2 The nine adult learner profiles in Flanders, Belgium

This chapter describes the population segmentation methodology used to identify the nine adult learner profiles in Flanders, Belgium. It explains why applying a segmentation approach matters for Flanders, introduces the model and describes in detail the nine adult learner profiles generated based on the shared motivations and obstacles adults face. The nine identified profiles are analysed and compared in detail to provide new insights into adult learning in Flanders.

Strengthening adult learning policies through population segmentation

Segmentation approaches and adult learning policies

The segmentation of markets is a well-established strategy when seeking to bring a new product to consumers. The concept of "market segmentation" was first articulated by Wendell R. Smith in 1956, and is defined as the practice of dividing a heterogeneous market into a number of smaller homogeneous markets in response to differing preferences among these individual segments (Wendell R. Smith, 1956[1]). Traditionally, market segmentation enables firms to maximise profit by focusing on the segments where they can bring the highest value added or by offering differentiated products to customers with different preferences or tastes. For example, the marketing strategies of companies involves understanding the needs and wants of segments, designing or tailoring their products to a segment, and then reaching out to the individuals in that group (Wind, 2007[2]). Segmentation can be based on a number of factors such as geography, demography, psychographic and behavioural traits (Goyat, 2011[3]).

Whilst segmentation strategies are most known and used for product marketing strategies, they also have a high value for policy makers, including 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. For example, segmentation allows policy makers to identify groups of adults currently under-served by existing lifelong learning incentives (Australian National Training Authority, 2000[4]). In general, for segmentation to be an appropriate tool for a particular policy area the corresponding market must be sufficiently large, have significant differences between the characteristics of members, and lead to groups that can tangibly inform the development and implementation of better policy (Australian National Training Authority, 2000[4]). Due to its characteristics, the adult learning "market" likely meets these criteria.

The population segmentation of Flemish adult learners – which will be described in more detail in this chapter – places motivational profiles and obstacles to participation at the centre of the approach by identifying subgroups in the adult population based on similar motivations and obstacles (as measured by the European Union's Adult Education Survey 2016). This enables a detailed assessment of the main reasons for individuals engaging or not in learning.

Using a segmentation approach to better target and tailor Flemish adult learning policies

In the context of budgetary pressures and in the interests of ensuring the efficient and equitable expenditure of public funds, countries are increasingly looking at how to better target and tailor polices to those most in need. This is as true for skills policy as it is for any other policy area. However, effectively reaching and engaging the groups most in need of learning has proven an enduring challenge for adult skills systems across all OECD countries, including for Flanders (see Chapter 1) (OECD, 2019[5]).

To address the challenge of reaching the groups most in need of learning, many lifelong learning initiatives in Flanders are already targeted and tailored to certain specific groups. Stakeholders consulted during this project indicated that eligibility criteria for learning initiatives are often defined by target groups, such as adults with low levels of education, unemployed adults and non-native speakers. However, as discussed in Chapter 1, efforts to tailor policies to these existing target groups in Flanders have not yet led to a significant increase in their participation, and Flanders still faces challenges in reaching adults most in need of upskilling or reskilling.

There are various reasons why these targeted and tailored initiatives have not been fully effective. Flanders, as with most OECD countries, currently targets and tailors policies to specific groups defined by a single characteristic, such as age, educational attainment or labour market status. This approach ignores the fact that adults not participating in learning typically have different attitudes towards learning and face multiple obstacles to participation (e.g. lack of time, cost, health and age). Groups such as "adults with low education levels" or "unemployed" are highly diverse. For example, adults with low levels of education could consist of early school leavers, long-term unemployed and older generations, all of whom would require different sets of policy interventions to encourage their participation.

Current targeted and tailored initiatives also do not consider the varying motivational profiles of adults. Throughout this project, stakeholders noted that a lack of willingness to participate in learning is a primary driver of the low rate of participation in Flanders, and should be considered when targeting and tailoring policies to specific groups. In Flanders, the relevance of motivations for participation in learning was extensively discussed in the 2019 *OECD Skills Strategy Flanders: Assessment and Recommendations*, as well as in recent Flemish studies (see also Chapter 1) (Van Langenhove et al., 2020[6]; Van Langenhove and Vansteenkiste, 2020[7]). However, existing incentives mostly target the direct costs of education and training (e.g. subsidies, tax incentives), and do not address some of the most important reasons adults do not participate in learning, such as this lack of willingness to participate.

Applying a population segmentation approach to adult learning could help with understanding how to develop lifelong learning policies, programmes and courses that are better targeted and tailored to the needs of adults with different profiles. Population segmentation facilitates the creation of more granular and insightful profiles of potential learners by allowing policy makers to better understand how a constellation of factors (e.g. motivations, obstacles to learning) influence the likelihood that adults will participate in learning. This can help to raise the impact of lifelong learning policies by more accurately addressing the profile-specific issues that prevent adults participating. In addition, dividing the whole adult learning market into smaller segments will help Flanders to assess whether existing policies, programmes and courses reach the right groups, evaluate if Flanders currently has the right mix of policy measures, and establish if existing target groups could be further refined (see Chapter 3 for a discussion on the policy implications of segmentation).

While well-known indicators of adults' willingness to learn and the obstacles they face have been explored in many reports, the added value of segmentation is that it shows with greater granularity the different types of learners by identifying how certain combinations of motivations and obstacles are manifested in people – what is referred to in the report as "learner profiles" – and by providing insights on the different types of motivation of participating adults based on reasons to learn (e.g. extrinsic vs. intrinsic motivations).

Examples of segmenting exercises for education and training markets

The application of segmentation methodology to facilitate the more precise targeting and tailoring of adult learning policies is still relatively underutilised in OECD countries. Nonetheless, several OECD countries have undertaken studies to segment their adult learning populations. In 2000, the Australian National Training Authority commissioned a *National Marketing Strategy for Skills and Lifelong Learning,* which used segmentation methods to identify eight groups of adult learners based extensively on attitudinal and behavioural factors (Australian National Training Authority, 2000[4]). The United Kingdom has also been at the forefront of using these methods and has commissioned two studies, one in 2008 and one in 2016, to more precisely segment the adult learning population (see Box 2.1).

Within the education and training sector, segmentation methods have primarily been used in higher education (Aydin and Ozturk, 2015[8]). Universities have used these methods to understand different categories of students and to support the design of programmes and services that meet their distinct needs. For example, many universities use demographic segmentation to differentiate between younger and mature students, which allows for the design of more targeted and relevant messaging for each segment (Hemsley-Brown, 2017[9]). Segmentation can also be used to identify the common characteristics of individuals least likely to apply to university, which can help universities to widen access. Digital and distance learning similarly benefit from the application of segmentation strategies by supporting the tailoring of more individualised messages to learners and the design of personalised (i.e. responsive to their specific needs) online services (Aydin and Ozturk, 2015[8]).

Box 2.1. Segmentation strategies for adult learning in the United Kingdom

Segmentation of Adults by Attitudes Towards Learning and Obstacles to Learning, 2008

The United Kingdom has relatively extensive experience of applying population segmentation methods to adult learners. In 2008, the Department for Innovation, Universities and Skills (DIUS) commissioned Continental Research to develop a segmentation analysis of attitudes and obstacles to learning among adults. This study used data from the UK National Adult Learning Survey (2005), which focused on adults aged 19-69 living in England and Wales (3 173 respondents). To produce the segments, the dataset was subjected to a hierarchical cluster analysis, which led to a ten segment solution. For this study, the most important predictors of segment membership were obstacles to learning (such as "no time because of family" and "employer would not support learning"), rather than attitudinal or motivational factors. A summary of their findings is included in Table 2.1.

Table 2.1. Segments from UK 2008 cluster analysis

	% of population	Socio-demographics	Obstacles to learning
Enthusiastic and enlightened	29.2%	Mainly no children	None
Fulfilled and family-focused	14.5%	Mainly younger women with children	Too busy with family
Hampered hard workers	7.1%	More male than average	Too busy at work
Looking for learning	4.9%	Younger than average	Don't know where to look for training
Trapped on a treadmill	5.9%	Younger than average	Can't afford learning and busy at work
Older into other things	11.1%	Mainly older men	Not interested in any learning
Too late to learn	10.6%	Mainly older women	Low confidence and busy with family
Sceptical but scraping by	5.5%	More male than average	Not interested and busy with work
Unfulfilled and unhappy	8.6%	More female than average	Low confidence and multiple obstacles
Disaffected and discouraged	2.6%	More male than average	Basic skills and multiple obstacles

Decisions of adult learners, 2018

In 2018, the Department for Education commissioned Kantar Public and Learning and Work Institute to produce another segmentation of the adult learning market. This segmentation relied on qualitative research rather than survey data. The model was built from in-depth interviews with 70 learners, and focus groups with 16 adults not currently learning. The study found that participants' attitudes towards learning were essential for determining whether an individual participates in training. Attitude, or motivation, was considered the most influential determinant of learning. This led to the creation of an attitudinal typology with six types of learner identified: 1) life-long learners; 2) defiant learners; 3) outcome-focused learners; 4) tentative learners; 5) exhausted learners; and 6) stuck in status quo learners. The study uses this typology to discuss the "tipping point" for learners, whereby the benefits to learning outweigh the costs. According to the report, every learner faces four stages of decision making when deciding to participate in learning: 1) pre-contemplation; 2) contemplation; 3) determination; and 4) maintenance.

Source: UK DIUS (2008[10]), *Segmentation of Adults by Attitudes Towards Learning and Obstacles to Learning*, https://dera.ioe.ac.uk//8720/; Kantar Public and Learning and Work Institute (2018[11]), *Decisions of adult learners*, https://learningandwork.org.uk/resources/research-and-reports/decision-making-of-adult-learners/.

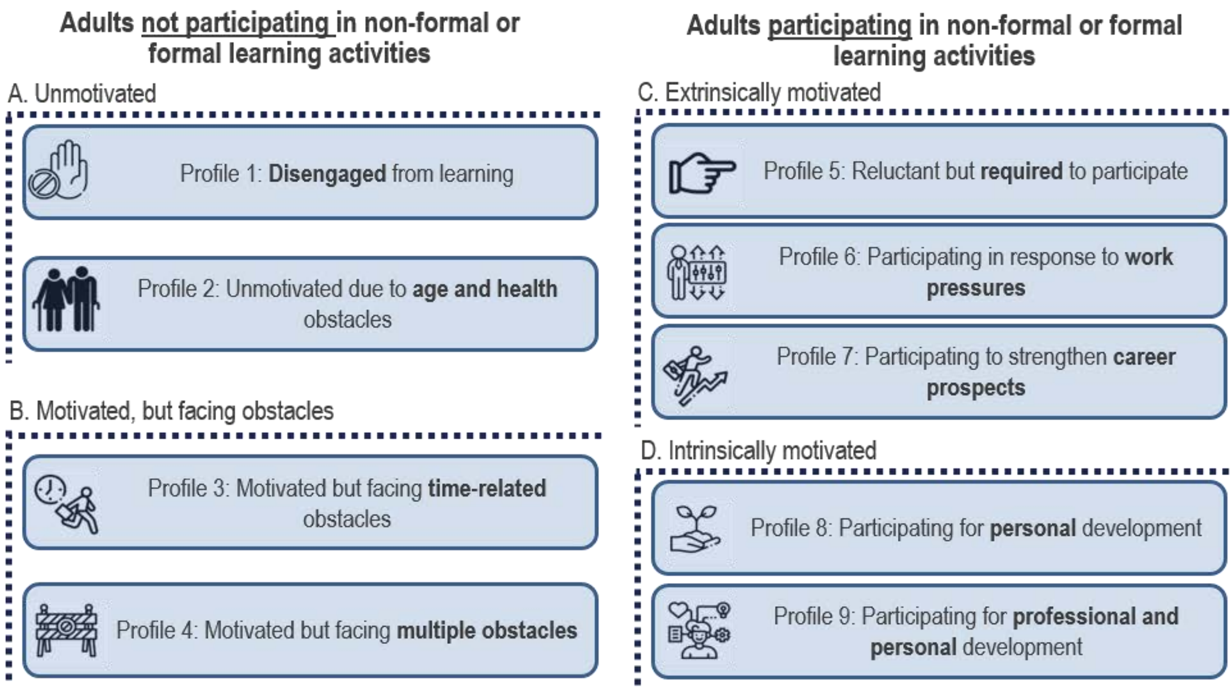
Segmentation strategies have also been applied to labour market policy. For example, the approach has been used to assess the employment obstacles faced by adults. The OECD *Faces of Joblessness* report (Fernandez et al., 2016[12]) develops a segmentation model that uses Latent Class Analysis (LCA) to identify groups of adults facing similar obstacles to employment. This methodology, which has now been applied to several countries, was one of the inspirations for the methodology employed in this report.

Applying a segmentation approach to identify different profiles of adult learners

Nine adult learner profiles based on shared motivations and obstacles

The OECD has developed a model to segment the adult learning population in Flanders, based on motivations to learn and obstacles to participation in learning activities – i.e. the main factors that determine participation. This model identifies nine adult learner profiles in the Flemish adult population (aged 25-64), each characterised by a shared combination of motivations and obstacles (see Figure 2.1).

Figure 2.1. The nine adult learner profiles



Note: See Annex 2.A for a full description of the underlying methodology.

The segmentation model is run separately for adults who are not participating in non-formal and formal learning activities, and those who are participating (see Box 2.2 for a description of this definition). Four profiles of "non-participating" adults are identified (representing 52% of the population). Conditional to their willingness to learn and the obstacles preventing their participation in learning activities, these four profiles of non-participating adults can be classified into those who are "unmotivated" and those who are "motivated but facing obstacles". Five profiles of "participating" adults are identified (representing 48% of the population). Based on their reasons for participating in learning activities, the five profiles of participating adults can be classified into those who are "extrinsically motivated" and those who are "intrinsically motivated". The identification of the nine profiles facilitates analysis of how they differ and, by extension, how policies, programmes and courses can be designed or redesigned to better respond to their unique characteristics and needs.

