean of the norm group (those who found a job).

Discussion

The steps described above were necessary to revise and maintain the predictive model that is the core of the profiling tool, Work Profiler. The new version, Work Profiler 2.0, consists of 18 factors and obtained the highest test-set accuracy of 70.3 per cent at the cut-off value of 0.45. The first version, Work

Profiler 1.0, had an accuracy of 69.0 per cent on the total sample when it was implemented, and its test-set accuracy dropped to 66.8 per cent at the cut-off value of 0.57. The revised model is based on a more recent and much larger sample of job seekers in the Netherlands, including various sub-categories of unemployed people. The results of this study can be used to help identify which job seekers may benefit – and in which ways – from the services provided by the UWV, as the revised tool accurately predicts reemployment success and shows which factors hinder reemployment.

The need for the maintenance of the profiling tool is important in terms of its predictive validity because of changing labour market demands as well as changes within the services provided by the PES. Caseworkers who assist job seekers to find work are especially familiar with the changes that can occur in the labour market, which can influence the professional services they provide. For instance, occupations for which there is high demand for recruitment may see such demand decline over the course of several years. More generally, periods of economic recession require a different approach than is the case during periods of economic growth. Maintenance of the profiling tool is thus not only essential for keeping the model up to date, but also for safeguarding that the model fits with current developments in the labour market and is aligned fully with job seekers' needs for services.

As well as maintaining the profiling model, policy makers should be aware of the need to think through their decision rule not only when they implement a profiling model in practice, but also when considering policy responses to economic and labour market developments. As illustrated in this article, there is a trade-off between sensitivity and specificity at different cut-off points. Van Landeghem et al. (2021) have discussed this trade-off and its moral implications. This current article would further suggest that the same trade-off and moral implications apply when responding to economic developments. For instance, in a period of economic growth, the total number of job seekers may decline and thus there may be sufficient resources to provide services to a larger portion of job seekers. This can be done by updating the decision rule so that the high-risk group increases. This means increasing the cut-off point, and consequently this will lead to a drop in sensitivity and an increase in specificity. The practical implications of this are that the number of those in the high-risk group would increase, but there will also be more job seekers in this group who may not actually become long-term unemployed and may not really need (or benefit from) the provision of additional services. The opposite outcome is possible when an economic downturn occurs, with the number of job seekers increasing and there may be less capacity to provide a larger portion of job seekers with additional services. In that case, tightening the decision rule lowers the high-risk group and increases sensitivity, meaning that the smaller high-risk group contains a higher portion of job seekers who do become long-term unemployed and may benefit from additional support.

To ensure that job seekers benefit from tailored services based on a profiling tool, such as the Work Profiler, maintenance of the model involves more than just monitoring predictive accuracy. Improving the model quality is only possible with an extensive revision of the model, such as has been described in this article. An option might be for a labour-intensive variant to revise the entire model, including its theoretical constructs, every five years. The advantage of this approach would be that new information from research or practice-based insights could be inserted and verified to see whether the model had been improved, or not. The alternative approach is for more regular maintenance, which would involve the constant monitoring of the predictive accuracy and periodically re-estimating the weights of the existing model. This approach is especially well suited for short-term adjustments. In our view, a combination of the two approaches would work best. Therefore, since 2020, the year that Work Profiler 2.0 was introduced into practice, the UWV has monitored on a continuous basis the predictive value of the model, re-estimating the model weights annually. A full revision is expected in 2025.

Currently, there are rising voiced concerns, especially in public debates, about the use of algorithms by governments, institutions and corporations (Shin, 2020). This is also observed in profiling tools for job seekers, with some of the criticism expressed leading to the abandonment of using profiling tools, for example in Poland and Switzerland (e.g., Sztandar-Sztanderska and Zieleńska, 2020). The main concerns involve undesirable discrimination and incorrect or inaccurate results that unfairly categorize a job seeker and do not do justice to their individual situation, without there being the possibility for the person concerned or a professional to understand, adjust or, indeed, ignore the outcome of the instrument. It is our opinion that the discussion about the use of profiling tools is shifting towards an unproductive polarization as either “good” or “bad”.

The UWV has chosen to use the Work Profiler not as a standalone instrument, but as a complementary tool for the professional. This means that instead of positioning the professional against a profiling tool (as often occurs in debates), and qualifying one as being better than the other, the Work Profiler and professional should complement one another. Professionals are not without bias, but neither are instruments. With the roles of both being used in concert, the risk of bias is reduced and the collective outcome of the two should be much more accurate than the use of just one.

In practice, the professional consults the Work Profiler and uses its outcome together with other available information, for example labour market information, to guide the first conversation with a recently unemployed person. A diagnosis is made by the professional of the job seeker’s situation based upon the input of the jobseeker and the Work Profiler, combined with their professional insights. The UWV professionals are also assisted in their work by a Service Selection Tool that supports decision making concerning types of services to offer to job seekers (see Box 1).

