

# SUPPORT FOR THE OPERATIONALISATION OF THE NINE LEARNER PROFILES: TECHNICAL PAPER



# **Support for the Operationalisation of the Nine Learner Profiles: Technical Paper**

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While the report draws upon data and analysis from the OECD, Flemish authorities and other published sources, any errors or misinterpretations remain the responsibility of the OECD team.

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# 1 Introduction

## Context

Segmentation strategies are most known and used for product marketing strategies, but they also have a high value for policy makers, including those in the field of adult learning. The identification of specific segments of the adult learning population can enable more effective policy design, implementation and resource allocation. Some OECD countries and regions have already used segmentation strategies to strengthen their adult learning policies.

Flanders (Belgium) is a leader in the use of a segmentation of the adult learning population to develop and implement skills policies. In 2022, the *OECD Skills Strategy Implementation Guidance for Flanders, Belgium: Faces of learners in Flanders* report (OECD, 2022<sup>[1]</sup>) (hereafter referred to as the *Faces of Learners in Flanders* report) was published. The project combined quantitative and qualitative techniques to identify nine distinct adult learner profiles (see Figure 1.1). A statistical method named Latent Class Analysis was used to identify subgroups of adults that possess a shared set of motivations to learn and obstacles to participation. Flemish stakeholders played a key role by sharing their expertise and perspectives on the methods, findings and potential uses of the profiles for policy-making purposes.

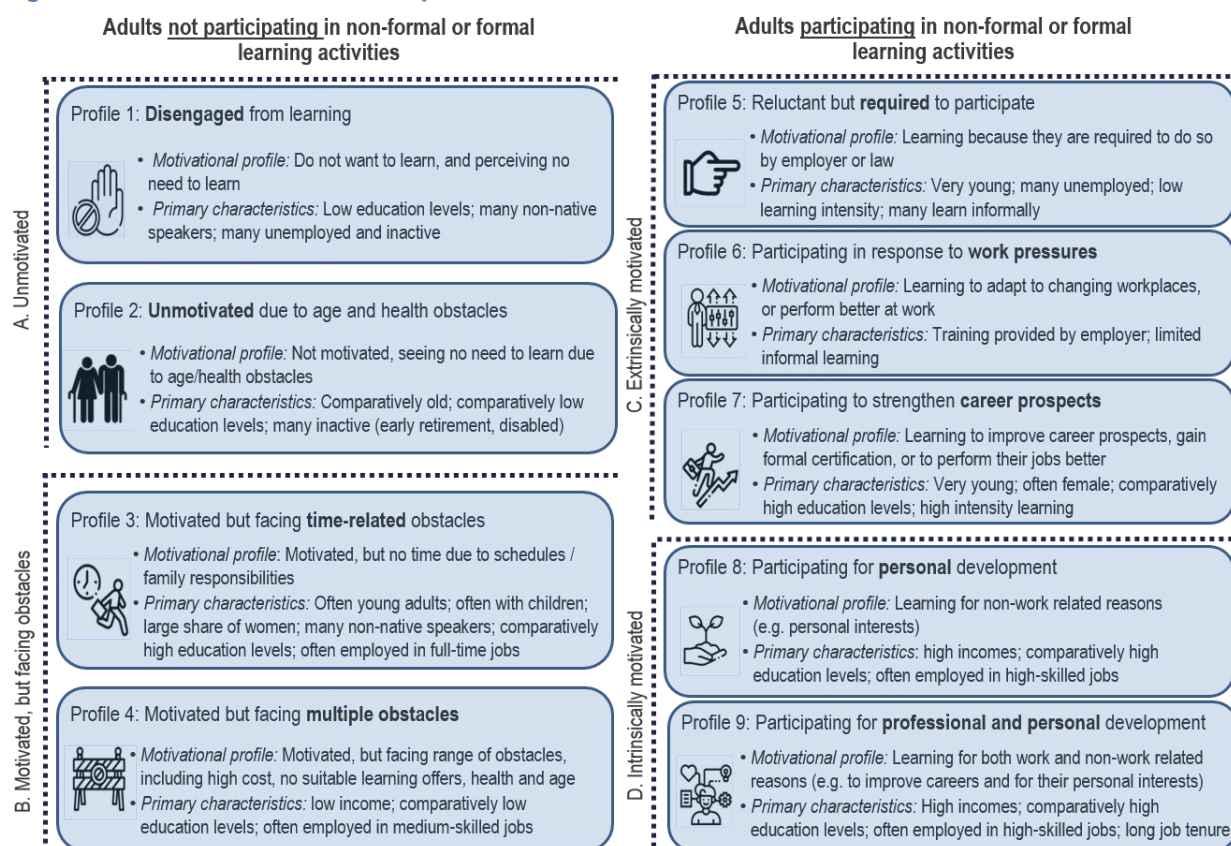
The nine learner profiles can help the Flemish Government to further strengthen adult learning policies. To start, the profiles provide new insights into the diverse set of factors driving decisions to either participate or not to participate in learning activities, which can help to inform the design and implementation of adult learning policies. For instance, insights from the learner profiles can highlight gaps in the current offer of incentives, training opportunities and resources, as well as support the identification of groups that do not receive sufficient support or the right type of support.

The learner profiles can also be used to inform skills policies more directly, by assessing how individuals or groups match the different profiles. For example, by assigning people to specific profiles, information and guidance on adult learning incentives and learning opportunities could be better tailored to learner's needs. Moreover, assigning people to profiles could strengthen policy evaluation, by providing insights on how well learning initiatives (e.g. incentives or training programmes) reach different groups of learners.

This project aims to support the Flemish Government to operationalise the nine learner profiles, by developing a screening tool that enables the assessment of how actual adults compare against the profiles. The *Faces of Learners in Flanders* report already proposed the development of such a screening tool, and in 2023, the Flemish Government decided to work with the OECD on a follow-up project to develop it. The project consisted of desk-based analysis by the OECD and was led by the Flemish Department of Work and Social Economy, which provided guidance and feedback throughout the project.

This technical paper provides a description of the context, methodology and outputs of the screening tool, and a short discussion of its potential applications.

Figure 1.1. The nine adult learner profiles and their characteristics



## Objectives of the screening tool

The objective of this project was to develop a screening tool that can assess which of the nine learner profiles identified in the *Faces of Learners in Flanders* report that an actual individual most resembles. More specifically, the tool aims to estimate how well individual's characteristics match the characteristics of the nine learner profiles. In this way, the screening tool will allow for the more concrete use of the learning profiles identified in the *Faces of Learners in Flanders* report for policy purposes. To achieve this, the OECD developed a model that assigns weights to different characteristics for the nine learner profiles in four steps (see section '2. Methodology').

The tool is offered in three different formats to facilitate its use for different purposes: i) an interactive version of the screening tool in Excel format; ii) a questionnaire and codebook; and iii) the tool in syntax format (see section '3. Project outputs').

As will be described in Section '4. Application of the tool', the tool will allow policy makers and other stakeholders to assess more accurately whether or not the different learner profiles are reached by existing initiatives, and adapt policies as required.