Box 2.2. Definition of participation in learning in the segmentation model

Adults can learn through formal, non-formal and informal learning opportunities:

- **Formal education/learning**: Formal education/learning is provided in schools, colleges, universities or other educational institutions and leads to a certification that is recognised by the national educational classification.
- **Non-formal education/learning**: Non-formal education/learning is defined as an education or training activity that does not necessarily lead to a formal qualification, such as on-the-job training, open or distance education, courses or private lessons, and seminars or workshops.
- **Informal learning**: Informal learning relates to typically unstructured, often unintentional, learning activities that do not lead to certification. In the workplace, this is often an automatic by-product of the regular production process of a firm.

In the segmentation model, to distinguish between participants and non-participants, the most common definition for participation in learning was used, specifically participation in formal and non-formal learning (in the last 12 months). This definition is the standard for most international comparable indicators of participation in education and training. However, while not part of the main model, participation in informal learning is explored in this study (see section on "Learning patterns and outcomes").

Source: OECD (2011[13]), *PIAAC Conceptual Framework of the Background Questionnaire Main Survey*, www.oecd.org/skills/piaac/PIAAC(2011_11)MS_BQ_ConceptualFramework_1%20Dec%202011.pdf.

Latent Class Analysis was the methodology applied to identify profiles in the adult population with similar characteristics. The European Union's Adult Education Survey (AES) 2016 was the primary data source used for this analysis (Eurostat, 2021[14]) (see Box 2.3 and Annex 2.A for a detailed description of the applied methodology). This quantitative approach was complemented by qualitative approaches to confirm the validity of the profiles identified by the model. Flemish stakeholders have played a key role in developing and validating this segmentation by sharing their views and providing expertise in multiple consultations.

Box 2.3. Identifying adult learner profiles with Latent Class Analysis

Latent Class Analysis (LCA)

LCA is a statistical method for identifying population subgroups based on multivariate categorical data. Similar to other clustering methods, LCA identifies mutually exclusive and exhaustive latent (or unobserved) classes based on patterns in observed data. LCA estimates class membership probabilities and uses iterative numerical methods to find the model that best fits the data (based on a statistical criteria). LCA is extensively used in several applications, such as to classify patterns of behaviour or attitudes, identify consumer preferences, and examine subpopulations based on their response to survey or test items.

The segmentation models based on motivations and obstacles

For the segmentation of the Flemish population based on the Adult Education Survey (AES) 2016, the LCA estimates two baseline models for two different groups of adults: 1) adults not participating in non-formal or formal learning activities; and 2) adults participating in non-formal or formal learning activities. The reason for this is that the most effective policies for these two groups are considerably different, and there will likely be different policy objectives (e.g. for non-participating adults, policies will mainly aim to ensure that adults will participate, while for participating adults, policies will mainly aim to ensure that adults participate more or in more relevant learning activities). These models include the indicators that best describe the main drivers behind not participating (i.e. a lack of motivation and obstacles to participation) and participating (i.e. the different reasons for participating and motivations to participate more).

For the first group of profiles (non-participating), the model includes indicators on both motivation and obstacles to participation (see first column in Table 2.2). In the AES, all adults who did not participate in learning activities were asked whether they would have liked to participate, thereby indicating their motivation. If they did not want to participate, they were asked if that was because they did not see a need for learning. Regardless of whether adults want to participate, they were also asked about the obstacles they face. For some cases, the obstacles are grouped to increase the statistical representativeness of the sample (e.g. time-related obstacles include variables on schedule constraints and family responsibilities).

For the second group of profiles (participating), the model relies primarily on indicators of their reasons for participating in learning, including both job-related and not job-related factors (see second column in Table 2.2). These indicators provide insights into their attitudes towards learning, which could be linked to different types of motivational profiles (e.g. extrinsic and intrinsic motivations to learn). In addition, to have a more comprehensive view of these motivational profiles, indicators in AES of their willingness to participate more – i.e. in addition to the learning activities they already participate in – are included, thereby providing insights into motivations *ex post* the learning activity (in contrast to the *ex ante* reasons to learn).

Table 2.2. Indicators in baseline models for participants and non-participants

Not participating	Participating	
Motivation preventing participation	**Reasons for participating**	
• Did not want to participate in education and training • Did not see a need for participating in education and training	• To do my job better • To improve my career prospects • To be less likely to lose my job • To increase my possibilities of getting a job, or changing a job/profession • To start my own business • Because of organisational and/or 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 a certificate • To meet new people/for fun • For health reasons • To do voluntary work better • Required by the employer or by law (in non-formal education and training) • Obliged to participate (in formal education and training)
Obstacles preventing participation	**Willingness to participate more**	
• Costs of participating • Schedule and family responsibilities • Lack of employer support or lack of public services support • Health and/or age obstacles • Personal reasons, including negative experiences; no access to computer/Internet • No suitable programmes, as well as lacking prerequisites for training and/or programmes are inaccessible as located too far away	• Did (not) want to participate in more education and training • Did (not) see a need for participating in additional education and training	

Covariates for identifying additional characteristics

After identifying the nine adult learner profiles through estimating two baseline models, additional variables have been included in the model to identify the associated characteristics of the profiles. Following a three-step approach, more detailed information on the nine profiles were examined, including socio-demographic characteristics (e.g. level of education, age, income), labour market characteristics (e.g. occupation, labour market status), skills requirements of their occupations, and learning patterns and outcomes.

Each of the nine profiles has a set of characterising indicators described by a unique combination of motivations and obstacles. In constructing the nine profiles, the OECD considered significance level (95%) and the strength of the relationship between indicators and the profiles (probability>0.3) of each coefficient. For each profile, a distinction is made between characteristics with the strongest coefficients (so-called “primary characteristics”) and characteristics with lower coefficients, but which still meet the criteria of significance and strength of relationship (“secondary characteristics”). Table 2.3 presents an overview of the main characteristics of each profile.

Some profiles are comprised of only primary characteristics, which are all very strongly associated with the profile. For example, Profile 1: “Disengaged from learning” is characterised by not wanting to participate in learning and not seeing a need to participate, both of which are primary characteristics. Other profiles are constructed from combinations of primary and secondary characteristics. For example, for Profile 4: “Motivated but facing multiple obstacles”, cost obstacles, health- and age-related obstacles, and the lack of availability of suitable programmes are all important primary characteristics, while a lack of support (e.g. from employers or public services) and personal reasons (e.g. no access to a computer or Internet) are relevant secondary characteristics.

It should be noted that LCA allocates individuals and characteristics to profiles in a probabilistic rather than deterministic way. As a result, specific characteristics could have strong associations with the specific profiles, but they generally are not linked with each other in a 1-to-1 relationship. This means that not every person associated with a given profile will have all of the characteristics of that profile.

Additional characteristics of the nine adult learner profiles

Table 2.4 below describes how additional characteristics map onto the nine learner profiles. These characteristics include socio-demographic characteristics, labour market status, the skills requirements of occupations typically associated with each profile, as well as their typical learning patterns and outcomes (see Box 2.3 for a brief description of the underlying methodology of these covariates, and Annex 2.A for a detailed description). These additional characteristics help to provide a more complete impression of each of the nine profiles.

Table 2.3. Characterising indicators of the nine adult learner profiles

● Primary characteristics
○ Secondary characteristics
x Insignificant or below treshold

	A. Unmotivated		B. Motivated, but facing obstacles	
	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
Share of population	19%	18%	6%	9%
Motivation preventing participation				
Did not want to participate in education and training	●	●	x	x
Did not see a need for participating in education and training	●	●	x	x
Obstacles preventing participation				
Costs of participating	x	x	x	●
Schedule and family responsibilities	x	x	●	x
Lack of employer support or lack of public services support	x	x	x	○
Health and/or age obstacles	x	●	x	●
Personal reasons, incl. negative experiences, no access to computer	x	x	x	○
No suitable programmes, including prerequisites and distance	x	x	x	●

	C. Extrinsically motivated			D. Intrinsically motivated	
	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
Share of population	16%	17%	5%	3%	7%
Job-related reasons for participating					
To do my job better	●	●	●	○	●
To improve my career prospects	x	x	●	x	●
To be less likely to lose my job	x	x	x	x	x
To increase possibilities of getting/changing a job	x	x	○	x	○
To start my own business	x	x	x	x	x
Because of organisational/technological changes at work		●	x	x	x
Not job-related reasons for participating					
Required by the employer or by law	●	○	x	x	x
To get knowledge/skills useful in my everyday life	x	x	x	●	○
To increase knowledge/skills on subject of interests	x	x	x	●	●
To obtain a certificate	x	x	●	x	○
To meet new people/for fun	x	x	x	○	x
For health reasons	x	x	x	x	x
To do voluntary work better	x	x	x	x	x
I was obliged to participate	○	x	x	x	x

Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

Table 2.4. The main additional characteristics of the nine adult learner profiles

Percentage (%) of adults with each profile and characteristics

	A. Unmotivated		B. Motivated, but facing obstacles		C. Extrinsically motivated			D. Intrinsically motivated	
	1. Disengaged	2. Age & health	3. No time	4. Multiple obstacles	5. Required	6. Work pressures	7. Career prospects	8. Personal	9. Professional and personal
Age groups									
Age 25-34	18	12	28	14	47	24	47	29	24
Age 35-44	12	17	30	17	23	28	30	24	23
Age 45-54	40	29	29	27	22	29	17	28	30
Age 55-65	29	42	12	41	7	19	5	19	24
Level of education									
Below upper secondary	41	34	14	35	10	11	9	4	12
Upper secondary	39	41	45	48	40	40	29	35	39
Tertiary	20	25	41	17	50	50	62	61	49
Gender									
Male	46	52	45	54	52	51	37	60	51
Female	54	48	55	46	48	49	63	40	49
Native speakers									
Yes	81	91	79	90	89	91	88	96	94
No	19	9	21	10	11	9	12	4	6
Household's income distribution[1]									
Bottom 40%	58	49	48	50	41	25	27	24	23
Top 40%	25	35	38	30	44	53	50	52	57
Household composition									
Couple with children	53	50	68	51	59	61	53	59	59
Couple with no children	14	23	8	23	15	13	21	19	21
Single parent	8	3	9	7	7	8	5	8	3
One person household	24	24	15	19	18	18	22	14	17
Labour status									
Worker	54	58	79	64	81	87	88	85	90
Unemployed	13	3	2	2	9	5	3	3	2
Inactive	34	39	19	34	10	8	9	12	9
Skill level of occupation									
Low	15	9	12	13	2	5	5	1	4
Medium	46	50	42	57	42	35	29	25	27
High	40	41	46	30	56	60	66	73	69
Risk of automation									
Low	18	22	14	16	25	34	32	38	35
Medium	29	25	38	21	36	38	39	41	40
High	53	53	48	63	40	28	29	21	25
Participation in informal learning									
No	39	50	33	55	24	31	13	16	18
Yes	61	50	67	45	76	69	87	84	82

Note: Only significant values are included in the table.
1. The values in the column do not add up to 100% because the middle of the distribution (i.e. 40%-60%) are not listed.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/5q3xyi

The box on the next page describes the nine profiles in more detail, including their associated motivations and obstacles, as well as other key characteristics.

The nine adult learner profiles

Adults not participating in non-formal or formal learning activities

A. Unmotivated

1. **Disengaged from learning:** These adults are unmotivated to participate in learning and do not see a need to participate.

   This profile is characterised by having the lowest education levels of all profiles (41% educated below the upper secondary level), the largest share of adults not in employment (13% unemployed and 34% inactive) and the lowest average income. These characteristics partly explain the low motivation of the profile (e.g. socio-economic challenges, such as poverty and inadequate housing may mean that learning is a lower priority). Adults with this profile are comparatively old, and non-native speakers represent a significant minority. Working adults with this profile tend to be employed in jobs requiring low- to mid-level skills, have a high likelihood of working in manufacturing, and tend to be in jobs facing a high risk of automation. Despite not participating in non-formal or formal learning, 61% participates in informal learning, such as learning on-the-job or visiting learning centres (e.g. libraries). Profile 1 represents 19% of the adult population in Flanders.

2. **Unmotivated due to age and health obstacles:** This profile consists of adults who are unmotivated to learn and perceive no need to participate in learning opportunities. However, this low motivation is largely the result of the age and health related obstacles they face (e.g. adults feeling too old to learn new things).

   Adults with this profile have the highest average age (42% of individuals aged between 55 and 65), education levels that are comparatively low, and a high likelihood of inactivity due to early retirement and/or disability (together representing 25% of adults with this profile). Compared to Profile 1, adults with Profile 2 are more likely to be employed and work predominantly in small businesses in jobs requiring low or medium levels of skills. In addition, adults with this profile are more likely than others to be working in a job at high risk of automation. 50% of adults participates in informal learning, which is one of the lowest shares of all profiles. Profile 2 represents 18% of the adult population in Flanders.

B. Motivated, but facing obstacles

3. **Motivated but facing time-related obstacles:** The majority of adults with this profile are motivated to participate in learning, but do not have enough time due to either a busy schedule (37% of adults), family responsibilities (29% of adults), or both.

   This profile is characterised by having the largest shares of both adults in a relationship with children (69%) and single parents (9%). Moreover, non-native speakers represent a significant minority for this profile (22%). Among non-participating profiles, this is the youngest (59% of adults are below 45 years of age), the highest educated (41% has a tertiary degree) and has the highest proportion of females (55%). Almost 80% of adults with this profile are working, with most employed in full time jobs. Some 67% of adults participates in informal learning, the highest share among non-participating profiles. Profile 3 represents 6% of the adult population in Flanders.

4. **Motivated but facing multiple obstacles:** Adults with this profile are motivated to engage in learning but face a range of obstacles, including high cost, the absence of suitable learning offers, and health and age related obstacles.

Adults with this profile are relatively old, but not as old as Profile 2, and have relatively low levels of education, but higher than adults in Profile 1. The income of adults with this profile is comparatively low, partly because a comparatively large share are inactive. Looking at different job characteristics, there is a large share of adults in medium-skilled occupations (57%), with jobs in small businesses (55%) and/or with jobs that tend to have a very high risk of automation (63% – the highest share of all profiles). This profile stands out as having the lowest share of adults participating in informal learning (45%). Profile 4 represents 9% of the adult population in Flanders.

Adults participating in non-formal or formal learning activities

C. Extrinsically motivated

5. **Reluctant but required to participate:** These adults are participating in learning, but only because they are required to do so by the employer or by law.

