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From Jobs to Journeys

Enhancing Forecasts With the Career Paths and Skill Transformations Model

PRIMER | February 26, 2026

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The Future Skills Centre (FSC) is a forward-thinking centre for research and collaboration dedicated to driving innovation in skills development so that everyone in Canada can be prepared for the future of work. We partner with policymakers, researchers, practitioners, employers and labour, and post-secondary institutions to solve pressing labour market challenges and ensure that everyone can benefit from relevant lifelong learning opportunities. We are founded by a consortium whose members are Toronto Metropolitan University, Blueprint, and Signal49 Research, and are funded by the Government of Canada's Future Skills Program.

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Contents

Highlights

- The Career Paths and Skill Transformations (CaST) model is a career path–driven approach to forecasting skills supply that incorporates how individuals' skills evolve through education and work experience and, in turn, how these ever-changing skill sets determine likely career pathways.
- Labour market outcomes make up the career paths, modelled using educational profiles and skill transformations to identify job transitions. These transitions are probabilistic, driven by the similarity of individuals' skill sets and the skills demanded in the job. They're constrained by factors such as educational requirements, relative wages, and macroeconomic conditions (e.g., unemployment rate).
- Skill transformations involve growth, decay, or atrophy along career paths, depending on whether a skill is actively used, underutilized, or unused in a given role, offering a more nuanced view of skill evolution than standard models.
- Career paths and skill transformations are interconnected – career trajectories drive skill growth or decline, while accumulated skills shape the likelihood of future job transitions. This dynamic feedback ensures that labour market matching in CaST responds to the ever-changing skills that individuals bring to the labour market.
- Unlike standard models that produce point estimates, CaST estimates distributions of skill proficiencies at each outcome in a career path, allowing for deeper analysis across occupations, educational profiles, and time periods, and revealing how career paths shape skills supply.
- CaST enables more targeted policy interventions, as it can be leveraged to forecast shifts in skills supply under different policy scenarios, identify skills most vulnerable to loss, and recognize the skill base of unemployed individuals, who are often overlooked in standard forecasts.
- The model opens new avenues for empirical research, including studies on wage progression, skill mismatch, and the economic return on skill investment, while also supporting scenario-based forecasting to anticipate future skill shortages and guide strategic workforce planning.

Moving beyond skills demand as a measure of supply

Understanding skills supply in the labour market requires examining how workers progress through different career paths. Current approaches to skills supply modelling overlook these paths, relying instead on the skills demands of a job to proxy for the skills supply of workers in that job. This is a major obstacle to assessing skill gaps.

Traditional approaches provide a limited view of the overall skill supplied across the economy—they estimate current and forecasted skills supply as an aggregation of the average skill proficiencies in each occupation, weighted by the employment distribution in the labour market.

The major shortcoming of this standard approach in which demand equates to supply is clear: There is no tracking of how skills are developed or lost through an individual's education and work experiences.[1] The assumption of traditional models is that each worker has only the set of skills associated with their current job—as if everything they have learned along the way is discarded with each positional change.

This isn't how workers develop skills in the real world. Career paths are shaped by job transitions that are driven by the ever-changing mix of skills supplied, introducing a dynamic link between skill development, career trajectories, and job-specific labour market outcomes.

1 Conference Board of Canada, The, "You Are Not Your Job."

Estimation techniques are available using skills assessment in surveys like the Organisation for Economic Co-operation and Development Programme for the International Assessment of Adult Competencies (OECD PIAAC), but they measure only three narrowly defined skill areas (literacy, numeracy, and adaptive problem-solving) and are prohibitively expensive.[2] In effect, they are analytically restrictive, particularly when the goal is to have economy-wide insights on skills supply and shortages. As a result, there is no comprehensive database of skills supply that can be used for economic and policy analysis.

To overcome this major conceptual shortcoming, we have developed the **Career Paths and Skill Transformations (CaST) model.** The CaST model anchors skills in career paths, capturing the dynamic evolution of skill proficiencies through time. It provides us with a career path–driven framework that models individuals' journey from education to their first job and through their subsequent occupations. At each career stage, the framework captures skills information and how skills evolve along unique career paths.

Because the framework is grounded in the idea that workers' actual skills often differ from the exact skill mix associated with their job, it allows us to assess occupation-level skill gaps—an aspect of the analysis that is not possible using standard approaches.

By modelling career paths and relating them to skill transformations and employment dynamics, we offer a methodology grounded in real-world skill progression, which we believe can positively transform education and workforce development policy tools.

How we built the CaST model

The CaST model leverages the occupation and skill matching algorithm from our Model of Occupations, Skills, and Technology (MOST) to characterize individuals' occupational mobility[3] and subsequently chart their overall career paths.[4] We tie these paths to skill treatment functions that determine how individuals' pathways through the labour market retain, grow, or atrophy their skills.

CaST is built on three foundational blocks. (See Exhibit 1.)

- Block 1: **Educational profiles –** Distribution of school leavers and their initial skill sets when first entering the labour market.
- Block 2: **Labour market outcomes** – Labour market dynamics, including skills-based job transition probabilities.
- Block 3: **Skill transformations** – Rules determining the evolution (growth or decline) of skills along career pathways.