# 2 Methodology

## Introduction

The OECD explored different methodologies for the development of the screening tool. These methodologies included, among others, logistic models estimating the probabilities of belonging to profiles based on a list of indicators, as well as Latent Class Analysis using combinations of indicators.

The objective was to develop a model for the tool that would meet the following criteria:

- The model had to be based on data from the EU Adult Education Survey 2016 (see Box 2.1), which was also used to identify the profiles in the *Faces of Learners in Flanders* report. To ensure alignment with these profiles, the model had to work with the same set of indicators.
- The outcomes of the model had to be easy to interpret. The outcomes should clearly indicate how well an individual's characteristics match against the characteristics of profiles, for instance in the form of a probability or score within a certain range that would measure the strength of the relationship.
- The screening tool had to be easy to use by both technical and non-technical audiences and for different purposes. To this end, the tool had to be designed in such a way as to make it easy to insert information on individual characteristics, provide results with as little information as possible, and be available in different formats (e.g. Excel tool, questionnaire, syntax).
- The model had to indicate how well individual's characteristics match each of the nine profiles rather than allocate people to one specific profile. This was necessitated by the fact that the profiles are generalised descriptions of different types of learners and the characteristics of a 'real' individual generally do not match profiles on a one-to-one basis. As a result, the tool needed to be designed in such a way as to indicate the probability that an individual is a match with each of the nine learner profiles.

### Box 2.1. The Adult Education Survey

The Adult Education Survey (AES) aims to measure adult participation in education and training (formal, non-formal and informal learning) and is one of the main data sources for European Union (EU) lifelong learning statistics. The survey covers the resident population aged 25-64. The reference period for participation in education and training is 12 months prior to the interview. The latest survey was carried out in 2016, with the sample for Flanders covering 2 782 observations. While other surveys also present information on participation, motivations to learn and obstacles to participation, the AES was selected as the basis for the segmentation developed in this project as it is specifically designed to provide insights on adult learning, it has a comprehensive set of indicators on learning activities and learner characteristics, and it took place comparatively recently.

Source: Eurostat (2021<sup>[2]</sup>), *Adult Education Survey 2016*, <https://ec.europa.eu/eurostat/web/microdata/adult-education-survey>.

In consultation with representatives from the Flemish Government, a model was developed that met these criteria. The tool that results from this model makes use of indicators of the EU Adult Education Survey 2016, presents final scores that are easy to interpret, is presented in different formats to facilitate the use for different purposes, and indicates the match of individual's characteristics with all nine learner profiles.



In short, the tool is based on a model that assigns weights to all relevant characteristics, thereby providing an indication of how important these characteristics are for each of the nine profiles. Based on an individual's set of characteristics, a total score can be calculated for each of the nine profiles by adding up the weights linked to the individual's characteristics. This model, and the steps that were taken to develop it, are described in more detail below.

## The four steps for developing the screening tool

The applied methodology can be described in the following four steps:

1. Computing weights for baseline indicators
2. Computing weights for socio-demographic and employment indicators
3. Computing weights of baseline vs socio-demographic and employment indicators
4. Combining all elements in the screening tool.

### Step 1: Computing weights for baseline indicators

The learner profiles from the *Faces of Learners in Flanders* report were identified using Latent Class Analysis, a statistical method for identifying population subgroups based on multivariate categorical data (see Annex 2.A of the full report for an explanation). The nine learner profiles are the result of Latent Class Analysis for two baseline models: i) adults not participating in non-formal or formal learning activities; and ii) adults participating in non-formal or formal learning activities. These models capture the indicators that best describe the main factors explaining who does not participate (i.e. a lack of motivation and obstacles to participation) and who does participate (i.e. reasons for participating and motivations to participate more), respectively (see Table 2.1).

**Table 2.1. Indicators in baseline models for participants and non-participants**

Adults not participating in non-formal or formal learning activities	Adults participating in non-formal or formal learning activities
<p><b>Motivation preventing participation</b></p> <ul style="list-style-type: none"> <li>• Did not want to participate in education and training</li> <li>• Did not see a need for participating in education and training</li> </ul>	<p><b>Reasons for participating</b></p> <ul style="list-style-type: none"> <li>• To do my job better</li> <li>• To improve my career prospects</li> <li>• To be less likely to lose my job</li> <li>• To increase my possibilities of getting a job, or changing a job/profession</li> <li>• To start my own business</li> <li>• Because of organisational and/or technological changes at work</li> <li>• To get knowledge/skills useful in my everyday life</li> <li>• To increase my knowledge/skills on a subject that interests me</li> <li>• To obtain a certificate</li> <li>• To meet new people/for fun</li> <li>• For health reasons</li> <li>• To do voluntary work better</li> <li>• Required by the employer or by law (in non-formal education and training)</li> <li>• Obligated to participate (in formal education and training)</li> </ul>
<p><b>Obstacles preventing participation</b></p> <ul style="list-style-type: none"> <li>• Costs of participating</li> <li>• Schedule and family responsibilities</li> <li>• Lack of employer support or lack of public services support</li> <li>• Health and/or age obstacles</li> <li>• Personal reasons, incl. negative experiences; no access to computer/Internet</li> <li>• No suitable programmes, as well as lacking prerequisites for training and/or programmes are inaccessible as they are located too far away</li> </ul>	<p><b>Willingness to participate more</b></p> <ul style="list-style-type: none"> <li>• Did (not) want to participate in <u>more</u> education and training</li> <li>• Did (not) see a need for participating in <u>additional</u> education and training</li> </ul>

Source: OECD (2022<sup>[1]</sup>), *OECD Skills Strategy Implementation Guidance for Flanders, Belgium, The Faces of Learners in Flanders*, <https://doi.org/10.1787/7887a565-en>.

Outcomes of Latent Class Analysis for the two baseline models were used as the basis for the weights. Using these outcomes ensures alignment with the methodology used in the *Faces of Learners in Flanders* report to identify the nine learner profiles, and ensures that the model captures the characteristics that best describe the profiles.

The first step of the development of the screening tool was to convert the Latent Class Analysis outcomes for the two baseline models to weights. To start, the OECD re-estimated the outcomes by running Latent Class Analysis for the two baseline models. Subsequently, the weights were obtained by standardising the outcomes of Latent Class Analysis. In short, the weights are the result of dividing the mean values from the Latent Class Analysis model by the total of mean values (excluding values that are not statistically significant). As a result, the weights add up to a value of 1 for each of the nine profiles. This standardisation helped to make the results comparable across the nine profiles (mean values for profiles have different ranges) and helped to ensure that insignificant values were dropped. The weights reflect the relative relevance of each baseline indicator, or in other words, the indicator's importance for the probability of being assigned to a specific profile. Table 2.2 presents an overview of the outcomes of Latent Class Analysis and the weights for these baseline model indicators.

For Profiles 5 to 9, the calculation of weights also involved actions to correctly reflect the importance of 'reasons for participating' that characterise the learner profiles. In addition to giving a higher weight to 'reasons for participating' compared to the 'willingness to participate more', also a minimum value was introduced for reasons to be taken into consideration for the calculation of weights. This helped to ensure that the 'reasons for participating' that are most important for profiles have significant weights.