   This is a very young profile (47% of adults under 35). While it is one the lowest educated participating profiles (only 49% of adults completed tertiary education), the profile is still more highly educated than any non-participating profile. This is also the profile with the second highest proportion of unemployed adults (9%). Working adults with this profile are typically employed in jobs requiring mid- to high-level skills, and these jobs face a relatively high risk of automation compared to those held by other participating profiles. While Profile 5 stands out with a comparatively low to medium intensity of learning (as measured by the number of hours in learning), a relatively large share participates in informal learning (76%). Profile 5 represents 16% of the adult population in Flanders.

6. **Participating in response to work pressures:** The majority of adults with this profile are extrinsically motivated learners who are participating in learning to adapt to organisational or technical changes in the workplace, or are participating to perform better in their current job.

   Compared to Profile 5, adults with this profile are older and more often employed, and their jobs have a lower risk of automation. Non-formal learning is often provided by the employer, and the participation rate in informal learning (69%) is the lowest among the participating profiles. Profile 6 represents 17% of the adult population in Flanders.

7. **Participating to strengthen career prospects:** Adults with this profile are participating to improve their career prospects, to improve their professional opportunities by gaining formal certification, or to perform their jobs better. Their motivation to learn could be characterised as "identified regulation", which is a type of extrinsic motivation characterised by the ambition to attain a personally valuable goal. This type of motivation is more self-determined and personal than the extrinsic motivations of adults with Profile 5 and 6, and not far removed from intrinsic motivation.

   Looking at their socio-demographic characteristics, adults in this profile are comparatively often female (63%), highly educated (62%) and/or very young (47% of adults are under 35 years of age). When analysing labour characteristics, many adults with this profile are employed in jobs requiring high levels of skills (66%) and/or are typically employed in medium-large enterprises (63%). This profile also has the largest proportion of part time workers (22%). Learning by adults with this profile is characterised by a comparatively high intensity (i.e. learning for many hours), as well as by participation in informal learning (87%). Profile 7 represents 5% of the adult population in Flanders.

D. Intrinsically motivated

8. **Participating for personal development:** Adults with this profile are intrinsically motivated and participating in learning for non-work related reasons, such as to gain knowledge/skills that are useful for everyday life or to explore their personal interests and passions.

   This profile has the highest share of adults employed in occupations requiring high levels of skills (74%). They are found in professional occupations, with a large share employed in health and social work and education. Working adults with this profile have the lowest risk of automation of any profile. Adults are typically highly educated and have comparatively high household incomes. Most adults with this profile participate in informal learning (84%). Profile 8 is the smallest profile, representing 3% of the adult population in Flanders.

9. **Participating for professional and personal development:** As with Profile 8, these are intrinsically motivated adults who want to participate in learning. Unlike Profile 8, their primary motivation for learning is to achieve work related objectives. For example, many adults with this profile participate to perform better in their current job or to improve career prospects.

   Looking at their socio-demographic characteristics, this profile has adults who are highly educated, work predominantly in high-skilled occupations (often managerial positions), and/or are generally employed in medium- to large-sized firms. This profile has the highest household income of all profiles. Adults with this profile have the longest tenure and the majority train with the support of their employers. A large share (82%) also participates in informal learning. Profile 9 represents 7% of the adult population in Flanders.

Motivations and obstacles to learning of the nine adult learner profiles

Categories of motivational profiles

Adults can have very diverse reasons for participating or not participating in learning activities that reflect differing motivations. In discussions with Flemish stakeholders, the importance of assessing the different types of motivation was a recurring topic of conversation.

There is an extensive body of literature on the motivational profiles of learners. Most of these studies apply self-determination theory, which distinguishes between three main learner profiles: the intrinsically motivated, the extrinsically motivated and the unmotivated (Deci and Ryan, 2000[15]). Only a few studies examine the motivational profiles of adult learners specifically, including a study in Flanders that assesses the motivations of adults in the context of online and blended learning (Vanslambrouck et al., 2015[16]). Based on a survey with 180 learners in adult education, three motivational profiles were identified: 1) an "extrinsic" profile with high identified regulation (which is a type of extrinsic motivation characterised by ambitions to attain a personally valuable goal); 2) an "autonomous" profile with high intrinsic motivation and identified regulation; and 3) a "motivated" profile with high intrinsic motivation and high identified introjected regulation (i.e. behaviour to maintain a positive view of themselves and/or to avoid feelings of shame and guilt).

In the segmentation, motivations were an input to the analysis for both participating and non-participating adult learner profiles. For adults not participating, differences in motivation can be identified based on the extent to which adults indicate that there is no need to learn, as well as to the extent to which they identify that obstacles are the main reason for not wanting to participate. For participating adults it was possible to identify their motivations based on the reasons they gave for participating in learning (e.g. out of interest in a subject, to improve job performance), as well as their self-reported attitudes towards learning more (e.g. being motivated to participate in more learning activities). The nine profiles can then be classified into four categories of motivational profiles: 1) "unmotivated"; 2) "motivated but facing obstacles"; 3) "extrinsically motivated"; and 4) "intrinsically motivated".

Those who are “unmotivated” are predominantly found in Profile 1: “Disengaged from learning” and Profile 2: “Unmotivated due to age and health obstacles”. Both profiles are primarily composed of adults who indicate that they do not want to learn, and who note that this is largely due to a (self-perceived) lack of a need to learn. To some extent, this lack of interest in learning is a result of their personal circumstances. For adults with Profile 1: “Disengaged from learning”, challenges related to high levels of unemployment, inactivity or employment in low-skilled occupations may mean that learning is often not perceived as a very high priority relative to other challenges. For example, some may prioritise job search over training to meet basic needs, while others may have limited expectations of returning to work. For many low-skilled workers employed in jobs that require low levels of skills, the benefits of learning may not be obvious and they may have limited understanding of what training they need and how to find it. Flanders should therefore aim to make these adults more aware of the benefits of learning, and to consider a broader range of policies (e.g. social policies such as income support and housing policies) to promote learning among these adults who often face various socio-economic challenges. Profile 2: “Unmotivated due to age and health obstacles” is characterised by many older adults who are often in early retirement, as well as many permanently disabled adults. These adults may perceive that they would benefit little from participation in learning, especially for job-related reasons.

Those who are “motivated but facing obstacles” are found in Profile 3: “Motivated but facing time-related obstacles” and Profile 4: “Motivated but facing multiple obstacles”. These profiles are more motivated than Profiles 1 and 2, with only small shares indicating that they do not want to participate in learning activities. Instead, they identify several obstacles that hinder their participation, including time-related obstacles (Profile 3: “Motivated but facing time-related obstacles”) and the cost of training, lack of resources and lack of suitability of the training offer (Profile 4: “Motivated but facing multiple obstacles”).

Those who are “extrinsically motivated” are found in Profile 5: “Reluctant but required to participate”, Profile 6: “Participating in response to work pressures” and Profile 7: “Participating to strengthen career prospects”. These adults participate in learning primarily due to external factors. Within this group of extrinsically motivated learners, there are important differences in their reasons for participation. Profile 5: “Reluctant but required to participate” is composed of adults required to participate or who want to participate to perform better in their job, and comparatively often they report that they do not want to participate more. Profile 6: “Participating in response to work pressures is composed of individuals whose motivation can be described as having a “controlled” character, meaning that their decision to participate is mainly the result of external incentives. For example, this profile is characterised by participation due to organisational and technical changes in the workplace, but also to perform their job better. The motivations of adults with Profile 7: “Participating to strengthen career prospects” could be described as having “identified regulation”, meaning that they are typically objective-driven adults who want to attain a personal goal, either personal or professional. For adults with this profile, the main reasons to participate are to improve career prospects, increase their professional possibilities by gaining formal certification and perform their job better. Profile 7: “Participating to strengthen career prospects” includes a large share of adults indicating that they do not want to learn more, which may be explained by the very high intensity of their existing learning activities – i.e. they may feel that they have already participated in all the learning they want and need. Some 61% of adults with this profile participate in high-intensity learning (defined as participation in learning activities of more than 36 hours in total or the top quartile of the distribution of hours participated), which is the highest share among participating profiles.

Those who are “intrinsically motivated” are found in Profile 8: “Participating for personal development” and Profile 9: “Participating for professional and personal development”. People with these profiles participate in learning for its inherent pleasure and satisfaction. Both profiles are characterised by learners participating to increase knowledge/skills on a subject of interest. However, these two profiles differ from each other in terms of the aims of their learning and the sorts of subjects typically of interest. While Profile 8: “Participating for personal development” typically participates in learning to gain knowledge/skills useful in everyday life and because of their personal interests and passions (e.g. personal development), Profile 9: “Participating for professional and personal development” typically participates to improve career prospects or to perform their job better (e.g. professional development).

Developing the intrinsic motivation of adults to learn was stressed as an important objective by stakeholders consulted in this project. In times of crisis, such as the COVID-19 pandemic, the relevance of intrinsic motivations becomes arguably even more important, with intrinsic self-motivation an important pre-condition for effective online learning. This is also reflected in the reasons people decided to learn during the pandemic – learning because of a specific interest in a topic (51% of participants) and for fun and relaxation (23%) were among the most important reasons given for participation in learning (Statistiek Vlaanderen, 2021[17]).

Obstacles to learning

To provide a holistic overview of the challenges that adults face to participation in learning, obstacles related to cost, health and age, lack of employer or public services support, time-related obstacles, and a lack of suitable education or training offers are all factored into the segmentation model.

Among non-participating profiles, adults with Profile 1: “Disengaged from learning” are less likely than adults in any other profile to claim that they face obstacles to participation. Adults with this profile do not report obstacles as the primary reason for their non-participation. As mentioned previously, their personal circumstances likely result in a relatively low priority for learning (e.g. they might prioritise trying to find a job). These circumstances could in a way be considered obstacles to their participation, but they are not directly captured by the model and are therefore not classified as such. Adults with Profile 2: “Unmotivated due to age and health obstacles” are unmotivated, but this likely stems from the obstacles that they claim to face – around 70% of adults with this profile cite problems with health and/or age as reasons for their non-participation. In this way, obstacles and lack of motivation are a self-reinforcing vicious circle.

For adults with Profile 3: “Motivated but facing time-related obstacles”, participation is desired but hindered by time-related obstacles. For 37% of adults with this profile their work schedule is the main obstacle to participation, and for 29% family responsibilities prevent participation. Adults with Profile 4: “Motivated but facing multiple obstacles” face a broad range of interlinked obstacles. Compared to other profiles, adults with this profile are the only ones that cite the cost of courses as an obstacle to learning. The lack of a suitable training offer, health and/or age, a lack of support (e.g. employer support or public services support) and personal reasons (e.g. no access to a computer or Internet) are also commonly cited obstacles for adults with this profile.

Among adults in all participating profiles (i.e. Profile 5 to Profile 9), time-related obstacles linked to schedule or family responsibilities are considered the most important obstacles to continued participation in learning. However, the proportion of adults facing these obstacles remains low for each of these participating profiles. The impact of other obstacles is comparatively negligible.

Analysis of characteristics of the nine adult learner profiles

In the following section, several characteristics of the nine adult learner profiles will be analysed in more detail, including social and demographic characteristics, labour market status, the most commonly held occupations and the skills requirements of those occupations, and learning patterns and outcomes. These characteristics, unlike the motivations and obstacles to learning, are not part of the baseline model, but were entered into the model after the nine profiles were determined in order to better understand the unique characteristics of each profile (as explained in Box 2.3). This analysis examines the main differences between profiles and assesses what lessons can be learned from this variation. Key findings of the analysis are presented in the box below.

Key findings of the analysis of characteristics of the nine learner profiles

Social and demographic characteristics

- Older adults are concentrated in Profile 1: "Disengaged from learning" and especially Profile 2: "Unmotivated due to age and health obstacles". These groups are characterised by having the lowest levels of motivation.
- Low levels of education and employment in jobs requiring low levels of skill are strongly associated with low motivation and non-participation in learning. Every non-participating profile has lower levels of educational attainment than every participating profile.
- The two profiles with the highest proportion of non-native speakers are Profile 1: "Disengaged from learning" (19%) and Profile 3: "Motivated but facing time-related obstacles" (21%), demonstrating that non-native speakers not participating in learning activities face significant and complex challenges to participation. Thus, non-native speakers need a wider range of support to increase their motivation to participate in learning and overcome the different obstacles.

Labour market status

- Adults participating in learning are more often in employment, indicating that employment is one of the best policies for promoting skills development. Between 82% and 90% of each participating profile consists of employed adults, while employed adults represent just 54% of Profile 1: "Disengaged from learning" and 58% of Profile 2: "Unmotivated due to age and health obstacles".
- Employed adults who do not participate in learning are most likely to be in Profile 3: "Motivated but facing time-related obstacles". For this profile, time-related barriers, such as work schedules and family responsibilities, are the greatest obstacles to participation.
- Unemployed adults in Flanders are strongly overrepresented in two profiles – Profile 1: "Disengaged from learning" (13% unemployed) and Profile 5: "Reluctant but required to participate" (9% unemployed). It is concerning that many unemployed adults in Flanders are not willing to and do not see a need to participate.
- Inactive adults are mainly concentrated in Profile 1: "Disengaged from learning", Profile 2: "Unmotivated due to age and health obstacles" and Profile 4: "Motivated but facing multiple obstacles". However, the reasons for inactivity vary across these profiles, with Profile 2 especially standing out for having large shares of permanently disabled adults and early retirees.
- Adults employed in firms with fewer than 50 employees need greater support to participate in learning. Most of the adults who do not participate in learning opportunities are working in small firms (52% of total adults in each non-participating profile, on average).

Skills requirements in the labour market

- Several skills are in demand for all nine groups in Flanders, particularly the "ability to adapt to change" (found in 75% of all Flemish online job postings in quarter 3 2021) and "social interaction" skills, which mainly comprise the ability to work in teams (found in 64% of online job postings).
- There are large differences in the types of skills required for the jobs that workers typically have in each of the nine profiles – for profiles characterised by employment in low- to medium-skilled

occupations (e.g. Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles"), more practical skills are typically required (e.g. manufacturing and processing, and using digital tools to control machinery), while profiles characterised by employment in more high-skilled occupations (e.g. Profile 8: "Participating for personal development" and Profile 9: "Participating for professional and personal development") typically have need of more soft skills (e.g. personal skills, and using digital tools for collaboration and problem solving).