Box 1. The Service Selection Tool

The UWV has created a complementary tool to assist professionals in taking decisions about which type of services to render. This was done in unison with the revised version of the Work Profiler. It is called the Service Selection Tool and makes use of two sources of information (Wijnhoven and Guiaux, 2019). The first source is the accumulated scientific knowledge of what works for whom and at what moment (De Groot and van der Klaauw, 2017; Heyma, 2015; van Hooft and van den Hee, 2017). The second source is the input of colleagues, in other words, their practice-based knowledge and experience. The factors from Work Profiler 2.0 form the starting point of the Service Selection Tool, as these are the factors hindering reemployment that can best be targeted with services. For each specific job seeker, the caseworker obtains an overview of the factors which act to hinder this specific person, and for each factor has access to the sum of knowledge on what services are appropriate. The caseworker will additionally see whether the evidence for the services is based upon scientific research or colleagues' experience. The tool is tailored, meaning that since certain services are only effective for people of a certain age, educational level, or stage in their unemployment, it will only show those that are appropriate to their client.

To offer an example of the use of the Service Selection tool, the professional may see in the Work Profiler that the job seeker has a negative view about the return to work. The Work Profiler does not indicate the reason why. The professional will discuss the situation with the job seeker and will try to ascertain the reason. The Service Selection tool shows the most common reasons for a negative view on return to work (e.g., lack of job prospects in their sector, (health) problems, care responsibilities). If the professional establishes that the negative view stems from a lack of job opportunities, the Service Selection tool indicates for which services there is evidence that these could work in that situation. In this specific case, these may be services that help the job seeker to understand their competencies and to explore the value of these in other sectors of activity. The Service Selection tool should be used only as an aid – its use is not mandatory, and the professional is not obliged to follow its outcome.

Ultimately, and besides the expectation of quality, any tool is only as good as how it is used. Key to this is the professional's trust in the tool being able to perform the job at hand. Regular maintenance of the tool is thus part of reinforcing that trust. However, this is not sufficient. Building trust also involves training professionals about how to balance the outcomes of the tool with their own insights as well as with the job seeker's wishes. Lastly, the tool should address an actual need, such that the professional knows with confidence what to do to enhance job seekers' employment opportunities. A good example of this has been the addition of amenable factors in the Work Profiler, besides non-amenable factors. Amenable factors can inform on the socio-emotional and behavioural circumstances of the unemployed person. While most non-amenable factors have little influence on PES services, amenable factors offer more opportunities for action. In fact, many PES services mainly target amenable factors. Thus, the incorporation of amenable factors may increase accuracy of the model and increase the quality of the profiling tool, as it facilitates the caseworker to be better able to understand the job seeker's situation. This proffers vital information about how to aid the job seeker and how to decide upon which services to offer to enhance the job seeker's opportunities in the labour market.

As argued above, the theoretical embedding of factors is also important, especially for job seekers, as professionals need to understand what hinders a job seeker and how to overcome these by providing tailored services. The ability of the caseworker to understand the profiling tool has also proven crucial for acceptance, readiness to work with the tool, and being capable of using the insights the tool generates in the daily work tasks. We found that a foundation of theoretical constructs is very important in this regard. These allow the caseworker to understand what the factors mean and how they influence the probability for return to work. The understanding of the profiling model and its theories allow the professional to become aware of in what ways, as well as how, they can influence the job seeker (or his or her situation) with services to enhance the probability of reemployment. In a sense, the caseworker obtains a dashboard and becomes aware of how to tailor services to specific needs.

Providing job seekers with tailored support and services starts with a profile of the job seeker's situation, the next step is building on the knowledge of what services are effective for whom and at what moment. The caseworker discusses the outcomes of the Work Profiler with a job seeker and will try to enhance the job seeker's chances for reemployment through services.

Concluding comments

To conclude, a related aim of this article is to stimulate more transparency amongst those responsible for making profiling tools. The insights concerning how a profiling tool works, especially which choices are made to make it function, are essential to its understanding. Not only is it necessary to know how well a model predicts, which is a key fact that few models publish information about (e.g., O'Connell, McGuiness and Kelly, 2012), but it is of value to have insights into the choices that led to this predictive outcome. One can and must make choices, such as regarding the type of analyses used and whether a tool's sensitivity or specificity was optimized. Sharing information on these choices will make it much easier to learn and understand whether a profiling model performs adequately and for which aspects enhancement is still required.

Transparency is also vital for job seekers, as it helps with the acceptance of, and trust in, the profiling tool. This concerns not only the prediction about work resumption, but the diagnosis offered by the instrument of the job seeker's personal situation. If the job seeker believes that the instrument, together with the actions of the professional, are keenly focused on their personal situation, then the PES can better target their services to enhance the job seeker's labour market position.

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Supporting information

Additional supporting information can be found online in the Supporting Information section at the end of this article.