Computing the relative relevance of the two motivational variables, 'motivation to learn' and 'need to learn' required a different approach. The reason for this is that only indicators of being 'not motivated' to learn and seeing 'no need' to learn were included in the baseline models. However, several profiles are characterised by being motivated to learn, and perceiving a need to learn, which are not captured by the indicators in the baseline model and, as a result, do not have weights. To address this issue, weights were calculated for the 'motivated' and those perceiving a 'need' to learn. Both the original indicators ('not motivated' and 'no need') and their corresponding variables ('motivated' and 'need') are included in the calculation of the weights, with the final weight being assigned to the variables that are most important for the profile (i.e. which had a highest statistically significant value).

**Table 2.2. Calculation of weights for baseline model indicators**

		1. Disengaged from learning		2. Unmotivated due to age and health obstacles		3. Motivated but facing time-related obstacles		4. Motivated but facing multiple obstacles	
		Mean	Weight	Mean	Weight	Mean	Weight	Mean	Weight
Not participating	Cost	0.05	0.00	0.01	0.00	0.22***	0.07	0.30***	0.10
	Lack of support	0.00	0.00	0.00***	0.00	0.08**	0.03	0.14***	0.05
	Time	1.00	0.00	0.02***	0.01	1.00***	0.33	0.23	0.00
	Health / Age	0.24	0.00	1.00***	0.38	0.07	0.00	0.35***	0.11
	Personal reasons	0.09	0.00	0.03	0.00	0.07	0.00	0.20***	0.06
	No suitable offer	0.02	0.00	0.05	0.00	0.09	0.00	0.32***	0.10
	No need	0.71**	0.42	0.62***	0.23	0.00***	0.00	0.00***	0.00
	Need <sup>1</sup>	0.29**	0.00	0.38***	0.00	1.00***	0.33	1.00***	0.33
	Not motivated	1.00***	0.58	1.00***	0.38	0.27***	0.00	0.23***	0.00
	Motivated <sup>1</sup>	0.00***	0.00	0.00***	0.00	0.73***	0.24	0.77***	0.25
	Sum (only statistical significant values)	1.71	1.00	2.64	1.00	3.03	1.00	3.07	1.00

		5. Reluctant but required to participate		6. Participating in response to work pressures		7. Participating to strengthen career prospects		8. Participating for personal development		8. Participating for professional and personal development	
		Mean	Weight	Mean	Weight	Mean	Weight	Mean	Weight	Mean	Weight
Participating	Better job	0.36***	0.25	0.55***	0.28	0.53***	0.16	0.32***	0.10	0.84***	0.18
	Career prospects	0.00	0.00	0.08***	0.00	0.82***	0.25	0.00	0.00	0.77***	0.17
	Not to lose job	0.01	0.00	0.02**	0.00	0.12***	0.00	0.00	0.00	0.25***	0.00
	Increasing possibilities	0.02	0.00	0.02***	0.00	0.45***	0.14	0.00	0.00	0.42***	0.09
	Start business	0.01	0.00	0.00	0.00	0.06**	0.00	0.01	0.00	0.16***	0.00
	Skills for life	0.13***	0.00	0.14***	0.00	0.18	0.00	0.74***	0.24	0.59***	0.13
	Interest in subject	0.15***	0.00	0.17***	0.00	0.28**	0.00	0.94***	0.31	0.76***	0.17
	Certificate	0.03***	0.00	0.05***	0.00	0.68***	0.20	0.09***	0.00	0.36***	0.08
	Meet people for fun	0.03**	0.00	0.04**	0.00	0.08	0.00	0.33***	0.11	0.28***	0.00
	Health	0.01**	0.00	0.03***	0.00	0.00	0.00	0.06***	0.00	0.05**	0.00
	Required	0.32***	0.22	0.28***	0.00	0.25***	0.00	0.21***	0.00	0.26***	0.00
	Voluntary work	0.00	0.00	0.02***	0.00	0.00***	0.00	0.04**	0.00	0.03**	0.00
	Changes at work	0.08***	0.00	0.46***	0.24	0.05	0.00	0.05	0.00	0.27***	0.00
	Obliged	0.11***	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.01	0.00
	No need	0.55***	0.19	0.00***	0.00	0.67***	0.11	0.13**	0.00	0.02	0.00
	Need <sup>1</sup>	0.45***	0.00	1.00***	0.26	0.33***	0.00	0.87**	0.14	0.98***	0.11
	Not Motivated	1.00***	0.34	0.17	0.00	1.00***	0.15	0.37***	0.00	0.31***	0.00
Motivated <sup>1</sup>	0.00***	0.00	0.83***	0.22	0.00***	0.00	0.63***	0.10	0.69***	0.08	
	Sum (only statistical significant values)	1.46	1.00	1.92	1.00	3.31	1.00	3.07	1.00	4.57	1.00

1. these indicators were manually added after the Latent Class Analysis computation by deducting the means for 'No need' and 'Not motivated', respectively, from 1.

Note: The \*\*\* indicate the significance level in standard deviation units – \*\* is for 90% confidence and \*\*\* is for 95% confidence.

The weights show a pattern that is consistent with the findings published in the *Faces of Learners in Flanders* report. For example, Profile 3 “Motivated but facing time-related obstacles” is described as adults who are motivated to learn, but who face time-related obstacles, and Table 2.2 shows that ‘time’ and ‘motivated’ are the indicators with the highest weights (0.30 for each, compared with weights ranging between 0 and 0.18 for other indicators).

## Step 2: Computing weights for socio-demographic and employment indicators

The *Faces of Learners in Flanders* study examined not only the baseline indicators, but also additional variables to provide more detailed descriptions of the profiles, including socio-demographic characteristics (e.g. level of education, age, income) and employment characteristics (e.g. occupation, labour market status). After identifying the nine learner profiles with the two baseline models, these additional characteristics were obtained using a so-called three-step approach (see Annex 2.A of the full report for an explanation).

In this second step of the development of the screening tool, the OECD assessed the importance of these additional characteristics for defining profile membership. The outcomes of the three-step approach were the starting point. Only variables that were found to be statistically significant were selected for the analysis, which are gender, age group, education level, fluency in the Flemish language, household types, household financial situation, labour status, type of occupation, tenure and company size.

The outcomes of the three-step approach were converted into weights that indicate the relevance of the categories of indicators (e.g. ‘male’ and ‘female’ for the variable gender) across all profiles and

characteristics. To do so, the following actions were taken (see Figure 2.1 for an example of these actions for the education level variable for non-participating adults):