- While digital skills are among the top three skills required in many profiles, the types of digital skills required vary across the profiles – ranging from "using digital tools for machinery" in Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles", to "using digital tools for collaboration and problem solving" in Profile 8: "Participating for personal development" and Profile 9: "Participating for professional and personal development".
- The profiles with the greatest need for upskilling and/or reskilling are also those characterised by non-participation in learning. Workers in the non-participating profiles (Profiles 1 to 4) are on average at greater risk of automation than workers in participating profiles (Profiles 5 to 9).

Learning patterns and outcomes

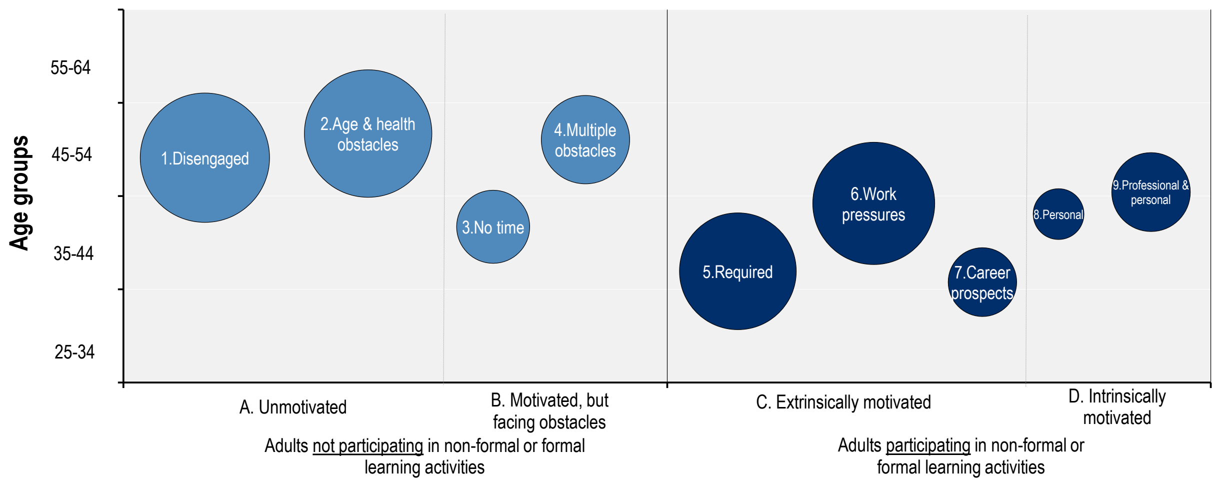
- While participation rates in informal learning are noticeably higher for adults who also participate in non-formal and formal learning, a significant share of non-participating adults (Profiles 1 to 4) are also learning informally. Some 45% of Profile 4: "Motivated but facing multiple obstacles" and 67% of Profile 3: "Motivated but facing time-related obstacles" are learning informally.
- Those required to participate in learning are much more likely to report not receiving a positive outcome (yet) from their participation in learning. Around 37% of adults in Profile 5: "Reluctant but required to participate" indicate that they experienced no positive outcome as a result of their participation in learning, which is a larger share than found among the other participating profiles.
- Learning in Flanders leads to positive outcomes for all profiles, but more so for intrinsically motivated profiles (e.g. Profiles 8 and 9) than extrinsically motivated profiles (e.g. Profiles 5 to 7). Profile 9: "Participating for professional and personal development" in particular is more likely to report more positive outcomes, including better performance in the current job, obtaining a new job and performing new tasks.

Social and demographic characteristics

The segmentation enables the examination of the socio-demographic characteristics associated with the nine adult learner profiles. Age and education level are the two socio-demographic characteristics that vary most across the nine profiles. In Flanders, adults who are relatively young and those who have attained high levels of education are much more likely to participate in learning (OECD, 2019[18]).

Adults with Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles", who have the lowest overall motivation, are also, on average, the oldest adults in Flanders (see Figure 2.2). Moreover, the average age of Profile 4: "Motivated but facing multiple obstacles" is only slightly lower. Overall, non-participating profiles are generally older than participating profiles, with the exception of Profile 3: "Motivated but facing time-related obstacles", which includes many young adults. Despite having very different characteristics and reasons for participating, Profile 5: "Reluctant but required to participate" and Profile 7: "Participating to strengthen career prospects" are by far the youngest profiles, with almost half of adults aged between 25 and 34 years old.

Figure 2.2. Predominant age groups of the nine adult learner profiles



Note: The size of circles reflects the relative size of profiles, and the colour reflects participation (dark blue) or non-participation (light blue). Age groups are based on weighted score of distribution over different categories.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

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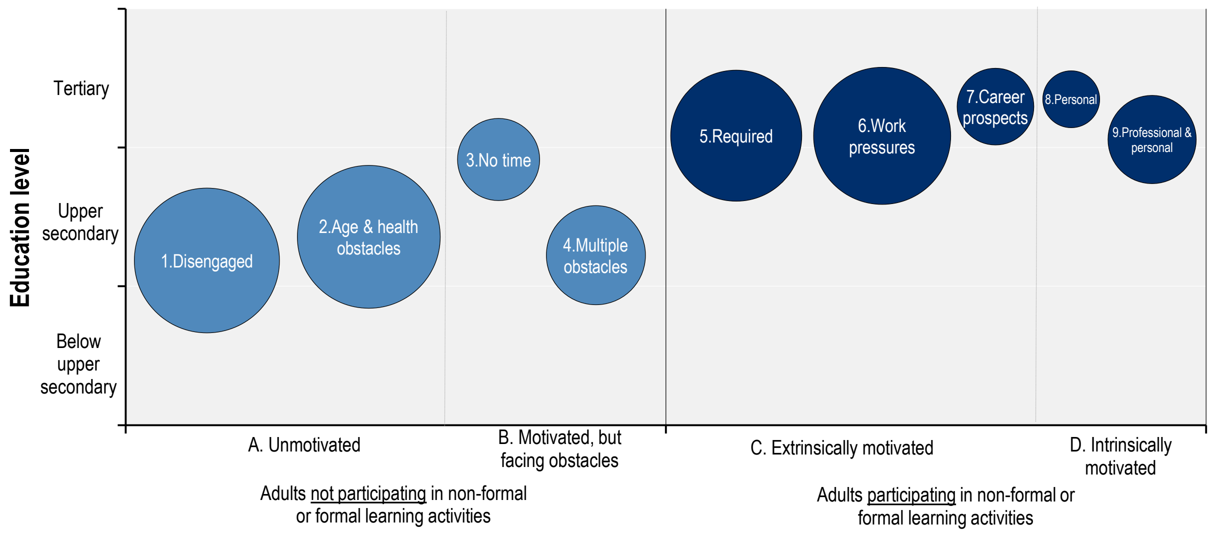
The education level of adults also impacts their motivation and participation. Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles" are not only characterised as being the oldest profiles, but also those with the largest shares of adults with comparatively low levels of education (see Figure 2.3). Again, these two profiles are followed by Profile 4: "Motivated but facing multiple obstacles", which also has one of the largest shares of adults with less than upper secondary education (35%). Every non-participating profile is associated with lower educational levels than every participating profile. This suggests that, as stakeholders interviewed for the project have warned, the adult education and training system may currently be reinforcing educational inequalities because it is the most highly educated who are participating the most, and the current lifelong learning system may not be effectively compensating for existing inequalities in educational outcomes. The segmentation also suggests that the higher the education level, the more likely it is that adults will be intrinsically motivated to engage in further education, which supports the argument that the best way to create lifelong learners is to give people a good start in learning in the first place (OECD, 2019[5]).

Finally, non-native speakers are an important target group for the adult learning system in Flanders, and the segmentation shows that their motivational profile is diverse. The two profiles with the highest proportion of non-native speakers are Profile 1: "Disengaged from learning" (19%) and Profile 3: "Motivated but facing time-related obstacles" (21%). This shows that non-native speakers not participating in learning activities face significant and complex challenges to participating in learning – i.e. they are either unmotivated and do not see a need to learn, often due to personal circumstances, or they are motivated but do not have the time to learn. These two profiles would likely need a wider range of support to increase their motivation to participate in learning and overcome the different obstacles.

Figure 2.3. Predominant education levels for the nine adult learner profiles



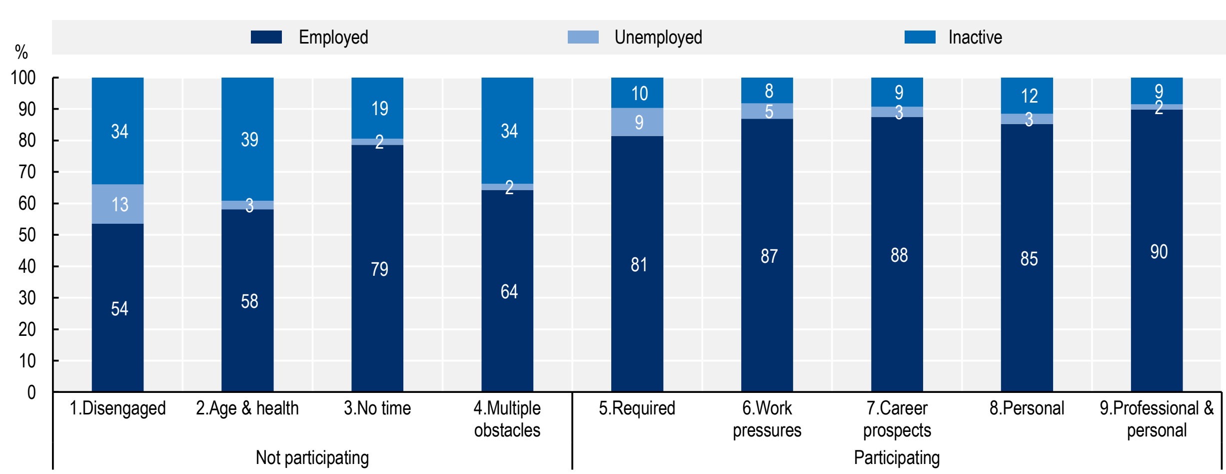
Note: The size of circles reflects the relative size of profiles, and the colour reflects participation (dark blue) or non-participation (light blue). Educational attainment level is based on weighted score of distribution over different categories.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/e91d5n

Labour market status

The segmentation also provides insights into the association between labour market status (i.e. employed, unemployed and inactive) and motivations, obstacles and participation in learning (see Figure 2.4). A main finding is that adults participating in learning are more often in employment, which suggests that having a job is arguably one of the best instruments to strengthen skills development. Between 82% and 90% of each participating profile consists of employed adults, compared with 54% of Profile 1: “Disengaged from learning” and 58% of Profile 2: “Unmotivated due to age and health obstacles”. Employed adults who do not participate in learning are most likely to be found in Profile 3: “Motivated but facing time-related obstacles”, which suggests that time-related obstacles are the most important obstacles for working adults.

Figure 2.4. Distribution of labour status for the nine adult learner profiles



Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/guix27

While the share of unemployed adults in Flanders is relatively small – the unemployment rate is 2.9% in March 2022 (StatBel, 2022[19]) – they are strongly overrepresented in Profile 1: “Disengaged from learning” (13% unemployed) and Profile 5: “Reluctant but required to participate” (9% unemployed). It is concerning that many unemployed adults in Flanders are not willing to and do not see a need to participate in learning. In addition, many of the unemployed adults who do participate in learning do so because they are obliged to. For example, many unemployed adults with Profile 5: “Reluctant but required to participate” are likely to be participating because of public employment service requirements.

Inactivity (defined as neither working nor looking for a job) is strongly associated with not participating in learning and not being motivated to learn. Profile 1: “Disengaged from learning”, Profile 2: “Unmotivated due to age and health obstacles” and Profile 4: “Motivated but facing multiple obstacles” all have very high shares of inactivity (between 34% and 39%). As previously mentioned, the reasons for inactivity between these groups are different, and there are likely a variety of reasons why the inactive adults with these profiles show little interest in learning. For example, early retirees might not see how learning would be relevant for them, while learning might be necessary for their full participation in an increasingly digital society (i.e. by strengthening their digital skills) – almost 58% of Flemish adults aged between 55 and 74 have no or very low levels of digital skills (Statistiek Vlaaderen, 2022[20]).

For employed adults, there are also various work-related factors that affect participation in education and training. For example, the size of business where adults are employed has been found to be important, with workers in small businesses (fewer than 50 employees) participating less frequently. Around 50% of employed adults with non-participating profiles are employed in small firms, while the share for participating profiles ranges between 27% and 38%. The share of adults employed in large firms (250+ employees) is particularly large for Profile 7: “Participating to strengthen career prospects” and Profile 8: “Participating for personal development” (around 40%). This aligns with international and Flemish literature which suggests that small and medium-sized enterprises are more likely than larger firms to face time and resource constraints to providing training to their employees (Sourbron and Vansteenkiste, 2021[21]).

Finally, adults’ occupations and their associated skill requirements also impacts whether they participate in training. Adults in high-skill occupations are more likely to be participating and more likely to be intrinsically motivated. Around 47% of adults with Profile 8: “Participating for personal development” are professionals, and adults with participating profiles are overwhelmingly in high-skilled occupations (between 56% and 73%). Adults in both low- and middle-skill occupations are more likely to be non-participating than participating, and the largest share of adults in low-skill occupations (e.g. elementary occupations) can be found in Profile 1: “Disengaged from learning”. Overall, the pattern is comparable with the education level of adults.

The sector of employment also has an impact on participation. For example, workers with Profile 1: “Disengaged from learning” are strongly overrepresented in manufacturing (34% of working adults with this profile are in this sector), and adults with Profile 8: “Participating for personal development” often work in education or health and social work activities. These findings demonstrate the relevance of considering learners’ occupations and sectors of employment when developing adult learning policies.