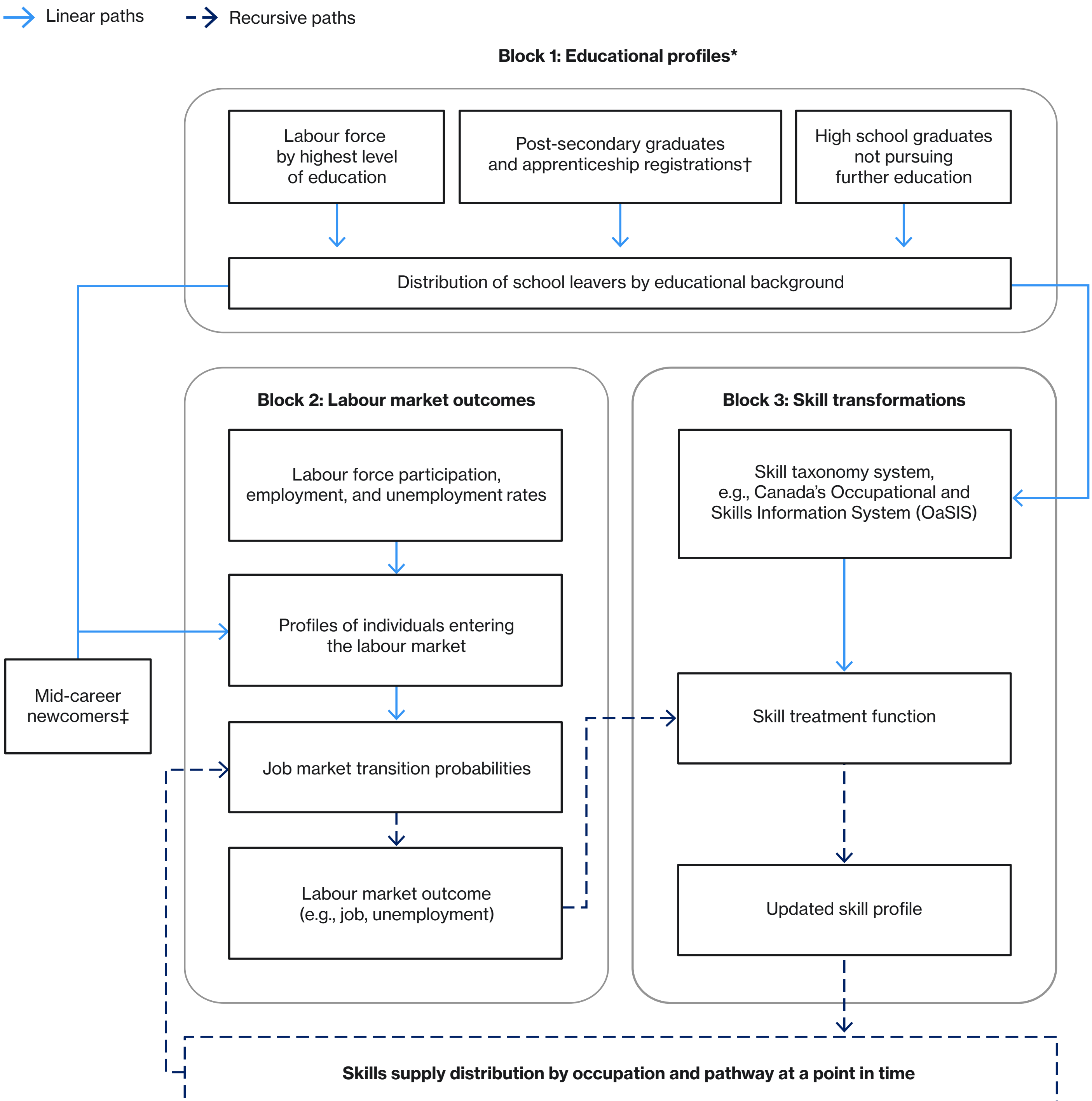
Each block produces a distinct output that feeds into the next, allowing our model to remain adaptable and support incremental improvements in how we represent educational profiles, labour market outcomes, and skill transformations. Inherently recursive, the skill transformations in Block 3 feed back into the labour market dynamics in Block 2, updating job transition probabilities based on existing skills supply. We run blocks 1 to 3 for each batch of new labour market entrants, with each run uniquely associated with only one cohort.

2 The OECD PIAAC offers a good measure of economy-wide skills supply. Due to the high cost of administration, the survey is conducted only once every 10 years, with the most recent round carried out in 2022–23. In Canada, the estimated cost of administering the 2012 survey in the three territories alone was approximately C$3 million. See PIAAC Canada, "Frequently Asked Questions"; and Strong, "No Money to Include the North."

3 Occupational mobility refers to the ability of workers to transition across different occupations.

4 MOST generates detailed occupational and industry-level labour market projections (employment, unemployment, vacancies, labour demand and supply, and skill gaps) across provinces and territories in Canada. Its key innovation lies in estimating labour market transitions based on skill matching between job seekers and job openings to get an estimate of the natural rate of unemployment and vacancies. Find more information on MOST.

Exhibit 1
Career Paths and Skill Transformations model infrastructure



* See Appendix A for a discussion on what makes up one CaST cohort.
† We use apprenticeship registrations in estimating the distribution of school leavers because they are considered part of the labour force when they start working as apprentices, even prior to earning their certification.
‡ The model does not consider immigration status to define transitions in the labour market. Immigrants graduating from Canada's school system and subsequently joining the labour force are considered school leavers in Block 1.
Source: Signal49 Research.

The power of distributions over point estimates

Individual cohort groups are not fixed in our model. Even when people follow an identical education and career path, their skill proficiencies differ. To capture the variety of individual competencies and experiences not explicitly part of our model, CaST tracks the distributions of skill proficiency at every stage, for every skill. This distributional approach improves on standard approaches, which capture only a single point estimate of skill proficiency.

To better understand the distributional component of CaST's skills forecasts, consider the supply of skills in "instructing" and "quality control testing" for two occupations: secondary school teachers and electricians. In the Occupational and Skills Information System (OaSIS) framework, the skill proficiencies associated with these two occupations are single point values representing the average requirement across jobs in these occupations. (See Table 1, and Appendix C for discussion on the OaSIS framework.)

In standard skills supply forecasting approaches, these point estimates of skill proficiency are also used as the estimate for the supply of skills in these jobs. Thus, all 150,965 secondary school teachers and all 89,875 electricians have the same skill level, all the time.

In contrast to point estimates, the CaST model estimates the distribution of skill proficiencies supplied by workers throughout their career paths.[5] We assume skill proficiencies are normally distributed, and we can sample from these distributions at any time to get a more realistic measure reflecting the variability in skill proficiencies embodied in individuals with similar backgrounds and career paths. The results from CaST can also be simplified to point estimates by analyzing only the average skill proficiencies, which can be compared with standard skills supply forecasts.

Table 1
OaSIS average skill proficiencies of secondary school teachers and electricians

	Employment count, 2021 Census	**Instructing proficiency**	**Quality control testing proficiency**
Secondary school teachers	150,965	5	1
Electricians	89,875	2	4

Sources: Signal49 Research; Statistics Canada, Table 98-10-0449-01; Employment and Social Development Canada, "Welcome to the Occupational and Skills Information System."

5 The maximum and the minimum provide us the upper and lower boundaries of the distribution. The mean (average) and standard deviation pertain to the centre and the spread, respectively, providing a summary of the shape of the distribution.

Career paths begin in educational profiles

People who complete or discontinue their education to join the labour market are known as **school leavers** in labour market information terminology. (See Appendix A for further discussion on school leaver cohorts.) CaST uses **profiles** to classify school leavers according to their educational background, which is the starting point of their career paths.

We identify six profiles characterized by the educational attainment of school leavers, which align with the National Occupational Classification (NOC) training, education, experience, and responsibilities (TEER) categories.[6] (See Table 2 and "Why start with the six profiles?")

In 2022, there were over 780,000 school leavers in Canada,[7] distributed across the six educational profiles. (See Chart 1.) These six distributions align with the educational profiles developed in CaST, such that people within the same profile share the same starting point in their career paths. (See Appendix B for technical discussion.)