- 1. Calculate the average share for categories across profiles:** The outcomes of the three-step approach present the distribution across categories for all socio-demographic and employment indicators. In the first step, the average share for each category was computed, which serves as a reference point for calculating the distributions between profiles. Averages were calculated separately for non-participating and participating profiles, since it helps to refine the weights and because it is known if the individual participates or not when additional characteristics are assessed in the tool (see Step 4 for an explanation).
- 2. Calculate difference with average for comparison across profiles:** The difference between the average share and the share for each profile-category was computed, which can be used to compare the values across profiles. Positive values indicate that a specific category of a profile is overrepresented, whereas negative values indicate that the category is underrepresented. For example, in Figure 2.1 the positive value of 0.15 for category 'Tertiary' and Profile 3 "Motivated but facing time-related obstacles" reflects that a relatively large share of adults with this profile completed tertiary education.
- 3. Standardise to compare values with other characteristics:** The deviations of the shares were standardised, by adjusting values from 0 (the minimum value for the indicator) to 1 (the maximum value for the indicator). This standardisation was needed to allow for a comparison of the differences to the averages across indicators. For example, a difference to the average of 0.15 might be a comparatively large difference for the education level (from the example above), but not necessarily for other indicators (e.g. because of more categories, a different distribution, etc.). Standardisation results in a value of 1.00 for this example of 'Tertiary' and Profile 3 "Motivated but facing time-related obstacles", since it is the largest difference observed for the education level, and it can now be compared with values for other indicators (e.g. age, labour status, etc.).
- 4. Calculate the standardised value in proportion to the total of all characteristics:** The final weights of characteristics were computed using the standardised deviations in proportion to their total. This weight indicates the significance of each category across all socio-demographic and employment indicators and profiles, or in other words, the relevance of each 'category x profile' combination (e.g. 'Tertiary' and Profile 3 "Motivated but facing time-related obstacles"). The sum of the weights of all the categories adds up to 1. An overview of the final weights is presented in Table 2.3.

**Figure 2.1. Four actions to convert three-step approach outcomes to weights in practice**

Example of actions for the education level and non-participating adults

	1. Calculate average share for each category across profiles					2. Calculate difference with average for comparison across profiles					3. Standardise (min=0; max =1) in order to be compared with other characteristics					4. Calculate standardised value in proportion to total of all characteristics as indication of relevance of 'category x profile'				
	Outcomes 3-step approach					Deviation to the average proportion for each category of sociodemographic characteristic					Standardisation of the deviation (min=0; max=1)					Computing relative relevance of sociodemographic characteristics across sociodemographic characteristics.				
By level of education	P1	P2	P3	P4	Average	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4			
Below upper secondary	0.41	0.34	0.14	0.36	0.31	0.10	0.03	-0.18	0.04	0.84	0.62	0.00	0.66	0.05	0.04	0.00	0.04			
Upper secondary	0.39	0.41	0.45	0.48	0.43	-0.05	-0.02	0.02	0.04	0.39	0.47	0.59	0.66	0.02	0.03	0.04	0.04			
Tertiary	0.20	0.25	0.41	0.17	0.26	-0.06	-0.01	0.15	-0.09	0.36	0.50	1.00	0.27	0.02	0.03	0.06	0.02			
Sum	1.000	1.000	1.000	1.000		Max	0.155	Min	-0.175											
										Sum (all characteristics)	14.4	14.4	14.4	14.4	Sum (all characteristics)	1	1	1	1	

Table 2.3. Overview of weights socio-demographic and employment indicators

		Non-participants				Participants				
		1. Disengaged from learning.	2. Unmotivated due to age and health obstacles	3. Motivated but facing time-related obstacles	4. Motivated but facing multiple obstacles	5: Reluctant but required to participate	6: Participating in response to work pressures	7: Participating to strengthen career prospects	8: Participating for personal development	9: Participating for professional and personal development
Gender	Female	0.05	0.01	0.06	0.00	0.03	0.03	0.07	0.01	0.03
	Male	0.01	0.05	0.00	0.06	0.04	0.04	0.00	0.06	0.04
Age groups	Age 25-34	0.04	0.03	0.06	0.03	0.07	0.00	0.07	0.02	0.00
	Age 35-44	0.02	0.04	0.06	0.04	0.02	0.03	0.04	0.03	0.02
	Age 45-54	0.06	0.03	0.04	0.03	0.02	0.04	0.01	0.04	0.04
	Age 55-65	0.04	0.06	0.00	0.06	0.01	0.04	0.00	0.04	0.05
Migrant status	Migrant	0.00	0.02	0.05	0.06	0.02	0.04	0.06	0.00	0.05
	Non-migrant	0.06	0.05	0.02	0.00	0.05	0.02	0.01	0.07	0.02
Language spoken	Native speaker	0.01	0.06	0.00	0.06	0.01	0.03	0.01	0.07	0.05
	Non-native speaker	0.05	0.01	0.06	0.01	0.05	0.04	0.06	0.00	0.02
Level of education	Below upper secondary	0.05	0.04	0.00	0.04	0.04	0.04	0.03	0.01	0.04
	Upper secondary	0.02	0.03	0.04	0.04	0.05	0.05	0.00	0.03	0.04
	Tertiary	0.02	0.03	0.06	0.02	0.01	0.01	0.07	0.06	0.01
Household type	Couple with children	0.02	0.01	0.06	0.01	0.05	0.06	0.00	0.04	0.04
	Couple with no children	0.02	0.04	0.00	0.04	0.02	0.00	0.06	0.05	0.06
	Single parent	0.03	0.02	0.03	0.03	0.05	0.05	0.03	0.05	0.02
	One person household	0.04	0.04	0.01	0.02	0.04	0.04	0.07	0.01	0.03
Household's financial situation	Very difficult to make ends meet	0.12	0.07	0.05	0.09	0.11	0.07	0.09	0.08	0.06
	Fairly difficult to make ends meet	0.00	0.03	0.06	0.02	0.01	0.04	0.01	0.05	0.04
	Fairly easy to make ends meet	0.02	0.04	0.02	0.03	0.02	0.02	0.04	0.01	0.04
	Very easy to make ends meet	0.09	0.04	0.04	0.05	0.11	0.04	0.05	0.04	0.03
Labour status	Fulltime	0.00	0.02	0.06	0.04	0.03	0.02	0.02	0.01	0.07
	Parttime	0.03	0.03	0.04	0.02	0.00	0.04	0.05	0.04	0.02
	Unemployed	0.05	0.03	0.02	0.02	0.06	0.03	0.02	0.02	0.01
	Student	0.03	0.03	0.03	0.03	0.03	0.02	0.05	0.02	0.02
	Retired	0.03	0.03	0.01	0.05	0.02	0.04	0.02	0.04	0.03
	Permanently disabled	0.04	0.05	0.01	0.02	0.03	0.03	0.03	0.03	0.03
	Domestic task	0.03	0.03	0.04	0.03	0.03	0.02	0.02	0.05	0.03
	Other inactive	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03

An adjustment was made to the weights of the employment indicators of workers (type of occupation, tenure and company size). These characteristics are based on a sub-section of the sample – the employed population, including both full-time and part-time workers – and cannot be considered at the same level as the other characteristics. To this end, the weights for these employment indicators are recalibrated to ensure that their total weight does not exceed the weight of the ‘full-time’ or ‘part-time’ worker variable. In other words, the combined adjusted weights of the employment variables should be, at most, equivalent to the weight of the variable indicating the employment status (full-time or part-time). For instance, in Profile 1 “Disengaged from learning” the weight of the ‘full-time workers’ variable is 0.03, and the combined weights of variables such as occupation and firm size should not exceed 0.03.

The pattern presented for the nine profiles is consistent with the findings published in the *Faces of Learners in Flanders* report. For example, Profile 3 “Motivated but facing time-related obstacles” was described in the report as a profile characterised by many adults with children, a large share of non-native speakers, a low average age, high education levels, a large share of females, and many full-time employed workers. Table 2.3 shows that these are also the categories with the highest weights for this profile.