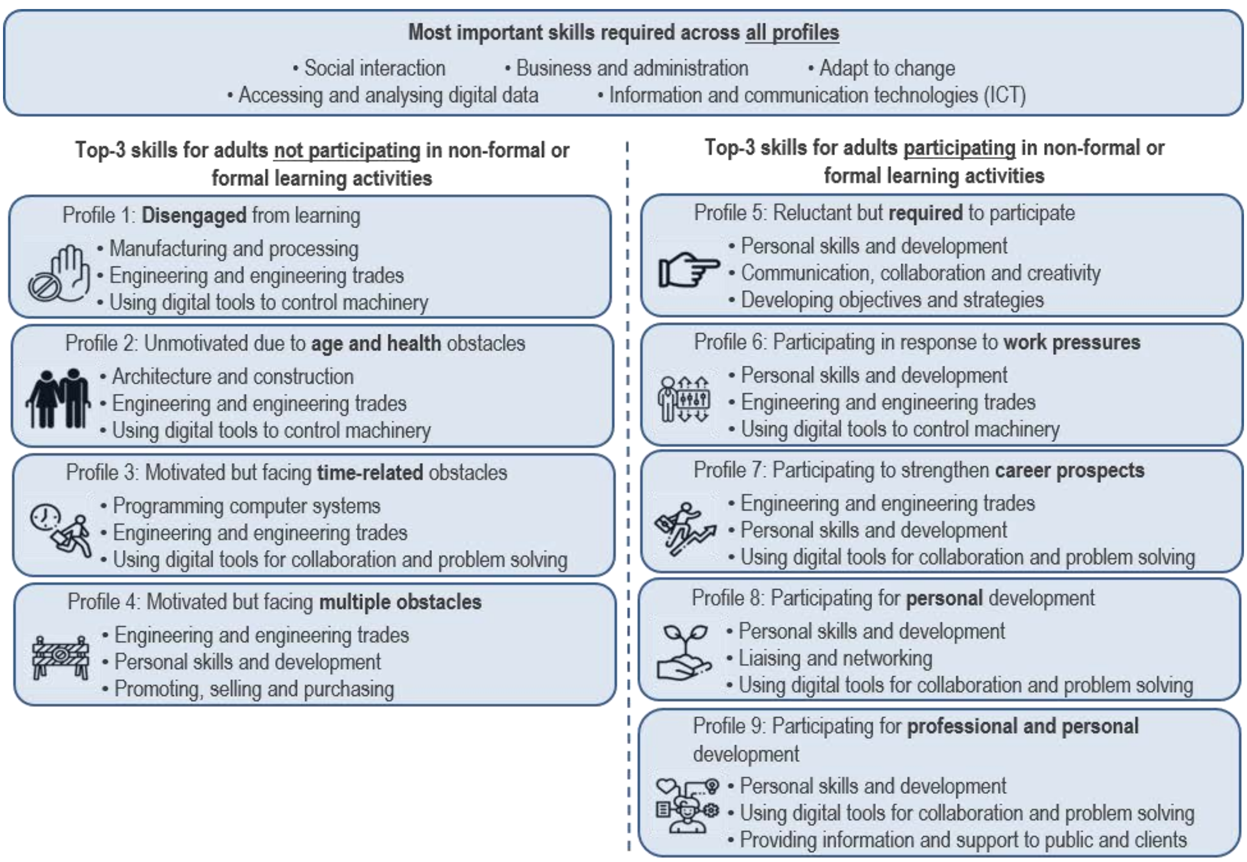
Skills requirements in the labour market

The segmentation also allows for an examination of the skill requirements of the occupations most commonly held by working adults in each profile. Stakeholders consulted during this project emphasised the need for Flanders to address current and future skills gaps. Countries need to ensure that adults develop the skills that address these gaps, which can involve both reskilling workers in jobs at risk of disappearing and upskilling workers in jobs where tasks are expected to change.

Big data sources provide new, up-to-date insights into the skills required in labour markets. Based on online job postings data from Burning Glass in quarter (Q)3 2021, a number of skills can be identified that are frequently mentioned for almost all occupations in Flanders (see Annex 2.B for a description of the underlying methodology) (Burning Glass Technologies, 2022[22]). The five most important skills requested in Flemish job postings are: 1) the ability to adapt to change; 2) social interaction; 3) information and communication technologies (ICT); 4) business administration; and 5) accessing and analysing digital data and business administration. The ability to adapt to change particularly stands out as being important as it is mentioned in 75% of all Flemish job postings in Q3 2021. Social interaction skills, such as the ability to work in teams, is also very often required for jobs in Flanders (mentioned in 64% of online job postings).

There are, however, still large differences in the types of skills required for the jobs where adults in each of the nine profiles are typically employed (see Annex 2.B for a description of the methodology). Analysis of the skill requirements described in online job postings at the occupational level (International Standard Classification of Occupation – ISCO 2-digit) allows for the identification of the skills most frequently required in the nine profiles. In Figure 2.5 the top three skills (excluding the five most important skills for all profiles) are presented for each profile.

Figure 2.5. Most important skills required by the occupations in which the nine adult learner profiles are typically employed, Q3 2021



Note: The top three most important skills for each profile exclude the five most important skills identified across all profiles.
Source: Burning Glass job postings data, 2021 Q3 – Burning Glass Technologies (2022[22]), *Burning Glass database - online job postings*, https://www.burning-glass.com/.

A main finding is that for profiles comprised of adults primarily working in low- to medium-skill occupations (e.g. Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles"), more practical skills are typically required, such as architecture and construction, manufacturing and processing, and using digital tools to control machinery. Profiles comprised of adults typically employed in more high-skill occupations (e.g. Profile 8: "Participating for personal development" and Profile 9: "Participating for professional and personal development") often require more soft skills, including personal skills and development, and liaising and networking.

While digital skills are among the skills most often required for all profiles (e.g. accessing and analysing digital data, and information and communication technologies), the types of digital skills required vary. For example, for the profiles in which adults are generally employed in low- to medium-skill occupations (e.g. Profile 1: "Disengaged from learning" and Profile 2: "Unmotivated due to age and health obstacles"), one of the most important skills is the ability to use digital tools to control machinery. In contrast, for the profiles in which a large share of workers are employed in high-skill occupations (e.g. Profile 3: "Motivated but facing time-related obstacles" and Profile 7: "Participating to strengthen career prospects"), using digital tools for collaboration and problem solving are more often required.

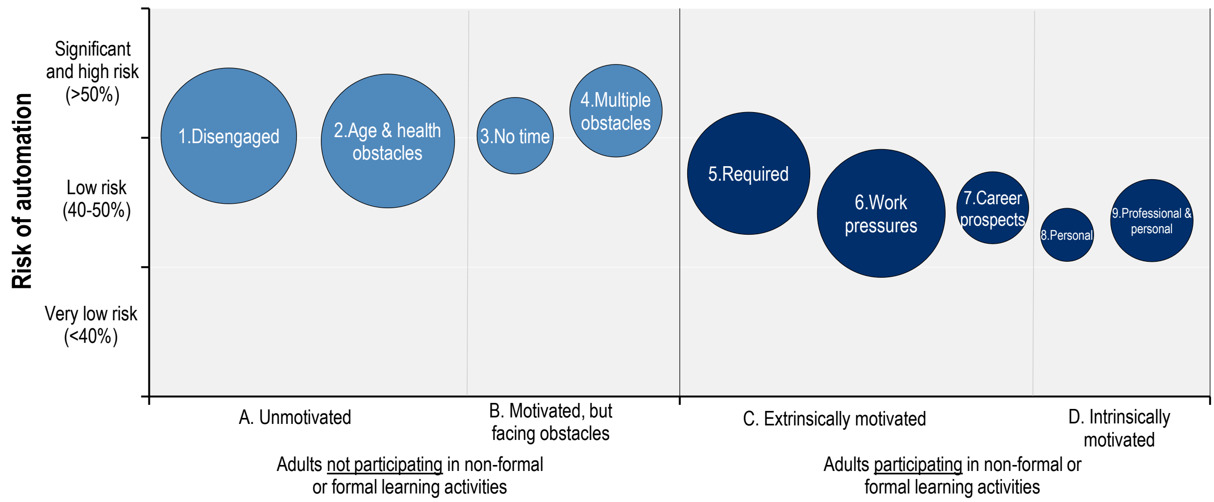
These findings unfortunately provide only limited insight into the skills that need to be strengthened (i.e. the skills gaps), as existing data does not enable distinguishing between those with or without the skills required for their existing occupations. Overall, Flemish adults are more proficient in literacy and problem solving in technology-rich environments than adults in most OECD countries (as measured by the Programme for the International Assessment of Adult Competencies, PIAAC) (OECD, 2019[18]). In terms of numeracy skills, Flanders is even among the top-performers in the OECD – only Finland and Japan have higher average scores. However, these averages hide large differences across the population, with several groups lagging behind. When considering education levels as a proxy for skills, it can be expected that especially Profile 1: "Disengaged from learning", Profile 2: "Unmotivated due to age and health obstacles" and Profile 4: "Motivated but facing multiple obstacles" have comparatively low levels of skills. However, more analysis is needed to better understand the precise skills gaps of the nine adult learner profiles, potentially by using the next round of PIAAC data (see section 'Potential next steps' in Chapter 3).

An additional factor that complicates the analysis of skills gaps is that skills requirements are continuously evolving because of changes in labour markets – i.e. the skills required in future labour markets will likely be very different from the skills required today – and it might not be beneficial to develop the skills currently required in the profile as these jobs could actually be at risk of being automated.

COVID-19 has already had a major impact on the types of skills required for jobs. Looking at trends in the skills, knowledge and abilities identified in online job postings before and after COVID-19, there are major accelerations in the importance of certain abilities, such as the ability to adapt to change (Burning Glass Technologies, 2022[22]). In addition, various digital and soft skills have become much more important, including skills related to communication, collaboration and creativity (e.g. liaising, negotiating with other people, developing solutions to problem), as well as working with computers.

The digital transformation, which has been accelerated by COVID-19, will not only have implications for skills needs, but will likely also drive a broader shift in the economy – creating jobs in some sectors while destroying jobs in others. The risk of automation in particular will create many challenges for skills systems. As a result of these shifts, profiles characterised as already at risk of automation may find themselves under even greater pressure. Figure 2.6 shows that adults currently not participating in learning are more likely to be found in jobs facing the highest risk of automation – calculations are based on automation probability for occupations (2-digit ISCO-08) by Nedelkoska and Quintini (2018[23]). It is problematic that the adults facing the highest risk of automation are often not participating. For many of them, lifelong learning will be vital to ensure that they still have jobs in the future.

Figure 2.6. Predominant automation risk for the nine adult learner profiles



Note: The size of circles reflects the relative size of profiles, and the colour reflects participation (dark blue) or not (light blue). Automation risk is calculated based on automation probability for occupations (2-digit ISCO-08) from Nedelkoska and Quintini (2018[23]).
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey; Nedelkoska and Quintini (2018[23]), "Automation, skills use and training", *OECD Social, Employment and Migration Working* Papers, No. 202, https://dx.doi.org/10.1787/2e2f4eea-en.

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Learning patterns and outcomes

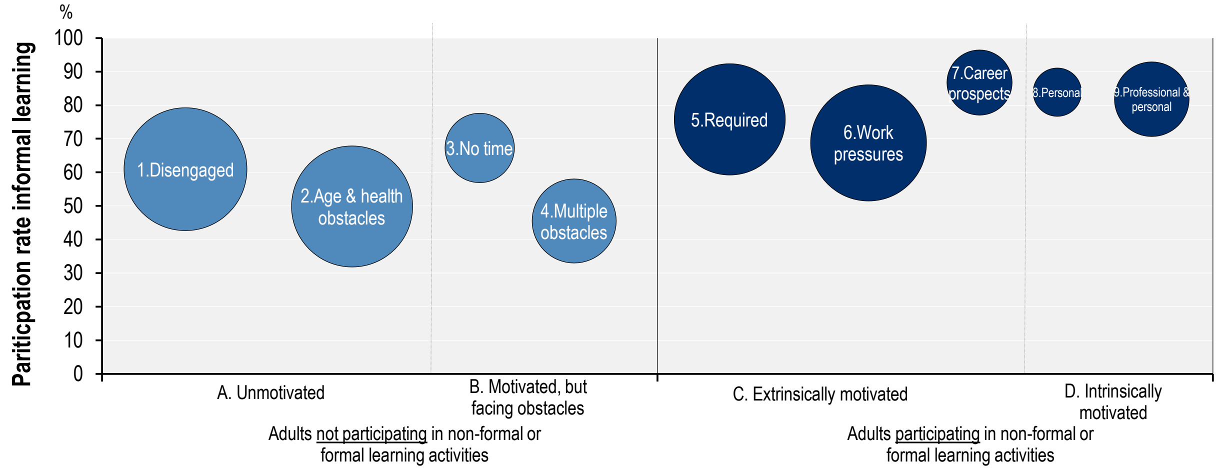
The segmentation enables policy makers to analyse in greater detail how the type and pattern of learning varies across the different learner profiles. This section analyses the type of learning undertaken (formal, non-formal and informal), the intensity of learning (e.g. the number of hours participating in training) and the outcomes that adults gain from their participation for the nine leaner profiles.

As previously noted, participation in education and training in the model is defined as participation in formal and/or non-formal participation. However, adults can also participate in informal learning, such as learning on-the-job; interacting with a family member, friend or colleague; or visiting learning centres (e.g. libraries). This more unstructured learning, which is often unintentional, also matters. And while informal learning may be the most difficult to quantify, it should not be overlooked when analysing adult learning patterns.

It is important to note that for the profiles classified as not participating in non-formal or formal learning (Profiles 1 to 4), there are many adults who do still participate in informal learning (see Figure 2.7). While participation rates in informal learning are noticeably higher for adults who also participate in non-formal and formal learning, a significant share of adults with all four non-participating profiles are also learning informally, ranging from 45% for Profile 4: "Motivated but facing multiple obstacles" to 67% for Profile 3: "Motivated but facing time-related obstacles".

However, as is the case with formal and non-formal learning, there is a clear link between motivation to learn and informal learning – for example, the highest rates of participation in informal learning can be found in the most motivated profiles. Moreover, the lowest participation rate in informal learning among the participating profiles (69% for Profile 6: "Participating in response to work pressures") is still higher than the highest participation rate among the non-participating profiles (67%: for Profile 3 "Motivated but facing time-related obstacles"). Therefore, those who learn tend to learn in multiple ways, which lends credence to the adage that learning begets learning. On the other hand, those profiles most strongly associated with unemployment and inactivity are least likely to be engaged in informal learning, which underscores the importance of the workplace as a site of learning and that employment policies can *also* be important learning policies.