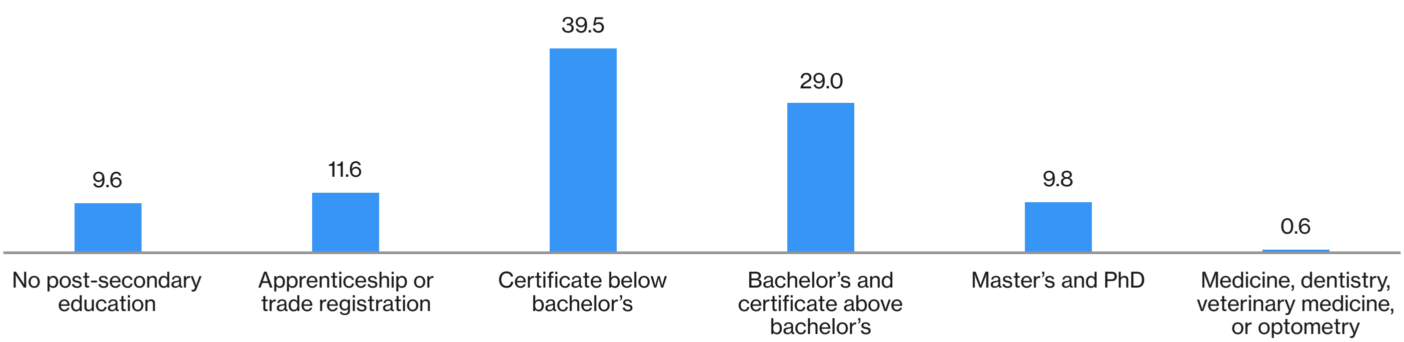
These 2022 graduates represent only one cohort in the labour market. Because CaST is built at the cohort level, its different blocks are looped over to capture multiple cohorts graduating at different times. (See Appendix A.)

Table 2
Six profiles and their educational background

Profile	Educational background
1. No post-secondary education	No certificate, diploma, or degree High (secondary) school diploma or equivalency certificate
2. Apprenticeship or trades certificate or diploma	Non-apprenticeship trades certificate or diploma Apprenticeship certificate
3. Certificate below bachelor's	College, CEGEP, or other non-university certificate or diploma University certificate or diploma below bachelor's level
4. Bachelor's and certificate above bachelor's	Bachelor's degree University certificate or diploma above bachelor's level
5. Master's and PhD	Master's degree Earned doctorate
6. Medicine, dentistry, veterinary medicine, or optometry	Degree in medicine, dentistry, veterinary medicine, or optometry

Sources: Signal49 Research; Statistics Canada, Table 98-10-0402-01.

Chart 1
A large share of school leavers have at least some post-secondary education
(per cent, 2022 cohort)



Sources: Signal49 Research; CaST model preliminary estimates; Statistics Canada, Tables 37-10-0276-01; 98-10-0401-01; 37-10-0219-01; 37-10-0008-01; 37-10-0176-01; and 37-10-0130-01.

6 The NOC TEER categories represent the training, education, experience, and responsibilities requirements to work in a specific occupation.

7 We estimate school leavers using 2022 data, the most recent year available in the latest Postsecondary Student Information System release (updated November 20, 2024).

Why start with the six profiles?

Choosing the number of profiles involves balancing detail in the model's results with data availability and computational efficiency. While we have the flexibility to define profiles at a highly granular level—for instance, by treating all 2,119 classes in Canada's Classification of Instructional Programs (CIP) as distinct profiles—we adopt a narrower set for ease of analysis and to identify common themes.

Having too few profiles risks oversimplifying career paths and skill variations tied to educational backgrounds. For example, if we use only three profiles—no post-secondary, below-bachelor's, and bachelor's or higher—we lose distinctions between, for example, apprentices and non-apprentices with below-bachelor's diplomas. This can eventually flatten meaningful skill transformation patterns into broad averages.

The "medicine, dentistry, veterinary medicine, or optometry" profile represents only a small share of the distribution. However, we consider it a distinct profile because individuals with this educational background follow unique career pathways and experience higher levels of work-integrated learning compared to those with other post-graduate education.

Conversely, having too many profiles increases computational demands and risks redundancy. Also, with limited granularity in existing skills taxonomies, too many categories would mean we might not even capture differences in skill development trajectories between individuals with closely similar profiles, wasting resources without adding insight.

Job transitions chart the career path

A career path tracks an individual's journey through the world of work. In the CaST model, we define a career path as a sequence of transitions, beginning with labour market entry and continuing along a journey of work and life. This journey includes employment in a variety of occupations, unemployment, and non-participation in the labour force. Collectively, we refer to these activities as **labour market outcomes**. (See "Defining labour market outcomes in CaST.")

CaST models these transitions probabilistically based on skill similarities. This constraint reflects a core idea from job search theory: Individuals typically target roles that match their existing qualifications and skill sets.[8]

8 Whipple, "A Generalized Theory of Job Search."

Defining labour market outcomes in CaST

Labour market outcomes include all activities that individuals may pursue upon reaching working age. Some choose to participate in the labour market, by either securing employment or actively seeking a job. In labour statistics, employed individuals are classified under an occupation according to Canada's NOC system,[9] while individuals actively seeking work are considered unemployed. In contrast, people may opt out of the labour market for a variety of reasons, such as pursuing further education, managing illness, taking care of loved ones, or feeling discouraged by limited job prospects.

CaST can accommodate the 516 five-digit unit groups of the 2021 NOC as employment outcomes. However, in CaST 1.0, we focus on 45 unique occupations defined by the NOC two-digit major occupational groups. This level is the most granular that still identifies TEER categories, allowing us to systematically categorize viable transitions from educational profiles to occupations. (See discussion on profile-to-outcome transitions.)

Unemployment and non-participation in the workforce are treated as general outcome categories in CaST. Individuals in these groups may still engage in activities that affect their skill level, such as engaging in employment-related training or obtaining a new certification. Tracking skill development outside of employment is not currently possible.

9 An *occupation* is a broad category of work defined by common tasks and skills in Canada's NOC system, while a job is a specific position held by an individual. Two different jobs can be classified under one occupation.

Profile-to-outcome transitions are constrained by educational requirements

Profile-to-outcome transitions define the initial link between an individual's educational profile and their first job. The profile determines which occupations an individual can access immediately after leaving formal education. These transitions are constrained by the educational requirements associated with each occupation (i.e., education barriers) and general labour market conditions.

We use Canada's TEER categories to define the minimum educational entry requirements for each occupation. (See Table 3 and Appendix D for further information on Canada's NOC and TEER system.) For example, individuals in the "no post-secondary education" profile are not eligible for TEER 1, 2, or 3 occupations based on education barriers alone. In contrast, those in the "medicine, dentistry, veterinary medicine, or optometry" profile meet the minimum educational requirements for all TEER categories.