In addition to weights for socio-demographic and employment indicators, also weights for participation in informal learning was calculated in this step. Informal learning is a more unstructured type of learning, examples of which include learning from colleagues, learning from visiting learning centres, and learning by doing. In the *Faces of Learners in Flanders* report, informal learning was added through the three-step approach, just like the socio-demographic and employment indicators. Therefore, for including informal learning as an indicator in the model, the same methodology had to be applied for the calculation of the weights.

### **Step 3: Computing weights of baseline vs socio-demographic and employment indicators**

In this third step, weights were computed for the groups of baseline indicators (from Step 1) and socio-demographic and employment indicators (from Step 2). This was needed for the calculation of a final score on how well individual’s characteristics match those of learner profiles, which is based on a combination of the weights of the two groups of indicators.

The Incremental R-squared method was selected after exploring and assessing the advantages and disadvantages of different methods. The R-squared value is a measure that indicates the proportion of the variance in the dependent variable that is explained by the independent variables. With the Incremental R-squared method, variables are added to a regression model one at a time, and the change in the R-squared value is observed with each addition.

For the comparison between baseline indicators and socio-demographic and employment indicators, the following actions were undertaken:

1. **Setting up the initial model:** In this model, the dependent variable was a dummy that indicates membership to a specific profile, and the independent variables were the baseline indicators. A Linear Probabilistic Model (LPM) was used to calculate the R-squared value for this initial model ( $R1^2$ ).
2. **Adding comparison variables:** All socio-demographic and employment indicators were added to the initial model as additional predictors. This resulted in a new R-squared value ( $R2^2$ ).
3. **Computing the Incremental R-squared:** Based on the outcomes of these two models, the incremental R-squared for the socio-demographic and employment indicators was obtained by computing the difference between the two R-squared values ( $R2^2 - R1^2$ ). This value shows how much the new predictors increased the R-squared value, i.e. how much more variability in the dependent variable is explained by including the new predictor in the model.
4. **Evaluating the significance:** The weights were obtained by calculating the relative R-squared values of the baseline indicators ( $R1^2$ ) and the socio-demographic and employment indicators ( $R2^2 - R1^2$ ), with the total for each profile adding up to 1 (see Table 2.4 for an overview of the final weights). The statistical significance of this incremental R-squared was evaluated using hypothesis tests such as the F-test.

**Table 2.4. Weights of baseline indicators and socio-demographic and employment indicators**

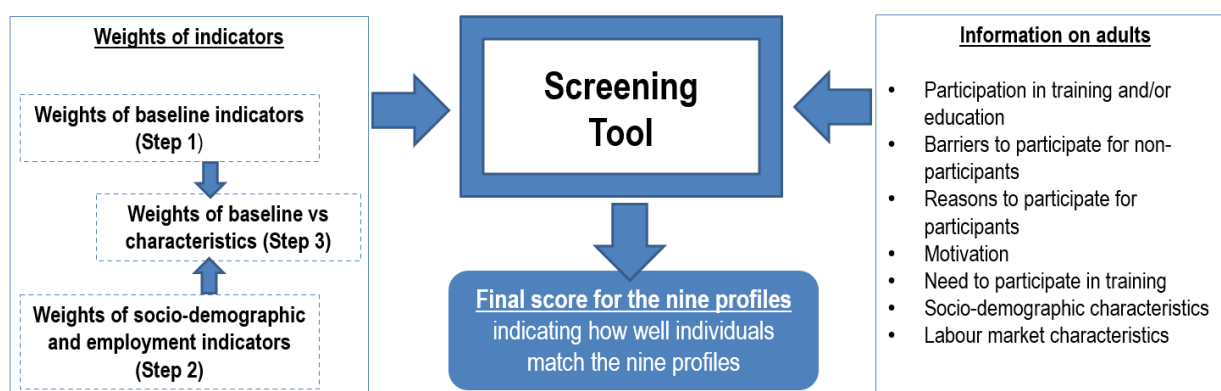
		Baseline indicators	Socio-demographic and employment indicators
Not participating	1. Disengaged from learning.	0.872	0.128
	2. Unmotivated due to age and health obstacles	0.909	0.091
	3. Motivated but facing time-related obstacles	0.985	0.015
	4. Motivated but facing multiple obstacles	0.987	0.013
Participating	5. Reluctant but required to participate	0.980	0.020
	6. Participating in response to work pressures	0.990	0.010
	7. Participating to strengthen career prospects	0.857	0.143
	8. Participating for personal development	0.996	0.004
	9. Participating for professional and personal development	0.982	0.018

The Incremental R-squared method is easy to implement and interpret, and it helps to identify the most important variable(s) among a set of potential predictors, but it has some limitations. Firstly, it does not handle multicollinearity well. If predictors are correlated, then the incremental R-squared may not provide an accurate picture of the importance of individual variables. Secondly, the stepwise inclusion of variables can lead to overfitting, especially if the sample size is small. Finally, the importance of variables can appear differently depending on the order in which they are entered into the model. Despite these limitations, the Incremental R-squared method was still considered the best method for the comparison of baseline indicators and socio-demographic and employment indicators.

A clear finding of the weights presented in Table 2.4 is that baseline indicators are more important than socio-demographic and employment indicators for assessing profile membership. Weights for baseline indicators range from 0.857 for Profile 7 “Participating to strengthen career prospects” to 0.996 for Profile 8 “Participating for personal development”. However, this was expected given that these baseline indicators underpin the nine learner profiles. Other methods that were explored showed similar patterns.

#### **Step 4: Combining all elements in the screening tool**

In the fourth, and final, step, all the information was combined and a total score was calculated for each of the nine profiles by adding up the weights linked to the individual's characteristics. Three main components can be distinguished (see Figure 2.2 for an overview): weights of indicators; information on adults; and the final score of the nine profiles.

**Figure 2.2. Overview of screening tool**

### *Weights of indicators*

A main input to the tool are the weights from Steps 1-3. The weights of baseline indicators (Step 1) and weights of socio-demographic and employment indicators (from Step 2), both with a minimum of 0 and maximum of 1, are linked by the weights calculated in Step 3. The result is a sum of weights that ranges from 0 to 1.

### *Information on the characteristics of the adults who are being compared against the profiles*

A key input to the tool not yet described is the information on the 'actual' individual that will be assessed against the characteristics of the profile. This information refers to information on whether people are participating in learning activities or not, socio-demographic and employment characteristics of the individual, which can be obtained through a variety of methods depending on how the tool is intended to be used.

The tool is designed primarily for the purposes of supporting policy evaluation. For this purpose, information on the actual adults who participated in a given intervention that is being evaluated can be obtained through surveys. The Flemish Government already runs several surveys on adult learning (e.g. to measure impact of existing incentives), which could be expanded to ensure that all information for the screening tool is collected – i.e. whether or not they participated, motivations and obstacles to learning, and more. This information can then be matched with the weights of indicators and result in final scores (representing the match with profiles – see next section) for each respondent's input. The tool has been designed with this in mind and the number of indicators has been limited to reduce the burden for respondents to surveys.