Figure 2.7. Participation in informal learning for the nine adult learner profiles



Note: The size of circles reflects the relative size of profiles, and the colour reflects participation (dark blue) or not (light blue). Informal learning is defined here as deliberately trying to improve knowledge or skills by interacting with a family member, friend or colleague; using printed material (e.g. professional magazines); using computers; learning through television/radio/video; participating in guided tours in museums, historical, natural or industrial sites; and visiting learning centres (e.g. libraries).

Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/xsz7my

With respect to the intensity of formal and non-formal learning as measured by the number of hours spent in training, several differences can be observed between the participating profiles. While the analysis is not entirely conclusive, there are indications of a positive association between the intensity of learning and the level (type) of motivation: adults in intrinsically motivated profiles (e.g. Profiles 8 to 9) tend to participate more in mid- and high-intense training programmes than their peers in externally motivated profiles (e.g. Profiles 5 to 7). For instance, Profile 7: "Participating to strengthen career prospects" is characterised by a comparatively high intensity of learning (defined as participation in learning activities of more than 36 hours in total or the top quartile of the distribution of hours participated), while Profile 5: "Reluctant but required to participate" stands out with a comparatively low to medium intensity of learning, defined as participation in learning activities of less than 12 hours (the bottom quartile). The result for Profile 5 likely reflects requirements to participate in short, compulsory courses. Perhaps unsurprisingly, the findings suggest that adults with greater motivation to learn are also more likely to spend a greater number of hours learning.

There is also noticeable variation in field of study choices across learner profiles. The three most popular fields of study in Flanders are "health", "business" and "services", while studies in fields such as "sciences and mathematics", "agriculture", and "social journalism" are comparatively uncommon. What stands out is the relatively large share of adults with Profile 9: "Participating for professional and personal development" taking courses in "business" and "ICT", and the large share of adults with Profile 7: "Participating to strengthen career prospects" taking courses in "health" and "arts and humanities".

There is also some variation in the types of learning providers typically used by different profiles. While education institutions are the most common provider for all profiles, they are particularly important for Profile 5: "Reluctant but required to participate" and Profile 7: "Participating to strengthen career prospects". On the other hand, employers are comparatively more often providers of learning activities for adults with Profile 9: "Participating for professional and personal development".

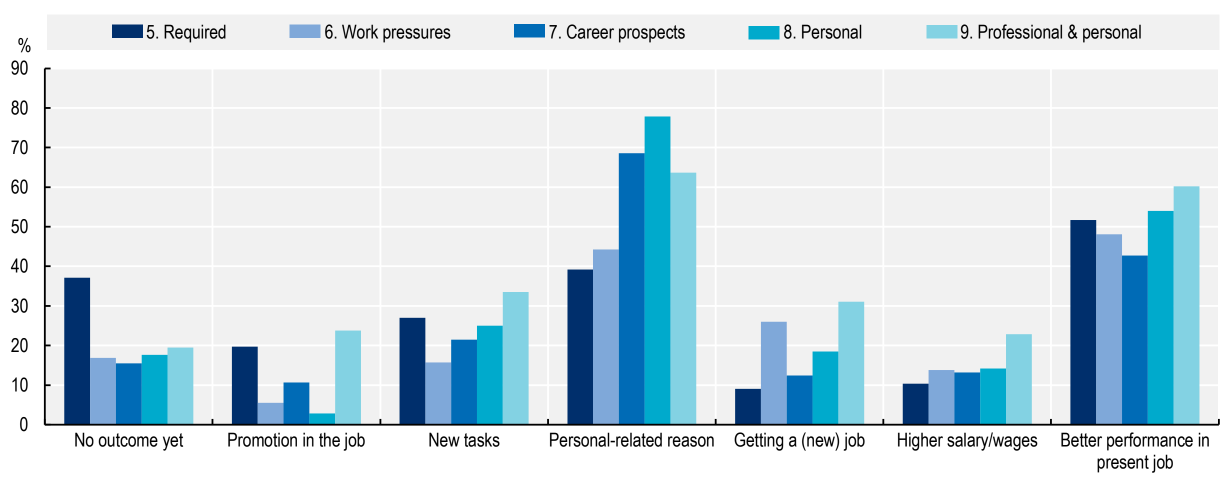
There are significant differences in the learning outcomes reported by the different profiles of learners (see Figure 2.8). Most adults participating in both formal and non-formal learning (Profiles 5 to 9) report that learning led to positive outcomes (Eurostat, 2021[14]). A vast majority also indicate that the skills or knowledge acquired during training are used actively, or even intensively, in their work. The most commonly reported outcomes of learning activities are personal outcomes (e.g. meeting other people, refreshing skills on general subjects), followed by better performance at work.

A main finding is that a comparatively large share (37%) of adults with Profile 5: “Reluctant but required to participate” indicate that they have had no tangible outcome from one or more learning activities, meaning that they do not believe their learning led to any positive impact for themselves, which is a share much larger than that of other profiles. This finding is also consistent with the fact that many adults with this profile report that they have low motivation to learn more. Nonetheless, 40% of learners obliged to participate in education and training indicate having received important personal outcomes from one or more learning activity, such as refreshing skills on a particular subject, and 52% indicate better performance at work after training – the largest share of all profiles.

Adults with Profile 9: “Participating for professional and personal development” are most likely to report positive learning outcomes, such as better performance in the job, higher salaries, getting new tasks or a new job (see Figure 2.8). These findings suggest that while some profiles may be more likely than others to report a positive outcome, most people in any given profile report a positive outcome, which underscores the positive value of learning in adulthood.

Figure 2.8. Types of learning outcome for the five participating adult leaner profiles

Share of adults reporting outcomes from learning for the profiles



Note: Respondents can indicate multiple outcomes for different learning activities.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/y2tgai

Several insights can be drawn from the analysis of the learning outcomes of different profiles. For instance, intrinsically motivated learners are generally more likely to report having positive outcomes, which is likely to be a self-reinforcing, virtuous circle. More motivated learners get more out of their learning because they are more invested in their training content, which leads to better outcomes that drives motivation to participate further. This also suggests that ensuring the quality of learning opportunities may be key to boosting motivation among participating adults by ensuring that participants are able to reap tangible benefits from learning. In addition, adults with Profile 8: “Participating for personal development” report comparatively often positive personal outcomes, which underscores the importance of intrinsic motivation for the achievement of successful learning outcomes.

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Annex 2.A. Detailed description of methodology behind the segmentation model

Latent Class Analysis (LCA) to segment the adult learning population

This study employs a Latent Class Analysis (LCA) methodology to segment the adult learning population in Flanders (see Annex Box 2.A.1 for the technical description). This method exploits the interrelation between an array of indicators through a fully specified (i.e. parametric) statistical model for organising the target population into more homogenous groups. LCA has three main advantages relative to other common segmentation (or clustering) methods: 1) formal statistical tests guide the selection of the optimal number of profiles and other models' features; 2) LCA does not allocate individuals into specific groups in a deterministic way, but provides probabilities of profile membership, thus reducing possible classification errors in any post-estimation analysis; and 3) LCA deals better with common data issues (e.g. missing data, complex surveys) (Collins and Lanza, 2009[24]).

Annex Box 2.A.1. A brief theoretical description of Latent Class Analysis

LCA is a means to uncover unobserved groupings in data. Based on a set of observed (categorical) variables (e.g. obstacles to learning and motivations to participate in training in the context of this project), a latent categorical variable can be estimated.

For the case of two independent categorical variables *A* (with j categories) and *B* (with k categories) the joint probability of being category *j* and category *k* is:

$$P_{jk} = P_j^A P_k^B$$

If X is a latent (unobserved) variable with T classes, then (under conditional independence assumption):

$$\pi_{jkt} = \pi_t^X \pi_{jt}^{AX} \pi_{kt}^{BX}$$

Where π_{jkt} is the joint probability of being in category j, category k and class t; π_t^X is the probability of being in class t; π_{jt}^{AX} is the probability of being in category j (of A) conditional on being in class t (of X); and similarly, π_{kt}^{BX} is the probability of being in category *k* (of B) conditional on being in class t (of X).

The class membership probability is the estimate of the proportion of the sample that belongs to a certain class. In other words, for a two class model, $\hat{\pi}_1$ would represent the proportion of cases expected to be members of the first class, where $t = 1$.

The estimation is by maximum likelihood (ML) using the expectation maximisation (EM) algorithm. It starts with a random split of observations into classes, and iteratively reclassifies them based on an improvement criterion until the best classification of observations is found. For the case of categorical variables, the logarithm of the ML function is given by:

$$\ln L = \sum_{j=1}^{R} \sum_{k=1}^{R} f(X_{jk}) \ln\{\pi_t^X \pi_{jt}^{AX} \pi_{kt}^{BX}\} = \sum_{j=1}^{R} \sum_{k=1}^{R} f(X_{jk}) \ln \pi_{jkt}$$

Where $f(X_{jk})$ is the observed frequency of response patterns and R represents the possible number of response patterns. Since all variables are dummy, R is equal to 2 in this case. This iterative estimation process ends when the difference between the ML estimate and the ML estimate of the preceding iteration reaches a minimum value.

As there are two baseline models targeting two different set of adults, the LCA aims to estimate two different ML function for participants and non-participants separately, which are represented in equation (1) and equation (2), respectively:

$$\ln L = \sum_{j=1}^{R}\sum_{k=1}^{R} f(X_k) \ln\left\{\pi_t^X \prod_{i=1}^{15} \pi_{kt}^{X_i}\pi_{jt}^{X_i}\right\} = \sum_{j=1}^{R}\sum_{k=1}^{R} f(X_k) \ln \pi_{jkt} \quad (1)$$

$$\ln L = \sum_{j=1}^{R}\sum_{k=1}^{R} f(X_k) \ln\left\{\pi_t^X \prod_{i=1}^{8} \pi_{kt}^{X_i}\pi_{jt}^{X_i}\right\} = \sum_{j=1}^{R}\sum_{k=1}^{R} f(X_k) \ln \pi_{jkt} \quad (2)$$

Where X_i are categorical variables, $X_1, \ldots, X_i$. For participants and non-participants there are 15 and 8 binary indicators, respectively. Each X_i takes value on the finite set $[k_i] \equiv \{0,1\}$. Given that all indicators are binary, π_{jkt} is the joint probability of being in category k, category j and class t; , π_{jt}^{Xi} is the joint probability of being in category j of (X_i) and class t; similarly, $\pi_{kt}^{X_i}$ is the joint probability of being in category k (of X_i) conditional on being in class t; and π_t^X is the probability of being in class t. As mentioned, R represents the possible number of response patterns (2 for this case).

In this project, the most common estimator for latent class models, maximum likelihood using an expectation maximisation algorithm, was applied (Dempster, Laird and Rubin, 1977[25]). In the EM steps of the ML process, conditional expectations and the posterior class membership probabilities are computed in the expectation step and parameter estimates are updated. The fit is then maximised through iterations in the maximisation step. This process alternates between the two steps until an optimisation criterion is reached. Estimation can be sensitive to start values, and it is wise to retest any model with different start values to be certain that convergence was reached at a global not local solution (Hipp and Bauer, 2006[26]), a testing process that may be automated within the software program. Many packages now employ random starts, and the user can specify the number of sets of random start values the computers uses. A log-likelihood value obtained upon convergence is used to compute fit indices.

Source: Collins and Lanza (2009[24]), *Latent class and latent transition analysis: With applications in the social, behavioural, and health sciences*, https://www.wiley.com/en-us/Latent+Class+and+Latent+Transition+Analysis%3A+With+Applications+in+the+Social%2C+Behavioral%2C+and+Health+Sciences-p-9780470228395; Lanza, Bray and Collins (2012[27]), *An introduction to latent class and latent transition analysis*, https://doi.org/10.1002/9781118133880.hop202024.

In this project, the statistical algorithm identifies population subgroups sharing similar factors that impact their participation in adult learning. The applied methodology is partly based on the methodology used in the OECD Faces of Joblessness reports, which apply the LCA method to identify key employment obstacles that may prevent individuals from participating fully in the labour market (Fernandez et al., 2016[12]).

The LCA was undertaken using data from the Adult Education Survey 2016, which includes variables on participation in learning and on motivations and obstacles to participate in learning. The survey also collects socio-demographic and labour market status information. The total sample for Flanders was 2 782 observations. Annex Table 2.A.1 shows the summary statistics for the main socio-demographic and labour market characteristics. For some variables, the sample is relatively small (e.g. inactivity condition), thus any statistical inference based on them is limited.

Annex Table 2.A.1. Summary of descriptive statistics for participants and non-participants

	Non-participants				Participants			
Variables	Mean	Std dev	N	N (x1000) (Weighted)	Mean	Std dev	N	N (x1000) (Weighted)
Socio-demographic characteristics								
Gender								
Male	0.54	0.49	729	924	0.5	0.5	709	802
Female	0.46	0.49	632	869	0.5	0.5	712	837
Level of education				0				0
Below upper secondary	0.29	0.45	401	598	0.08	0.27	115	162
Upper secondary	0.42	0.49	575	801	0.32	0.47	459	623
Tertiary	0.28	0.45	385	395	0.6	0.49	847	855
Migrant Characteristics								
Speaks Dutch/Flemish	0.89	0.3	1 218	1 584	0.93	0.25	1 325	1 513
Does not speak Dutch/Flemish	0.11	0.3	143	210	0.07	0.25	96	126
Migrant	0.13	0.33	176	263	0.08	0.27	116	156
Not migrant	0.87	0.33	1 167	1 503	0.92	0.28	1 288	1 461
Quintile of the household income								
Quintile 1	0.22	0.41	196	294	0.09	0.28	93	125
Quintile 2	0.24	0.42	216	303	0.14	0.35	151	191
Quintile 3	0.19	0.39	168	217	0.21	0.41	224	266
Quintile 4	0.17	0.37	154	191	0.28	0.45	299	339
Quintile 5	0.18	0.38	160	181	0.29	0.45	315	329
Labour characteristics								
Labour status								
Employed	0.65	0.48	879	1 100	0.87	0.34	1 237	1 409
Unemployed	0.05	0.21	62	58	0.04	0.2	57	55
Inactive	0.28	0.45	383	587	0.07	0.26	102	144
Inactivity condition								
Student	0	0.03	1	2	0.01	0.09	11	16
Retired	0.13	0.33	166	233	0.03	0.18	45	58
Disabled	0.06	0.24	82	127	0.01	0.1	13	17
Domestic activities	0.07	0.25	87	151	0.01	0.12	20	30
Other inactive	0.04	0.19	47	74	0.01	0.1	13	20
Occupation								
Managers	0.06	0.24	83	98	0.09	0.28	122	134
Professionals	0.1	0.31	142	151	0.33	0.47	470	495
Technicians and associate professionals	0.08	0.27	108	123	0.16	0.36	223	251
Clerical support workers	0.09	0.29	128	167	0.11	0.31	156	189
Service and sales workers	0.08	0.27	111	146	0.06	0.23	80	102
Skilled agricultural, forestry and fishery	0.01	0.1	15	18	0.01	0.1	14	17
Craft and related trades workers	0.06	0.24	81	107	0.04	0.19	53	66

Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/anv9um

Implementing the LCA in four steps

For this project, the LCA was undertaken in four steps. In the first step, the baseline model and indicators were defined. The baseline model uses indicators that are considered as playing an important role in defining class membership. In the second step, the statistical fit of LCA was assessed using relative fit information criteria to guide the decision on the optimal number of classes (profiles). In the third step, additional covariates (socio-demographic and labour variables) were included in the analysis to better characterise the classes generated of participating and non-participating adults. Finally, to validate the decisions made and test the results obtained from the LCA, a couple of additional robustness checks were conducted.