Table 3
Training, education, experience, and responsibilities (TEER) categories in Canada's National Occupational Classification system

TEER	Education requirements
0	Management occupations, no specific education requirements
1	University degree
2	College diploma or an apprenticeship training of two or more years
3	College diploma or an apprenticeship training of less than two years
4	High school diploma or several weeks of on-the-job training
5	Short-term work demonstration, no formal education

Sources: Signal49 Research; Employment and Social Development Canada, "TEER Categories."

Although individuals with higher educational attainment are eligible for occupations across all TEER categories, they are more likely to match with occupations that align with their education level. Therefore, we model the probability of a worker transitioning into an occupation to be higher when their educational profile aligns with the occupation's TEER requirements. As a result, school leavers cluster initially in occupations that match their educational background. (See Table 4.) For example, a person with a bachelor of education is more likely to enter a professional role in education services (TEER 1) than an assisting role in the same field (TEER 3).

Table 4
Profiles and their most likely TEER categories

Profile	Most likely TEER
1. No post-secondary education	4 and 5
2. Apprenticeship or trades certificate or diploma	2 and 3
3. Certificate below bachelor's	2 and 3
4. Bachelor's and certificate above bachelor's	1
5. Master's and PhD	1
6. Medicine, dentistry, veterinary medicine, or optometry	1

TEER = training, education, experience, and responsibilities
Source: Signal49 Research.

TEER 0 jobs are typically reached through career progression from roles in other TEER categories. However, individuals from any educational profile can enter TEER 0 occupations even without work experience. For instance, a person graduating with a bachelor of business administration might start a food-service business and take on the role of restaurant manager, a TEER 0 job, immediately after graduation.

We model the transition probabilities from educational profiles to first occupations using the observed distribution of employment by NOCs from the 2021 Census. To focus specifically on occupations taken immediately after leaving school, we restrict the calculation to age groups that align with the median graduation ages for each educational level.

To account for the probability of not securing employment, we further constrain the transitions to employment using occupation-specific employment rates, allowing us to model the probabilities of being unemployed or otherwise out of the workforce at the start of one's career.[10]

Chart 2 shows the flow of the masses of educational profiles into their first labour market outcomes after applying profile-to-outcome transitions. Consistent with job search theory, workers begin their careers in occupations whose TEER category aligns with their educational background. Specifically, we observe:

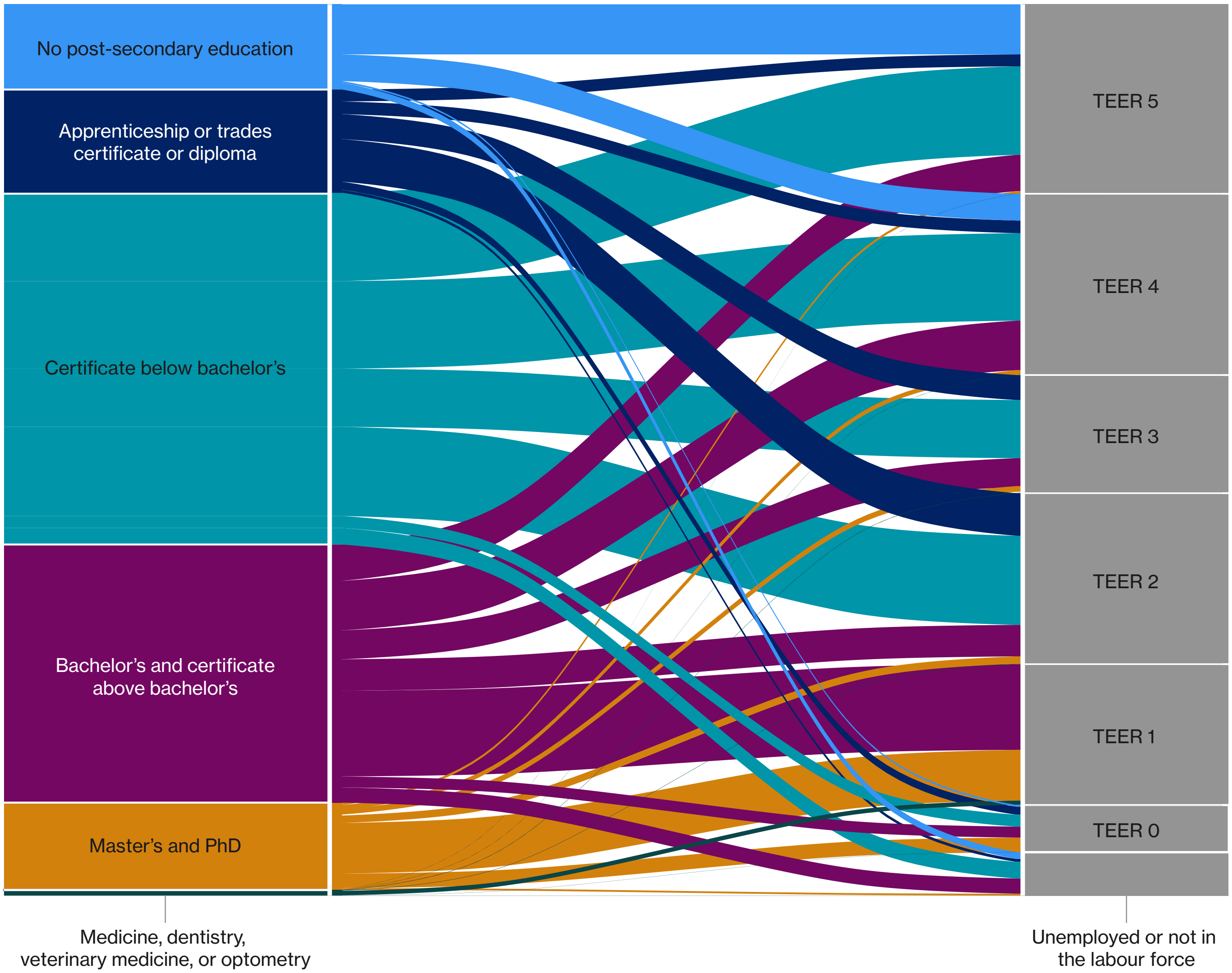
- **No post-secondary education:** Most likely to enter sales and service support jobs, a TEER 5 occupation.
- **Apprenticeship or trades certificate or diploma:** Most likely to enter technical trades and transportation jobs, a TEER 2 occupation.
- **Certificate below bachelor's:** Primarily enters sales and service support jobs like those with no post-secondary education, but has a strong presence in TEER 2 and 3 roles like public protection services and health support occupations.
- **Bachelor's and certificate above bachelor's:** Most likely to enter professional roles in law, education, and social and government services, a TEER 1 occupation.
- **Master's and PhD:** Clusters in professional roles in law, education, and social and government services roles as with bachelor's-degree holders, but less likely to enter TEER 5 roles.
- **Medicine, dentistry, veterinary medicine, or optometry:** Predominantly enters professional health jobs, a TEER 1 occupation.