As will be described in the section '4. Application of the tool', the Flemish Government also envisions that the tool will be used by other stakeholders in the future for other purposes. In such cases, the information may be obtained through a variety of different channels, such as completed by career guidance counsellors or via online forms completed by the adults themselves.

To improve the accuracy of the estimation of a given individual's match with profiles, it is important that as much information as possible is collected. Some data could be considered essential, such as whether the individual participates in learning activities or not. In addition, the information on the baseline indicators is of great importance, such as information about an individual's motivations to learn, barriers to participation (for adults who not yet participate), and reasons for participating (for adults who do participate). Additional information on socio-demographic and employment characteristics could further improve the accuracy of the estimation.

### *The final scores as a measure of the strength of the association between the individual and the nine profiles*

Based on the combination of weights of indicators and the information on the adults being assessed, final scores are calculated for all nine profiles to understand which one (or ones) the individual is closest to.

This score is the sum of the weights of indicators associated with the individual. It can range from a value 0, meaning that the individual has not a single characteristic in common with the profile, to a value of 1, meaning that all characteristics of the individual match the characteristics of the profile. In short, the higher the score, the better the match with the profile. Moreover, it is important to interpret scores in comparison to scores of other profiles. The OECD did not identify specific thresholds within the range of 0 to 1 for scores to be considered 'high' or 'low', for instance. The reason for this is that the distribution of final scores is unknown and depending on the inputs of the model. Any indication of a high or low score would be somewhat arbitrary.

A notification appears when scores are based on insufficient data. The only condition for the score is that individuals must provide information regarding participation in education and training, information



concerning the obstacles preventing them from participating (for non-participants), and reasons for participating in education and training (for participants). If this information is not provided, scores will be presented but the tool flags that they are calculated based on insufficient information.

Figure 2.3 presents an example of how the score is calculated for Profile 3 “Motivated but facing time-related obstacles”. The dummies for the different categories indicate the characteristics of the individual (1=yes; 0=no) and weights for the categories are presented next to it on the right. The scores for the baseline indicators and socio-demographic and employment indicators are the sums of the weights for which the related dummy is 1, and the total score is calculated by applying the weights from step 3 of the process. With this method, characteristics that are positively associated with Profile 3 “Motivated but facing time-related obstacles” (e.g. time obstacles, being motivated to learn) contribute directly to the score, whereas characteristics that are not positively associated with the profile (e.g. not suitable offer, being female) do not contribute to the score.

**Figure 2.3. Example of calculation score for Profile 3 “Motivated but facing time-related obstacles”**

Profile 3's score membership	0.89		
Missing information (*=yes)			
		<b>Weights</b>	
Indicators' score	0.901		0.985
Characteristics sociodemographics' score	0.285		0.015
<b>Baseline indicators</b>			
Indicators' score	0.901		
		<b>Weights</b>	
Cost	0		0.07
Lack of support	0		0.03
Time	1		0.33
Health / Age	0		0.00
Personal reasons	0		0.00
No suitable offer	0		0.00
No need	0		0.00
Need	1		0.33
No motivated	0		0.00
Motivated	1		0.24
<b>Characteristics sociodemographics</b>			
Characteristics sociodemographics' score	0.285		
		<b>Weights</b>	<b>Input*Weight</b>
Age group			
Age 25-34	0	0.061	0.000
Age 35-44	1	0.063	0.063
Age 45-54	0	0.035	0.000
Age 55-65	0	0.000	0.000
		<b>Gender</b>	
Male	0	0.000	0.000
Female	1	0.063	0.063

Note: The figure presents only a selection of the indicators included in the analysis.

## 3 Project outputs

Three main outputs were created to support the operationalisation of the nine learner profiles from the *Faces of Learners in Flanders* report:

1. **an interactive version in Excel**, in which the final scores can be calculated by selecting different sets of characteristics. It demonstrates how the screening tool works in practice and it could be used for an assessment of how closely specific individuals' match with the learner profiles – i.e. what profile(s) most closely fit the individual's characteristics.
2. **a questionnaire and codebook**, which is designed to facilitate the collection of information on the adults being assessed against the profiles. Among other things, it presents an optimal order of the questions in English and Flemish as well as detailed descriptions of the information that needs to be collected.
3. **the tool in syntax format**, which can be used by policymakers to calculate scores at the individual and aggregate level on data collected through surveys on adult learning (e.g. impact surveys of learning incentives). The syntax helps to ensure that indicators are in the correct format and links information on adults with the weights of indicators.

### An interactive version in Excel

An interactive version of the screening tool is provided in the form of an Excel file, which can be completed for an individual for the purposes of assessing how closely they match with each of the nine learner profiles. The file allows the user to assess how different combinations of characteristics affect the scores of the learner profiles. When questions about the characteristics of the individual are answered, the scores for each of the nine profiles are automatically calculated and updated.

See Figure 3.1 for an example of how a selection of indicators resulted in final scores for the profiles. In this example, the individual did not participate in formal and/or non-formal learning (resulting in a 0 for profiles 5-9 of participating adults), but was motivated to learn, and indicated busy schedules and family responsibilities are the main obstacles (resulting in a high score for Profile 3 “Motivated but facing time-related obstacles”).

This file can be used in different ways. First of all, it provides insights into how the screening tool works in practice by demonstrating how sets of characteristics affect the scores of the nine learner profiles, which could help users to better understand the relative importance of different characteristics. Second, Flanders has been exploring the use of the tool by a broader group of stakeholders at a later stage, and this interactive version could facilitate this by providing an easy-to-use tool that allows individuals to explore the match with the nine learner profiles. For example, as will be discussed in section ‘4. Application of the tool’, career guidance counsellors could use the tool in intake meetings or during the counselling sessions to identify the profile(s) that most closely fit the individual's characteristics, which could be a starting point for providing advice on relevant training opportunities, available incentives, and more. While the tool allows individuals to explore the match with the nine learner profiles, people should be informed about the limitations of the nine learner profiles, which are in fact generalised descriptions of different types of learners. For the correct use of the tool, it is necessary for the Flemish Government to provide appropriate guidelines (see section ‘4. Application of the tool’).

Figure 3.1. Example of interactive use of screening tool

	P1: Disengaged from learning	P2: Unmotivated due to age and health obstacles	P3: Motivated but facing time-related obstacles	P4: Motivated but facing multiple obstacles	P5: Reluctant but required to participate	P6: Participating in response to work pressures	P7: Participating to strengthen career prospects	P8: Participating for personal development	P9: Participating for professional and personal development
Score	0.000	0.008	0.890	0.568	0.000	0.000	0.000	0.000	0.000
Missing info in modules A and B					*	*	*	*	*

**Profiling tool**

**A. Participation in formal or non-formal training**

1. In the last 12 months, have you been participating in any type of formal education or studying towards a formal qualification (e.g. university or vocational degree, or completing high school)?

2. In the last 12 months, have you been participating in any type of non-formal training such as courses, workshops, seminars, private lessons?

**B. Drivers behind participation and non-participation**

**B.1. For non-participants**

3. a. Previously you stated that during the last 12 months you did not participate in any kind of education or training. Despite this, would you have liked to participate in such activities?

4. a. Do you feel that you would benefit from participating in education or training?