Step 1: Defining the baseline model and selecting the indicators

The specification of the baseline model involved the selection of an entire set of indicators that, in the context of adult learning participation, relate to the motivations and main obstacles adults face to engaging with learning opportunities. Two different models were established for identifying the profiles in groups of non-participating and participating adults. These models include the indicators (all dummy variables) that best describe the main drivers behind not participating (i.e. a lack of motivation and obstacles to participation) and participating (i.e. the different reasons for participating and motivations to participate more).

The first model for non-participants includes indicators on both motivation and obstacles to participation. In the AES, all adults who did not participate in learning activities were asked whether they would have liked to participate, thereby indicating their motivation. If they did not want to participate, they were asked if it was because they did not see a need for learning. Regardless of whether adults want to participate, they were also asked about the obstacles they face. For some cases, the obstacles were grouped to increase the statistical representativeness of the sample (e.g. time related obstacles include variables on schedule constraints and family responsibilities).

The second model for participants includes indicators of their reasons for participating in learning, including both job-related and not job-related factors. These indicators provide insights into their attitudes towards learning, which could be linked to different types of motivational profiles (e.g. extrinsic and intrinsic motivations to learn). In addition, to have a more comprehensive view of these motivational profiles, indicators of their willingness to participate more in AES – i.e. in addition to the learning activities they already participated in – were included, thereby providing insights into motivations *ex post* the learning activity (in contrast to the *ex ante* reasons to learn).

Annex Table 2.A.2 lists all the indicators (all dummy variables) included in the baseline model for non-participants and participants. Some variables included in the analysis were recomputed based on information collected in the survey. Some of the variables combine multiple categories to increase their statistical representativeness. Instead of using all possible obstacles identified in the AES, some obstacles were created by combining two or more categories. For example, the variable “time constraint” was created by combining the variables relating to both family responsibilities and schedules. Furthermore, some variables were generated to split the sample in multiple categories to explore the heterogeneity of adults’ socio-demographic characteristics. For instance, household income quintiles relies on the sum of the income of all household members, and their distribution within the entire sample. Annex Table 2.A.2 provides more information on the questions used for generating all the indicators.

Annex Table 2.A.2. Indicators included in the LCA for adult learning non-participants and participants

Non-participants					Participants				
Indicator	Mean	Std dev	N	N (x1000) (weighted)	Indicator	Mean	Std dev	N	N (x1000) (weighted)
No need	0.46	0.50	632	850	No need	0.24	0.43	340	39
Unmotivated	0.80	0.40	1 083	1 439	Unmotivated	0.55	0.50	780	90
Health/age	0.32	0.47	137	193	Better job	0.42	0.49	602	67
No suitable programmes	0.18	0.38	76	96	Career prospects	0.16	0.37	230	27
Personal reasons	0.12	0.33	52	67	Certificate	0.10	0.29	136	15
Time	0.53	0.50	224	292	Changes at work	0.09	0.28	118	13
Cost	0.17	0.37	70	89	Health	0.03	0.17	38	4
Lack of support	0.09	0.29	39	47	Increasing possibilities	0.09	0.28	121	14
					Interest in subject	0.36	0.48	509	575
					Meet people for fun	0.11	0.31	153	175
					Not to lose job	0.04	0.21	63	74
					Obliged	0.01	0.10	14	18
					Required	0.28	0.45	367	425
					Skills for life	0.28	0.45	394	452
					Start business	0.03	0.16	36	41
					Voluntary work	0.02	0.14	25	28

Note: The "mean" is equivalent to the percentage of adults facing an obstacle (having a reason) to participate. The sum of all obstacles (reasons) do not add up to 100 because an adult may report facing more than one obstacle (reason to participate), thus the categories are not mutually exclusive. The question used for generating the obstacles for participating and the reasons to participate are described in more detail in Annex Box 2.A.2. Time related obstacles include schedule and family responsibilities. Personal reasons includes negative experience, no access to computer or Internet. Not suitable training or education offer includes prerequisites and distance.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

StatLink https://stat.link/q3lwxy

Annex Box 2.A.2. Adult Education Survey: Questions used to generate main indicators and variables for the model

Motivations to participate (more) in education and training

In the AES, all adults who did not participate in learning activities were asked whether they would have liked to participate (the exact question is *"Previously in the questionnaire 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?*"), thereby indicating their motivation. If they did not want to participate, they were asked if it was because they did not see a need for learning (question "*You answered no to the previous question. Is it because you did not need additional education and training?*").

For adults already participating these questions were also asked, but with an emphasis on whether they would like to participate in more training (e.g. "*Previously in the questionnaire you stated that during the last 12 months you participated in education and training. Would you have liked to participate even more in such activities?*").

Obstacles to participating in education and training

To identify the obstacles that adults face to engaging with adult learning, the AES includes a module that collects information on the difficulties of participating in education. This information is available for those who participated and wanted to participate more, those who did not participate but wanted to, and those who report not needing to participate or learn. The obstacle categories included in the model rely on the question "*Which of the following obstacles prevented you from participating in education and training? (Mark all that apply)*". The respondent can choose more than one obstacle that prevents him/her from participating in education and training. For the segmentation model, some of these categories are aggregated given the sample size. For example, "schedule" and "family responsibilities" are grouped in "time" related obstacles. "Negative experience" and "no access to computer or Internet" are grouped in "personal" reasons for not participating. The categories "prerequisites" and "distance" are included in "not suitable training or education offer".

Reasons for participating in non-formal learning activities

AES includes a module to collect detailed information on learning activities for respondents that have participated in formal and non-formal education, including the reasons and motivation for participating. The specific question included in the questionnaire is *"What were the reasons for participating in the non-formal (formal) learning activity? (Mark all that apply)".* As for the case of the obstacles for participating in education and training, respondents are able to choose more than one reason for participating in learning activities.

Source: Eurostat (2022[28]), *Adult Education Survey 2016 questionnaire*, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Adult_Education_Survey_(AES)_methodology#Questionnaire.

The indicators included in the estimations of the LCA are binary for several reasons. First, it greatly simplifies the statistical model for the LCA and facilitates an easier interpretation of the model outcomes. Second, the loss of information is reduced if variables are categorical and have multiple potential values.

The indicators of the baseline models are assumed to be independent, which means that they are only related to each other through an unobserved (i.e. latent) variable. There are no additional unobserved characteristics correlated with the indicators and the generated profiles. This assumption, called Local Independence Assumption (LIA), originates from the causal foundation of the LCA, which aims to ensure no residual association between the indicators.

Step 2: Assessing the statistical fit of the model

To determine the optimal number of profiles based on a statistical representative sample, two goodness-of-fit indicators were used for this project: The Bayesian Information Criterion (BIC) (Schwarz, 1978[29]) and the Akaike Information Criterion (AIC) (Akaike, 1987[30]) (see Annex Box 2.A.3). BIC and AIC capture the trade-off between how well the model fits the underlying data and the cost of complicating the structure of the model. Looking at the combination of BIC and AIC criteria helps to choose the optimal number of profiles (for participants and non-participants, separately). The model with a number of profiles that minimises in absolute terms the AIC and BIC is typically the best choice, as a smaller value of these indices indicates a more optimal balance between model fit and parsimony.

Additional indicators can provide information regarding how well the model is able to classify individuals into the profiles. The simplest classification statistic is computed as the number of individuals estimated to be misclassified as a proportion of the mode or most repetitive group assignment (Vermunt and Magidson, 2004[31]). It is natural to obtain a classification error, but studies on LCA suggest that it should not be above 30%. Values above 30% imply that the model is not able to differentiate among the groups in the allocation of individuals.

Annex Figure 2.A.1 shows the percentage variations of the BIC and AIC for an increasing number of profiles of adults not participating in learning (Panel A) and adults participating in learning (Panel B). For both samples, models with few generated classes have relatively large variations of BIC and AIC indices. This is because the model's ability to fit the data increases significantly compared to the model's parametrisation. For a higher number of classes the increment of goodness-of-fit is progressively compensated by the higher parameterisation, thus producing a smaller, and eventually positive, change in the two measures.

The selection of the optimal number of latent classes depends on the variation of the evaluated indices (from one cluster number to the other) being minimised in absolute value, or being closest to zero. For the sample of non-participating adults, the BIC and AIC index variation are closest to zero when the cluster number is four. For the sample of participating adults, the BIC and AIC is closest to zero for a model with five classes. Based on Fernandez et al. (2016[12]), the BIC normally points to a more parsimonious specification than the AIC, as the latter takes into account only the higher number of parameters, whereas the former also considers the overall sample size. Additionally, the classification error is also at its minimum for a model with four classes for non-participating adults and five classes for those participating.

Annex Box 2.A.3. Information criterion indexes and classification errors

Information criterion indexes

Part of the process of LCA involves deciding on the optimal number of classes, sometimes called class enumeration. Comparisons usually made among models with different numbers of classes provide evidence on the number of classes that best fit the sample and indicators. There are multiple information criterion (IC) to assess LCA fitness and the class solution. For this segmentation model, two information criterions are taken into account: Bayesian Information Criterion (BIC) (Schwarz, 1978[29]) and the Akaike Information Criterion (AIC) (Akaike, 1987[30]). Both IC indexes are based on the log likelihood of a fitted model, where each of the ICs apply a different penalty for the number of model parameters and/or sample size. Because of the different penalties across the ICs when using them, it is possible that each of the ICs point towards a different class solution as the best model.

BIC or adjusted BIC is the default information criteria used with LCA. It is commonly used for this purpose (lower values indicating better fit) and performs fairly well (Tofighi and Enders, 2007[32]). The BIC considers weights in two ways: first, the weights, which are modified to sum the effective sample size, are reflected in the log-likelihood; second, the effective sample size is used in the penalty when computing the BIC. The BIC is defined as:

$$BIC = -2\ln L + K\ln(n)$$

Where K is the number of independent variables used and n the sample size. L is the log-likellihood estimate (also known as the likelihood that the model could have produced the observed y-values). A variant of the BIC index, adjusted BIC defined by (Sclove, 1987[33]), replaces the sample size n in the BIC equation with $n^* = \frac{n+2}{24}$.

AIC is calculated from the number of independent variables used to build the model and the ML estimate of the model accounting for how well it reproduces the data. In other words, the AIC determines the relative information value of the model using the ML estimate and the number of parameters. The formula for AIC is:

$$AIC = -2K + 2\ln L$$

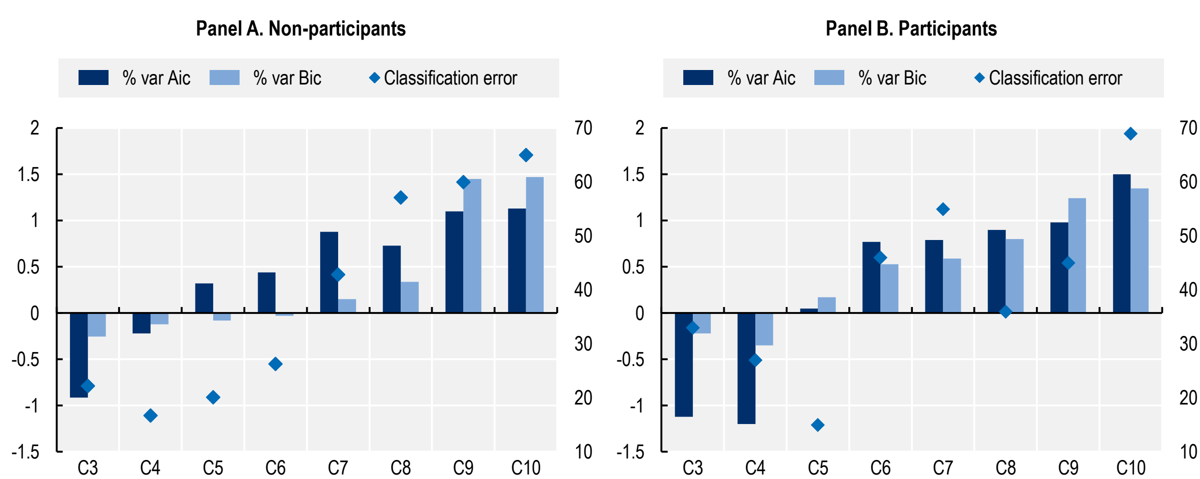
The default K is always 2. To compare models using AIC it is necessary to calculate the AIC of each model. If a model is more than 2 AIC units lower than another, it is considered significantly better than the former model. The best-fit model according to AIC is the one that explains the greatest amount of variation using the fewest possible independent variables.

Classification error

In addition to evaluating fit, reviewing classification diagnostics can be key to assessing LCA fitness (Maysing, 2013[34]). Although diagnostic statistics are not used to select the final class model, they are important for consideration. The average latent class posterior probability is the average probability of the class model accurately predicting class membership for individuals (Muthén and Muthén, 2000[35]). The average latent posterior probabilities are presented in a matrix, with diagonals representing the average probability of a person being assigned to a class given his or her scores on the indicator variables used to create the classes. Higher diagonal values (i.e. closer to 1.0) are desirable. Off-diagonal elements in the posterior probability matrix contain probabilities of cases that belong in one class being assigned to another class in the current solution. Lower values off the diagonal (i.e. closer to 0) are desirable. Some researchers use a .70 cut-off for acceptable diagonal probabilities (Weden and Zabin, 2005[36]). Others suggest a cut-off value of greater than .90 (Muthén and Muthén, 2000[35]).