10 School leavers have the intention to join the labour market. Our estimate of those out of the workforce in the first year includes individuals who are not in the labour force due to illness, personal or family reasons, job search dissatisfaction, or other factors (Statistics Canada, Table 14-10-0126-01, "Reason for Leaving Job"). We exclude those not in the labour force who are pursuing further education, as they are not yet part of the existing school leaver cohort. They will be included in the cohort once they complete their studies and join the labour force.

Chart 2

Each profile clusters into TEER categories that align with their education

(flow from profile to outcome, number of people; 2022 cohort)



Profile	TEER 0	TEER 1	TEER 2	TEER 3	TEER 4	TEER 5	Unemployed or not in the labour force
No post-secondary education	1,477	-	-	-	23,387	43,869	5,921
Apprenticeship or trades certificate or diploma	7,075	-	37,292	21,883	11,093	10,448	2,533
Certificate below bachelor's	10,452	-	78,084	50,929	76,629	77,554	14,560
Bachelor's and certificate above bachelor's	9,590	75,068	27,584	25,335	43,385	31,799	13,341
Master's and PhD	12,692	44,382	6,545	5,027	4,068	2,221	1,577
Medicine, dentistry, veterinary medicine, or optometry	121	3,858	268	305	169	123	132

TEER = training, education, experience, and responsibilities

Note: The flows are calculated using the mass of 2022 school leaver cohort multiplied by their profile-to-outcome transition probabilities.

Sources: Signal49 Research; CaST model preliminary estimates; Statistics Canada, Tables 98-10-0403-01; 98-10-0400-01; and 14-10-0126-01.

Outcome-to-outcome transitions are driven by skill matching

Once school leavers enter the labour market, they further accumulate skills through their work experience, complementing those already developed through education. These evolving skill profiles play a central role in shaping future transitions between labour market outcomes.

Outcome-to-outcome transitions represent the probability that an individual either remains in their current occupation (or labour market outcome) or moves to another. These probabilities are driven by the degree of skill match between the accumulated skills that job seekers supply and those that employers demand. Thus, outcome-to-outcome transitions are updated each year to reflect changes in workers' skills.

Transitions between outcomes are shaped by two key factors: the degree of skill match and wage thresholds. Transitions into jobs will be successful only if job seekers' skills sufficiently align with the job openings and if wages are acceptable to job seekers.[11] The Model of Occupations, Skills, and Technology already applies these two factors within its job-matching algorithm, and CaST builds on this foundation. In contrast to MOST, which calculates skill similarities between jobs themselves,[12] CaST compares workers' accumulated skills and the skills demanded in jobs.

Chart 3 presents the flow[13] of masses of people from one labour market outcome to the next for three sample career paths. Broadly, we observe that future transitions are influenced by education and strongly shaped by work experience:

- **Certificate below bachelor's, working in health support services:** Very likely to stay in healthcare, but good chance of moving into other client- or customer-facing roles.
- **Bachelor's degree, currently unemployed:** Broad transition probabilities across various professional occupations.
- **Completed apprenticeship, working in skilled trades:** Highly likely to remain in the skilled trades or other trades.

Apprentices tend to move into a limited set of similar trade jobs, reflecting the specialized nature of their training and initial work experience. In contrast, individuals with bachelor's degrees or other types of post-secondary education come from a wider range of educational backgrounds, typically less focused on technical skills. As a result, they have more diverse job transition opportunities.

11 Individuals are generally unwilling to accept large pay cuts. See Bewley, "Why Not Cut Pay?"

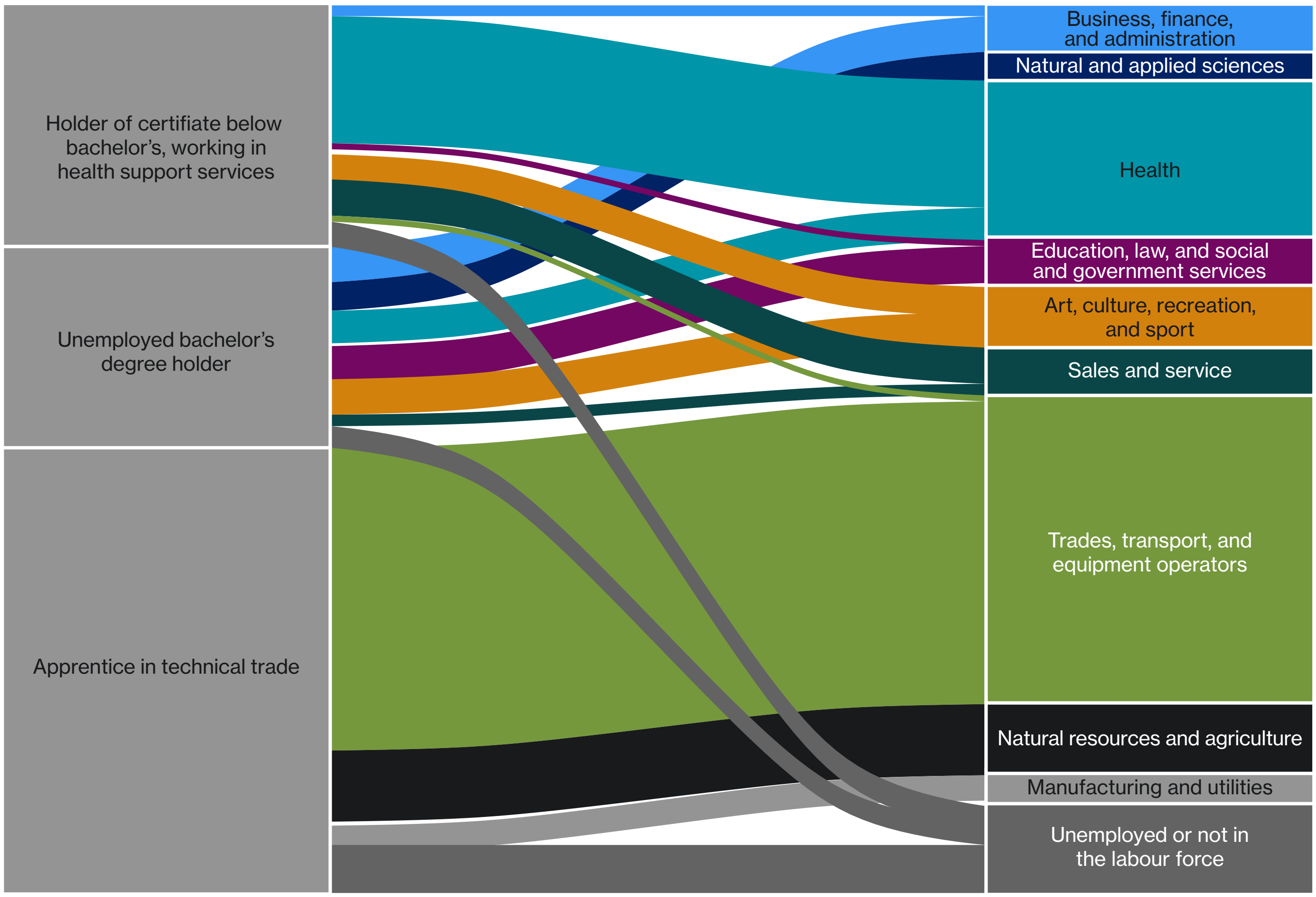
12 MOST compares similarities between the skills in the job that an individual has now and the skills required in another job.