5. a. Which of the following obstacles prevented you from participating in education and training? (mark all that apply)

- I did not meet conditions / required prior knowledge
- The cost/too expensive
- Lack of support from the employer or public services
- The training did not fit into my work schedule
- There was no training within an accessible distance
- No access to internet / computer for distance learning
- I didn't have time because of family responsibilities
- My health
- My age
- Other personal reasons
- Lack of suitable education or training activity
- Negative learning experience in the past

**B.2. For participants**

3. b. What were the reasons for participating in the education or training? (mark all that apply)

- To do my job better
- To improve my career prospects
- To be less likely to lose my job
- To increase my possibilities of getting or changing a job
- To start my own business
- Because of organisational / technological changes at work
- To get knowledge/skills useful in my everyday life
- To increase my knowledge/skills on a subject that interests me
- To obtain certificate
- To meet new people / for fun
- For health reasons
- To do voluntary work better
- Required or obliged the employer or by law

4. b. Previously you stated that you participated in education and training. Would you have liked to participate even more in such activities?

5. b. Do you feel that you would benefit from participating more in education and training?

**A questionnaire and codebook**

A questionnaire and codebook have been developed to support the use of the tool by policy makers and other potential users (see section '4. Application of the tool'). These outputs are an extension of the screening tool (available as an Excel file) and are designed to facilitate the collection of information on the characteristics of the adults being assessed. To ensure alignment with the definitions of the indicators underpinning the nine learner profiles, the questionnaire is based on the Adult Education Survey 2016 questionnaire.

The questionnaire has been developed with the aim to make it easy to use and to minimise data collection. It provides an overview of all questions and answer categories that are needed to optimally calculate scores for learner profiles. The questionnaire also suggests the optimal order of the questions, starting with the most important information for assessing individual's match with profiles and finishing with the least

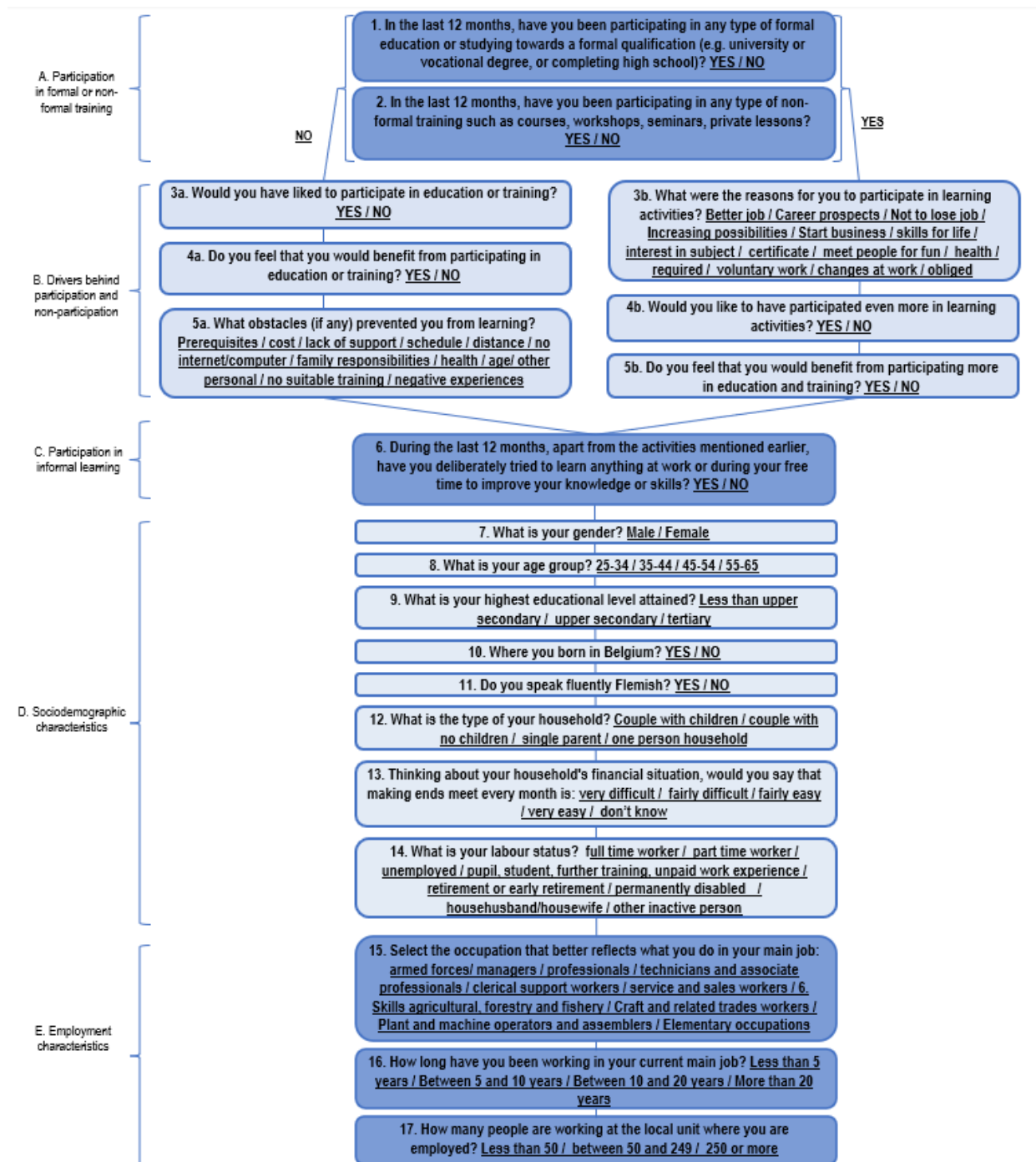
important information. While this is considered the optimal order of questions, it is not essential to follow this order to obtain final scores.

As presented in Figure 3.2, the Questionnaire consists of five main categories of questions:

- **Participation in formal or non-formal training:** two separate questions for formal and non-formal learning.
- **Drivers behind participation and non-participation:** these are the baseline indicators with questions for non-participants (motivation and need to learn, and obstacles preventing participation) and participants (reasons for learning, and motivation and need to learn more).
- **Participation in informal learning:** one question on participation in informal learning (e.g. learning from others, learning by doing and learning new things at work), for people who do and do not participate in formal or non-formal learning activities.
- **Socio-demographic characteristics:** including questions on gender, age group, education level, fluency in the Flemish language, household types, household financial situation and labour status. The indicators are organised by their respective importance for the learner profiles.
- **Employment characteristics:** including the type of occupation, tenure and company size.

The questionnaire is accompanied by a codebook, which describes in detail the indicators underlying each of these five categories of questions, including the variable names, value categories, and how the indicators are constructed.

Figure 3.2. High-level overview of the questionnaire



## The tool in syntax format

To support the operationalisation of the screening tool, the OECD converted the tool in a syntax format for both STATA and SPSS. This syntax facilitates the calculation of scores for the learner profiles, by ensuring that indicators are in the correct format and by linking information on adults with the respective weights. It is especially helpful to policy makers, who can use the syntax to calculate scores at the individual and aggregate level on data collected through surveys on adult learning (e.g. impact surveys of learning incentives).