Source: Nylund, Asparouhov and Muthén (2007[37]), *Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study*, https://www.statmodel.com/download/LCA_tech11_nylund_v83.pdf; Schwarz (1978[29]), Estimating the Dimension of a Model, https://doi.org/10.1214/aos/1176344136; Akaike (1987[30]), Factor analysis and AIC, https://doi.org/10.1007/bf02294359; Tofighi and Ender (2007[32]), Advances in Latent Variable Mixture Models; Maysing (2013[34]), The Oxford handbook of quantitative methods: Statistical analysis; Muthén and Muthén (2000[35]), Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes, https://pubmed.ncbi.nlm.nih.gov/10888079/.

Annex Figure 2.A.1. Selection of the optimal number of latent classes



Note: The X axis corresponds a number of classes (clusters) estimated in each model.
Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

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Step 3: Characterising the profiles with additional indicators

An important step of the empirical application of LCA is identifying specific population subgroups of interest, such as unemployed and non-native speakers, by including individual and household characteristics into the analysis. There are two ways to include additional variables to conduct a more detailed analysis using LCA. The first is the direct approach (or one-step approach) that involves estimating the LCA model with the additional characteristics (covariates) contributing to the definition of the class-membership probabilities. The second (the one used for this project) is the indirect approach (or three-step approach) that keeps covariates out of the estimation process, only using them in the post-estimation analysis. After estimating the model without covariates and allocating individuals to the latent classes using the estimated class-membership probabilities, the covariate analysis computes two-way tables summarising the relation between class-membership and covariates. The three-step approach brings clear advantages compared to the direct approach as it is easier to interpret the outcomes and computations can take less time to be obtained.

In the present segmentation analysis, the inclusion of additional variables is primarily driven by the interest in specific population subgroups typically considered in the breakdown of adult learning participation statistics. The selection of the variables also relies on the available information for each sample and the sample size in the AES. Annex Table 2.A.3 shows the main variables included to analyse adult learning participants and non-participants. The choice of some additional variables, such as "speaks Flemish" and "received guidance or information", relies on practical considerations based on suggestions made by stakeholders and the Flanders project team during workshops and interviews. The addition of "speaks Flemish" aims to provide insights into how adults facing language obstacles are distributed among the identified profiles. "Received guidance or information" allows the role of guidance and information provision (and its different modalities and mechanisms) in the different profiles to be analysed. Annex Table 2.A.1 showed the distribution of the socio-demographic and labour characteristics respectively by the nine profiles.

Annex Table 2.A.3. Additional variables included in the LCA for characterising the profiles

Covariates included for both participants and non-participants	Covariates included only for participants
Gender	Fields of training or educational programme
Group of age	Provider
Quintile of household income	Intensity of the training (in hours)
Speaks Flemish	Learning outcomes
Household composition	
Level of education	
Labour status	
Occupation (1 digit ISCO code)	
Level of qualification-occupation	
Tenure	
Enterprise size	
Sector (Industry 2 digits ISIC code)	
Automation risk	
Received guidance or information	
Source of guidance or information	
Type of information or guidance	
Engagement with informal learning	

Source: Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

Step 4: Robustness checks

To validate the decisions made and test the results obtained from the LCA, two additional exercises were conducted. The first aimed to test the set of indicators included in each model (for participants and non-participants). As mentioned, some indicators were aggregated, particularly to increase the sample size and thus improve the statistical power of the estimations (e.g. time obstacles that includes schedule and family responsibilities). To validate this decision, LCA estimations were run using the indicators separately (e.g. one dummy for “schedule” and another for “family responsibilities”, instead of a sole dummy to account for “time-related obstacles”). While reducing the statistical significance for some of the indicators, the LCA generated a similar profile structure with similar membership probabilities. This result shows that the indicator groupings contribute to increasing the statistical significance of indicators that, by definition, seem to be correlated, as well as to increasing the power prediction of the LCA.

Similarly, LCA estimations were conducted dropping the “unmotivated” and “no need” indicators to verify the consistency of profiles and its characteristics. The optimal number of profiles was verified and remained the same for both groups of adults (four for non-participants and five for participants). Annex Table 2.A.4 shows the variation of the two information criterions, AIC and BIC, by number of classes for the model that excludes both “unmotivated” and “no need”, and the models that exclude only one of them separately. In particular for profiles where obstacles (reasons for participating) are substantially more relevant (e.g. Profile 1 and Profile 2), the profile structure and the membership probability remains relatively the same.

Annex Table 2.A.4. Verifying the optimal number of classes after changes in LCA indicators

Percentage variation of AIC and BIC by number of classes

		Non-participants			Participants		
		C3	C4	C5	C4	C5	C6
No need and unmotivated variables excluded	% variation of AIC	-0.57	0.21	0.63	-0.73	-0.12	0.45
	% variation of BIC	-0.32	-0.18	0.44	-0.38	-0.25	0.32
Only no need variable excluded	% variation of AIC	-0.38	0.22	0.50	-0.77	-0.11	0.21
	% variation of BIC	-0.41	-0.21	0.22	-0.40	-0.13	0.17
Only unmotivated variable excluded	% variation of AIC	-0.29	0.25	0.54	-0.89	-0.23	0.27
	% variation of BIC	-0.19	-0.08	0.30	-0.25	-0.18	0.31

Source: Adapted from Eurostat (2021[14]), *Adult Education Survey 2016*, https://ec.europa.eu/eurostat/web/microdata/adult-education-survey.

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Limitations and considerations

LCA is a method based on structural equation modelling that aims to classify individuals into heterogeneous groups with homogenous developmental trajectories (i.e. where those within a group are very similar to one another, but the groups are very different from each other).

Although LCA is a powerful statistical procedure, it has limitations. LCA assigns individuals to classes based on their probability of being in classes given the pattern of scores they have on indicator variables (Muthén and Muthén, 2000[35]). Class assignment is not guaranteed, meaning that individuals cannot be assigned to a specific class as assignment is based on probabilities. Thus, the exact number or percentage of sample members within each class cannot be determined. However, through LCA estimation the probabilities of belonging to a class can be predicted, which allows the three-step approach for identifying the socio-demographic and labour characteristics of profiles to be run. Furthermore, names are usually assigned to the identified classes and, because of the complexity of the classes, there may be a risk of "naming fallacy," where the name of the class does not accurately reflect all the people in that group (Weller, Bowen and Faubert, 2020[38]).

In addition, the assumption underlying LCA is that membership in unobserved classes can cause or explain patterns of scores across assessment indicators (Muthén and Muthén, 2000[35]; Wolke et al., 2013[39]). The Conditional Independence (CI) assumption is the keystone of the classical latent class approach. The assumption states that, conditional on motivations (obstacles) for participating (non-participating), membership to a specific class is independent and the joint possible correlation does not give any additional information about the groups. This assumption is rather strong and cannot be easily tested. Additionally, the CI assumption often fails in practice to increase the risk of misleading inference for LCA of data that do not meet the independency between the indicators considered. However, its validation requires careful justification.

For this project, it is plausible that the main motivation (obstacles) to participate (not participate) in learning opportunities are uncorrelated with other reasons to participate (obstacles for participating), by definition. However, there are unobservable factors correlated with both indicators. For instance, "cost" and "time" obstacles are highly dependent on each other. Especially for adults with income depending directly on the numbers of working hours, the time assigned for training competes with the time assigned for working, thus with the ability to cover training expenses. Based on the statistical theory, individuals' values on a set of indicator variables are driven by their class membership. This concept is similar to the notion of a latent construct driving scores on scale items in factor analysis procedures (Kline, 2016[40]).

Estimations are conducted based on two models (adults participating and not participating) that rely for the most part on different sets of indicators. Outcomes of the models complement each other and related characteristics of profiles (socio-demographic and labour market) can be compared. The three-step approach resulted in the distribution of characteristics within each of the profiles, which helped to ensure this comparison. However, any comparison between profiles and their distribution of characteristics should take into account the underlying population used. Ideally, more common indicators would be added to strengthen the direct comparability of outcomes.

Consideration should also be given to the particularities of the survey data (AES) used in the analysis undertaken for this project. Definitions of key concepts used in this study such as "motivations to learn", "obstacles to participation" and "reasons to learn" were determined by how questions in the survey are phrased. For example, when asking adults for their reason to participate, a number of options are given to them (e.g. "to do my job better", "to improve my career prospects", "to be less likely to lose my job"), but it could very well be that other reasons might also have been relevant.

Annex 2.B. Methodology for measuring skills requirements in the labour market

Skills required in the labour market

The purpose of this exercise is to identify the skills required for the most commonly held occupations for each profile. While these outcomes should be interpreted with care, this information could, for instance, provide insights into the content of the training supply in order to better respond to labour market needs.

For this analysis, online job postings data from Burning Glass Technologies (BGT) were used, which covers the 27 European Union countries, as well as Australia, Canada, New Zealand the United Kingdom and the United States. The information can also be disaggregated by region, which enabled the dataset for Flanders to be selected

Based on the descriptions of job postings, BGT extracts information on the skills, abilities and knowledge required for the job using ESCO (the European Skills, Competences, Qualification and Occupations framework). For the sake of simplicity, this report uses “skills” when referring to these different dimensions. The dataset also has information on occupations (using ISCO-08), advertised salary, job location, contract duration and many other aspects related to the working environment.

Annex Table 2.B.1 shows that there are approximately 2.4 million unique jobs postings in Flanders from the first quarter of 2018 to the third quarter of 2021 (period of study). According to Annex Table 2.B.2 the demand is concentrated among professionals, and technician and associate professionals, which together account for 54% of total postings each quarter in Flanders. Because of the nature of the source of information, high-skilled occupations are overrepresented in job postings.

Annex Table 2.B.1. Number of unique job postings for Flanders per quarter, 2018 to 2021

Year	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Total
2018	NA	NA	151 512	180 312	331 824
2019	224 656	177 196	142 195	122 757	666 804
2020	227 841	150 000	250 950	323 843	952 634
2021	135 247	89 040	196 509	NA	420 796
Total	587 744	416 236	741 166	626 912	2 372 058

Note: Around 710 000 unique job postings do not indicate information on month and year. This is 6% of total observations.
Source: OECD calculations based on Burning Glass Technologies data, March 2022, Burning Glass Technologies (2022[22]), *Burning Glass database - online job postings*, https://www.burning-glass.com/.

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Annex Table 2.B.2.Number of unique job postings in Flanders by occupation and quarter-year of interest

Occupations at one digit level (ISCO-08)	Q3 2018	Q3 2019	Diff(1) = Q3 2019 - Q3 2018	Q3 2020	Q3 2021	Diff(2) = Q3 2021 - Q3 2020
Managers	16 521	12 510	-4 011	18 709	18 570	-139
Professionals	34 143	32 607	-1 536	50 953	47 425	-3 528
Technicians and associate professionals	25 548	25 077	-471	38 098	30 622	-7 476
Clerical support workers	18 328	15 706	-2 622	21 267	21 055	-212
Service and sales workers	14 743	11 902	-2 841	24 385	18 265	-6 120
Skilled agricultural, forestry and fishery workers	412	207	-205	455	229	-226
Craft and related trades workers	21 297	15 791	-5 506	36 587	17 059	-19 528
Plant and machine operators, and assemblers	15 271	13 494	-1 777	29 563	18 969	-10 594
Elementary occupations	14 492	11 323	-3 169	24 145	20 405	-3 740

Source: OECD calculations based on Burning Glass Technologies data, March 2022, Burning Glass Technologies (2022[22]), *Burning Glass database - online job postings*, https://www.burning-glass.com/.

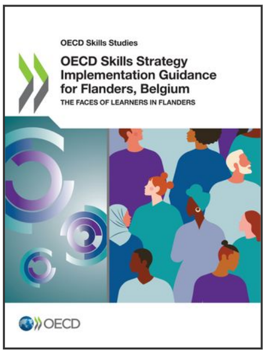
StatLink https://stat.link/3p5si4

For the analysis in this report, skills information (ESCO) from job postings was aggregated for occupations (ISCO-08) at the two-digit level. This skills information at the level of occupation was then linked to the information on occupations in AES. Subsequently, the three-step approach was applied to identify what skills are most important for each of the nine profiles. Trends in job postings and required skills were also analysed to review what skills have become more important in the Flemish labour market.

Only data on “unique” job postings were used for analysis in this report, meaning that duplicate job postings have been deleted (e.g. jobs published on multiple web and career portals), and any changes in sources were corrected for (e.g. job postings from newly added sources that raised coverage, but that distorted trends in job postings).

There are caveats and limitations to the use of job posting information that are important to highlight. For example, Burning Glass data only cover jobs posted online and may therefore not be representative of all vacancies. In addition, online vacancies can be somewhat skewed towards certain areas of the economy, although most differences are small in magnitude (Hershbein and Kahn, 2018[41]). Recent evidence shows that most countries display adequate representativeness overall, when considering only those years for which no break in time series was observed (Cammeraat and Squicciarini, 2021[42]). However, the study shows that occupational categories such as managers, professionals, and technicians and associated professionals are relatively overrepresented in Burning Glass data compared to other occupational categories, which underscores the importance of taking caution in interpreting the results and comparing occupational categories and their skills content. This implies that potential bias is more pronounced for low-skilled jobs, and less of concern for high-skilled occupations and sectors (Carnevale, Jayasundera and Repnikov, 2014[43]; Hershbein and Kahn, 2018[41]; Forsythe et al., 2020[44]).

Regarding linking skill needs information with the classes generated by the segmentation model, there are some important considerations. First, as the information is computed and merged by occupation, it relies on the proportion of workers in each profile, and thereby ignores the inactive and unemployed parts of profiles. Nevertheless, the analysis conducted for this section is based on the assumption that the identified skills needs can be extrapolated for all adults within the same group, regardless of labour market status. Second, due to a lack of information on the labour force supply and the skills adults possess, the analysis does not provide insights on the actual skills gaps.



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