13 Movement across 45 occupational groups, not movement from one employer to another.

Chart 3

Education and work experience shape future job opportunities

(flows from year 1 outcome to the next for three sample career paths, number of people; 2022 cohort)



Career paths	Holder of certifiate below bachelor's, working in health support services	Unemployed bachelor's degree holder	Apprentice in technical trade
Business, finance, and administration	359	2,167	-
Natural and applied sciences	-	1,741	-
Health	7,713	1,971	-
Education, law, and social and government services	370	2,178	-
Art, culture, recreation, and sport	1,826	2,153	-
Sales and service	2,200	701	-
Trades, transport, and equipment operators	364	-	18,378
Natural resources and agriculture	-	-	4,315
Manufacturing and utilities	-	-	1,416
Unemployed or not in the labour force	1,507	1,307	2,914

Note: The flows are calculated using the mass of 2022 school leaver cohort multiplied by their profile-to-outcome transition probabilities and their outcome-to-outcome transition probabilities from 2023 to 2024.
Sources: Signal49 Research; CaST model preliminary estimates; Statistics Canada, Tables 98-10-0412-01; 98-10-0400-01; 14-10-0416-01; and 14-10-0126-01.

Current roles drive future transition probabilities. Individuals who currently work in a specific occupation are likely to stay in the same occupation in the next year. Chart 3 illustrates this finding for individuals with a certificate below the bachelor's level who are working in health support services, and for apprentices in technical trades—both of whom show the highest probability of remaining in the same occupational group.

Because our cohorts develop skills through both education and work experience, they can also match with occupations that require similar skill sets and proficiencies, especially roles with TEER categories that align with their educational background. For example, apprentices from technical trades are also likely to transition into occupations in general trades and natural resources production (TEER 3 jobs). (See Chart 3.)

Beyond transitions from employment, CaST also accounts for skill-based matching during periods of unemployment. A key ability of the CaST algorithm is to retain skills information even within the unemployed population. This feature allows us to identify suitable job matches based on experience and qualifications. Bachelor's degree holders who were previously unemployed show a higher likelihood of matching with various TEER 1 jobs in finance and business, natural and applied sciences, health, and other professional roles, and a lower likelihood of matching with jobs outside these categories. (See Chart 3.)

Possible career paths for Sarah Skillz, BSc in economics

Suppose we take a sample from the distribution of school leavers who hold a bachelor's degree: Sarah Skillz, who graduated with a bachelor of science (BSc) in economics. Immediately after graduation, Sarah receives three invitations for a job interview: one for an economic analyst position, another for an investment analyst job, and the third for a bank teller role. These three roles require skills that align with her competencies. She is offered all three roles and decides to accept the economic analyst position as it most closely matches her skills and educational background. (See Exhibit 2.)

Thereafter, Sarah's skills and the general labour market conditions drive her labour market outcome for each period, recursively updating her career path. As she chose to work as an economic analyst in Period 1, her most likely career path over five periods is represented by an ordered sequence of outcomes: $\{\mathrm{E}, \mathrm{E}, \mathrm{I}, \mathrm{E}, \mathrm{E}\}$ (see Exhibit 2).

CaST associates one ordered sequence for each distribution of school leavers that follow the same career path. Across five periods, with six profiles and 45 major occupational groups, we model over 50,000 ordered sequences representing the unique career paths from a single cohort of school leavers. The number of possible paths will vary with the number of profiles, occupational groups, and periods. As the granularity of profiles and occupational groups increases, the number of potential career paths grows exponentially.

Exhibit 2
Career paths for Sarah Skillz after joining the workforce

Possible career paths	Period 1 Job options	Period 2	Period 3	Period 4	Period 5
{E, E, I, E, E}	Economic analyst (E)	Economic analyst (E)	Investment analyst (I)	Economic analyst (E)	Economic analyst (E)
{I, I, I, I, I}	Investment analyst (I)	Investment analyst (I)	Investment analyst (I)	Investment analyst (I)	Investment analyst (I)
{B, F, U, F, F}	Bank teller (B)	Financial analyst (F)	Unemployed (U)	Financial analyst (F)	Financial analyst (F)

Source: Signal49 Research.

Skills are transformed along career paths

Treating demand and supply as the same, as current skills forecasting models do, ignores skills that are developed along career paths not captured in an individual's current occupation. (See "You are not your job.") We address this fundamental limitation by using our modelled career paths to uncover three types of skill transformation pathways: growth, atrophy, and decay. These pathways are defined within the skill transformations block of CaST, which links sequences of labour market outcomes—generated by the labour market outcomes block—to **skill treatment functions**. As a result, skills in our model are no longer tied only to occupation codes but are instead linked to dynamic career trajectories. (See Appendix B for technical discussion.)

Our approach to skills also means that we account for when they increase or languish:

- Skills grow when there is a gap between what an individual has and what is needed in the job.[14]
- Skills decline when they are not used.

How an individual's skills evolve affects their job-matching probabilities.

14 In CaST 1.0, we base job requirements on the skill proficiencies associated with occupational categories in the OaSIS Skills and Competencies Taxonomy.

You are not your job

Early labour economics research on skills generally falls under the concept of human capital, a single, homogeneous measure of people's investment in themselves through formal education, acquisition of skills on the job, nutrition, and health.[15] More recent work is shifting from this catch-all metric to a more heterogeneous view of skills as a component of human capital.

Databases such as the U.S. Occupational Information Network (O*NET) and Canada's OaSIS provide occupational-level task data that have enabled researchers to construct multi-dimensional skill portfolios across occupations.[16] However, because these portfolios are coded only at the occupational level (not at the worker level), all individuals in the same occupation are assigned identical skill sets—a major drawback. This approach is adopted in occupational outlooks across Canada, in which forecasts of labour supply by occupation are mapped to O*NET or OaSIS to derive a measure of skills supply in the labour market.[17] Since the vast majority of labour supply *is* employment, skills supply are thus, by construction, identical to skills demand under the standard approach.[18]

Several scholars echo our criticism, pointing out that in occupation-coded skill portfolios, workers will *change* skills only when they switch occupations.[19] Even then, any skills not associated with the new occupation are simply lost, which fails to account for skill transferability. At the same time, skills that continue to be used are assumed to remain static, with no regard for skill growth or transformation over time.