The syntax follows five main steps:

1. **Preparing the dataset of inputs from individuals:** All the variables that are used in the screening tool are generated, including the baseline indicators and socio-demographic and employment indicators. The syntax shows, as an example, how the original variables from the Adult Education Survey need to be adjusted. The most common adjustment was transforming categorical variables into extended dummies and regrouping categories for increasing sample and statistical significance.
2. **Defining the weights per each profile:** The weights from steps 1-3 (see descriptions above) are incorporated in the do-file. In STATA, these weights are integrated as global (i.e. a user-defined macro that stores text or commands and is accessible throughout the entire session) to be used directly as part of the computations of the score membership.
3. **Computing profile's membership score:** The score for each profile is calculated in four parts:
  - a. Computing partial scores by labour status. Calculations begin by solving the inner brackets, which means in this context computing partial scores for the labour status. Partial scores are computed for employed (full- and parttime workers), unemployed, and the different inactive groups, by multiplying their weights respective weights from step 1 with the dummies with information on adults created in step 1.
  - b. Computing partial scores for all sociodemographic indicators, including informal learning and labour status (from above), resulting in indicators sd\_p1, sd\_p2, etc. for the nine profiles. These scores are computed by multiplying the weights on socio-demographic indicators from step 2 with the dummies with information on adults from step 1 and adding up the resulting scores.
  - c. Computing partial scores for baseline indicators for participants and non-participants, resulting in indicators bi\_p1, bi\_p2, etc. for the nine profiles. Weights on baseline indicators from step 2 are multiplied with the dummies with information on adults from step 1, and the resulting scores are added together.
  - d. Computing the total profile membership scores, resulting in Score\_P1, Score\_P2, etc. for the nine profiles. These scores are computed by multiplying the scores from part b (sd\_p1, sd\_p2, etc.) and part c (bi\_p1, bi\_p2, etc.) with the weights of baseline vs socio-demographic and employment indicators.
4. **Flagging scores that do not meet the minimum requirements:** After calculating the scores, the scores will be highlighted for which there is not sufficient information available, i.e. scores that are not based on information on participation in formal or non-formal training or the drivers behind participation and non-participation. In practice, this means that a message will appear alongside the score indication that the information is not complete.
5. **Computing total aggregate score for the profiles:** based on the calculations above, the profile membership scores are calculated for individual respondents. In this final step, a total aggregate score is computed for each profile, as well as the distribution of the profiles (i.e. the percentage of respondents in each profile).

# 4 Application of the tool

The three outputs described in this technical paper will support the Flemish Government to operationalise the nine learner profiles described in the *Faces of Learners in Flanders* report.

Discussions with representatives from the Flemish Government suggest that the tool could be especially useful for the evaluation of existing adult learning policies. By adding the questions from the questionnaire to impact or satisfaction surveys of adult learning programmes or incentives (e.g. the Flemish training incentives), the tool (in syntax format) could be used to calculate scores at both the individual and aggregate level, thereby providing insights on how programmes and incentives are used by the learner profiles of adults who already participated (i.e. Profiles 5-9). The Flemish Government already runs several surveys on adult learning (e.g. to measure the impact of existing incentives), which could be expanded to ensure that all information for the screening tool is collected, and administrative databases could be used to collect this information (e.g. on socio-demographic characteristics). These results allow policy makers to assess more accurately how well existing initiatives are reaching the five different learner profiles and, by extension, help them to identify whether adjustments need to be made to these policies and/or whether new measures may be required for certain groups. The aim is to enable the Flemish Government to make their initiatives more targeted and tailored to the needs of different learner profiles.

The *Faces of Learners in Flanders* report also proposed other methods for using the learner profiles, and the screening tool could help to facilitate this. Some possible applications of the screening tool could include the following:

- Stakeholders could also use the tool to support an assessment of how well their initiatives are reaching different groups of learners. For example, just like the Flemish Government, stakeholders could also use impact or satisfaction surveys to explore how their initiatives reach the profiles. This could be especially relevant for providers of education and training, but also HR companies, unions, and more. Some stakeholders already target specific groups of learners, and general insights into how initiatives reach the nine learner profiles could complement and strengthen these efforts.
- Career guidance counsellors could use the tool in intake meetings or during the counselling sessions as a starting point for discussion. By identifying the profile(s) that most closely fit the individual's characteristics, the counsellor could better tailor information and guidance to the needs of that person and make better referrals. This assessment could be a starting point for counselling sessions, followed by tailored advice based on the specific situation of the individual and informed by expert knowledge, including on the available training offer and incentives.
- The tool could be incorporated into online adult learning platforms (e.g. platforms that provide information about incentives and relevant learning opportunities) to enable them to better target and tailor information to the visitor's needs. This would involve asking visitors to complete a questionnaire that would identify which of the profile(s) most closely fit the characteristics of the visitor. Information that is relevant for the specific profile will then be presented to the visitor, who will benefit from information that is more closely aligned to his or her learning obstacles, motivations and learning needs.

When using the tool, the Flemish Government and other stakeholders should consider a number of factors. First, users should be aware that the profiles are generalised descriptions of different types of learners,

and not homogenous groups of people, but rather a bundle of different personalities with common motivational profiles and attitudes towards learning. As a result of this generalised nature of the learner profiles, it could be that outcomes of the tool are not suitable for all purposes. For example, the learner profiles might still be too broad and high-level for education and training providers to evaluate their training offer. In such a scenario, more tailored questionnaires might be required to provide relevant insights.

Second, not all combinations of characteristics result in a strong allocation to a specific profile. In fact, it is unlikely that people perfectly match a single profile and people could very well be related to multiple profiles. This could have implications for the use of the tool. For example, it might be difficult for career guidance counsellors to provide advice when people are associated with multiple profiles. Therefore, for the purpose of counselling, outcomes of the tool would always need to be complemented with a more personal, individual approach, informed by expert knowledge.

Third, users should be aware of the potential risk that people might feel stigmatised by being identified as belonging to a specific profile (e.g. Profile 1 “Disengaged from learning”, which has a somewhat negative connotation). This point was raised by stakeholders that were consulted by the Flemish Government for the project, despite considerable interest in the use of the learner profiles by these stakeholders. To address this issue, users should keep in mind the possible risk of stigmatising people when presenting the user with outcomes of the results, including by indicating that the profiles are generalised descriptions and that the person likely matches multiple profiles, albeit to a lesser extent.

Overall, to ensure the appropriate use of the screening tool, it will be important to provide guidelines on its use as well as clear definitions of the various indicators and categories that are input to the model. This will be especially important if not only policy makers, but also a broader range of stakeholders use the tool. In addition to the broader considerations presented above, the guidelines also would need to explain the practical use of the tool and the conditions that need to be met. For instance, it would be important to highlight that the questions and categories in the questionnaire should not be changed by users in a way that would change their meaning.

To conclude, the screening tool has the potential to support the development of adult learning policies and initiatives in Flanders that are better targeted and tailored to the needs of learners. While users of the tool need to be aware of its limitations, it provides policy makers and stakeholders in Flanders with an accessible tool that could support the operationalisation of the nine learner profiles for a diverse range of purposes, ranging from improved policy evaluation and more targeted and tailored training and incentives to the provision of more relevant information and guidance for learners.



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