15 Ben-Porath, "The Production of Human Capital."

16 This ability marks an improvement over earlier studies that relied solely on industry or occupation categories as proxies for skills, by shifting the focus from mere job titles to the underlying tasks that develop and reflect skills.

17 The Labour Market Information Council (LMIC) provides a compilation of methodologies adopted by provincial governments and research organizations in forecasting labour market outlooks.

18 Unemployment is a major gap in standard modelling approaches. The skills supply of unemployed individuals is often either overlooked or simplistically assumed to mirror their last held job.

19 Bowlus and others, "Ageing and the Skill Portfolio"; Sanders and Taber, "Life-Cycle Wage Growth"; and Woessmann, "Skills and Earnings."

In general, the skill *treatment*—the magnitude of the growth or decline in proficiency—is determined by the gap between the skill level demanded by the job and the individual's current proficiency (i.e., their skills supply). If the job demands a higher proficiency than is initially supplied, the individual learns and starts to close that gap. Conversely, if the individual's proficiency level is greater than what is needed for the job, their skill proficiency starts to fade, or decay. In more extreme cases, when a skill isn't required at all (e.g., during unemployment), proficiency atrophies, meaning it declines even more rapidly. (See "Skill transformation pathways for Sarah Skillz.")

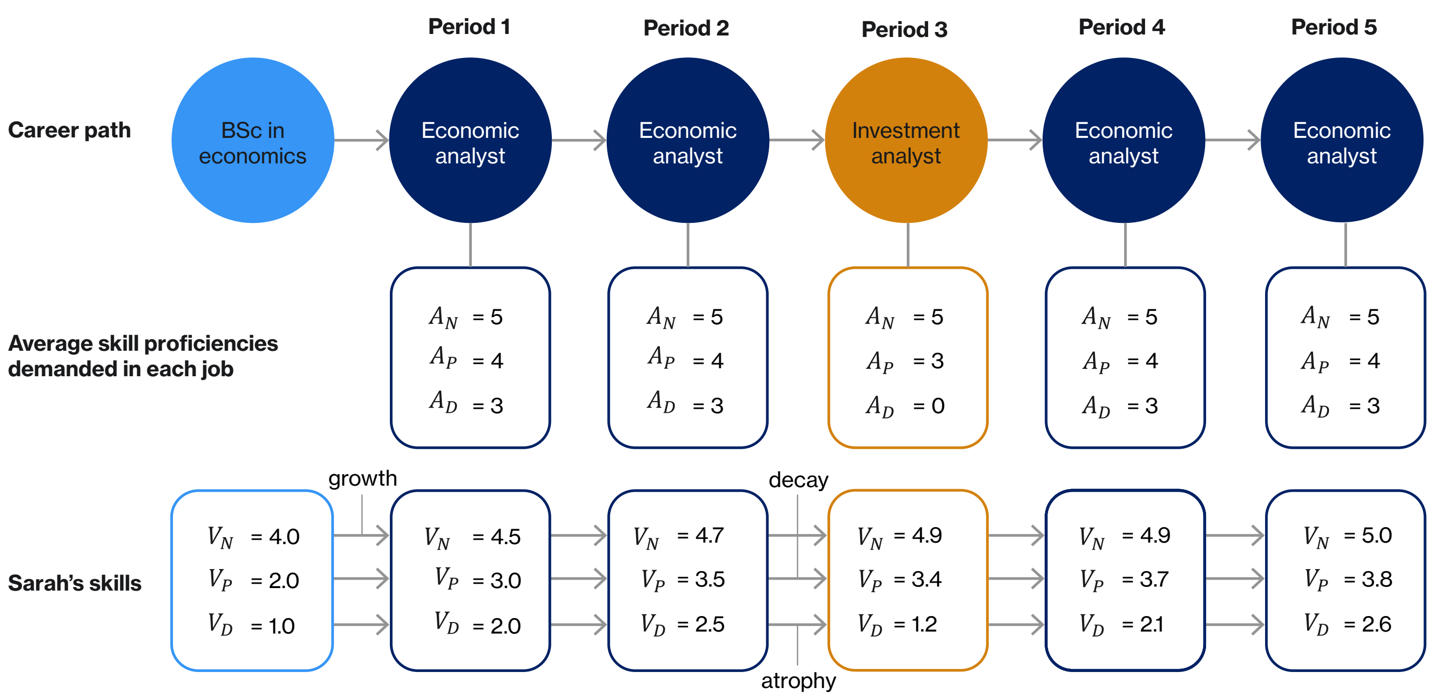
Skill transformation pathways for Sarah Skillz

Following the example in "Possible career paths for Sarah Skillz, BSc in economics," we assume that Sarah Skillz follows her most likely career path, {E,E,I,E,E}. We focus on the transformation of skills in numeracy (N), problem-solving (P), and digital production (D). Each skill is rated using a proficiency scale ranging from 0 to 5, in which 0 indicates that the skill is not used in the job, and values from 1 to 5 reflect increasing levels of use – 1 being the lowest proficiency and 5 being the highest. (See Exhibit 3.)

First, the full career path from education to Period 5 represents a **growth pathway** for Sarah's numeracy skill because the skill is continually used at the same proficiency level across all her occupations.

Second, Period 2 to 3 is a **decay pathway** for her problem-solving skill, because while Sarah still uses the skill as an investment analyst, she uses it at a lower proficiency compared to when she was an economic analyst. Thus, that skill will see some decay because of reduced application. Last, Period 2 to 3 is an **atrophy pathway** for her digital production skill. Digital production is not required in Sarah's role as an investment analyst, so that skill will deteriorate more rapidly compared to her problem-solving skill because of non-use.

Exhibit 3
Skill transformation pathways for Sarah Skillz



Note: Subscript refers to type of skill: numeracy (N), problem-solving (P), and digital production (D).
Source: Signal49 Research.

Skills grow rapidly with early use before slowing as mastery is gained

Skills are treated using a **growth factor** such that skill growth follows the generally observed skill-specific growth dynamics. The rate of skill growth is determined by the gap between the initial skill proficiency of the individual and the level demanded in their job, with the rate of increase greater when the gap is larger. As a result, average proficiency in each skill follows an *S*-shaped pattern, with rapid learning and improvement in early career stages, stabilizing mid-career, and then levelling off.[20] (See Appendix B for the technical discussion on how we are implementing this growth factor in the model.)

All school leavers enter the labour market with initial skills acquired through education. In our skill transformation block, our cohorts begin with a distribution of skill proficiencies from their educational backgrounds.[21] These skills can grow over time and are transferable across occupations.[22] A **growth pathway** for a particular skill occurs when an individual enters a job that requires the use of that same skill. Implicit in this assumption is that workers continue to learn and develop skills on the job and throughout their career.

The literature generally agrees that skills grow when actively used, though this growth is understood to vary by the type of skill.[23] Thus, even along growth pathways, skills evolve in a variety of ways.

We refer to the variation in skill transformation across different skill types—such as manual, cognitive, and social and emotional skills—as *skill-specific growth dynamics*. Manual skills tend to develop more rapidly than cognitive ones, while social and emotional skills grow more slowly but are more persistent over time compared to both manual and cognitive skills.[24]

Skills atrophy and decay with diminished skill use

Skills that follow an atrophy or a decay pathway are treated using an atrophy or a decay factor, respectively. The key distinction lies in how a particular skill is used in the new occupation. The **atrophy factor** applies when a previously acquired skill is not used at all, while the **decay factor** applies when a skill continues to be used, but at a lower level of proficiency. When applied, the atrophy factor results in more rapid deterioration in proficiency than the decay factor. Over time, skill proficiency declines in these pathways and eventually converges to a minimum level required by the job. (See Appendix B for the technical discussion on how we are implementing these factors in the model.)

Research on age-specific skill profiles suggests that skills tend to decline with age (some as early as age 30).[25] However, recent studies indicate that skill decline is more strongly influenced by usage than by age.[26] Reflecting this insight, CaST emphasizes the role of skill usage in shaping **atrophy** and **decay pathways**. Skill atrophy occurs during periods of non-use, while skill decay arises when skills continue to be used, but less frequently.

Similar skill-specific dynamics observed in the growth pathway also apply to atrophy or decay pathways. Manual and cognitive abilities tend to deteriorate more rapidly than social and emotional skills.[27] This is largely because the development of manual and cognitive skills relies heavily on regular practical application, which is often disrupted during periods of inactivity or unemployment.[28]

20 Our S-shaped skill growth pattern is similar to Ben-Porath's curve in his 1967 model of human capital accumulation and life cycle earnings. See Ben-Porath, "The Production of Human Capital."

21 Heckman and others, "Explaining Rising Wage Inequality."

22 Yamaguchi, "Tasks and Heterogeneous Human Capital."

23 Bowlus and others, "Ageing and the Skill Portfolio"; and Lise and Postel-Vinay, "Multidimensional Skills."

24 Lise and Postel-Vinay, "Multidimensional Skills."

25 Desjardins and Warnke, "Ageing and Skills."

26 Hanushek and others, "Age and Cognitive Skills."

27 Hanushek and others.

28 Ortego-Marti, "Differences in Skill Loss."

Skill transformations feed back into career path transitions

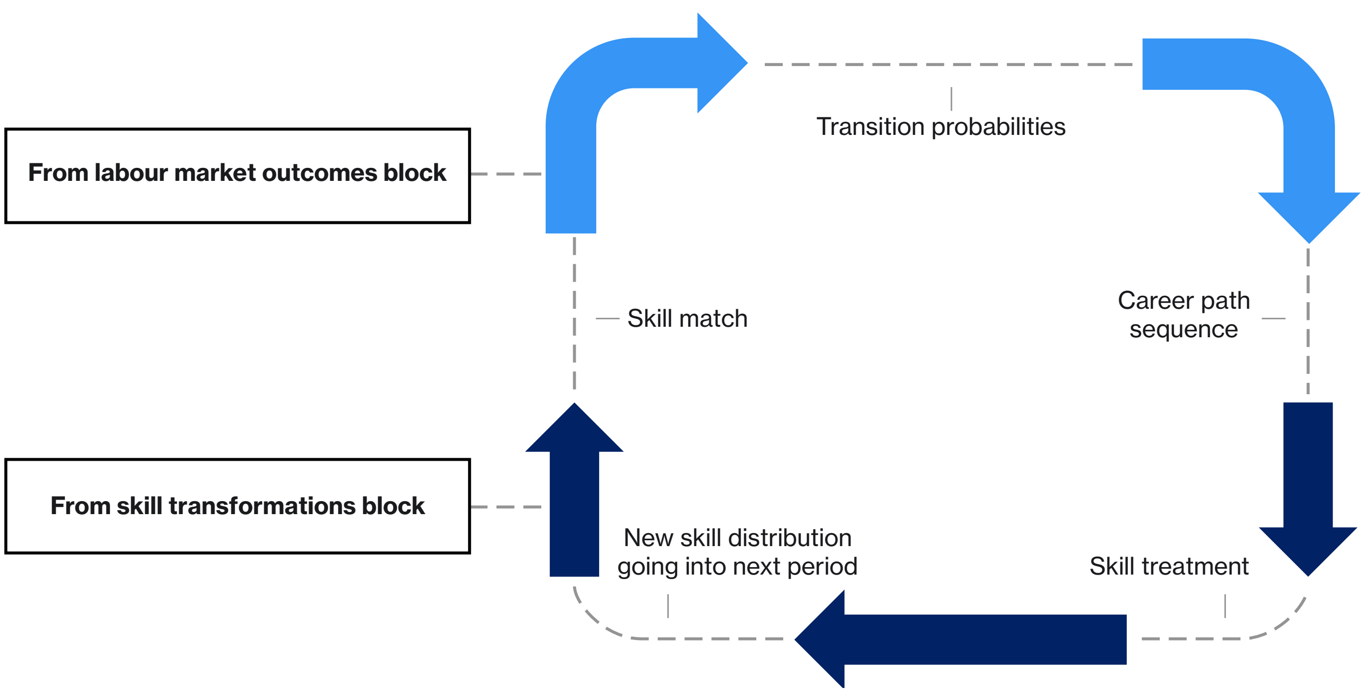
A key feature of the CaST model is the connection between the skill transformations block (which captures skills supply) and the labour market outcomes block (which estimates transition probabilities between jobs and other labour market outcomes like unemployment). This integration ensures that individuals in our model are matched to their target jobs based on their actual, accumulated skills.

Job transition probabilities determine the likelihood that an individual stays in their occupation, switches, or has some other labour market outcome. Those probabilities are primarily based on the skills the individual has to offer.

As an individual's skills develop, change, and—in some cases—decline over time, the likelihood of a transition to a different occupation also changes. Whatever job or labour market outcome an individual lands in, their skills are then augmented based on the skill transformation rules we described. Together, the constant evolution of their skills affects their career path, and their career path determines the evolution of their skills. (See Exhibit 4.)

Exhibit 4

Dynamic link between the labour market outcomes block and the skill transformations block



Source: Signal49 Research.

Same job, different skills: Why career paths matter

Consider a cohort of bachelor's degree graduates with diverging labour market outcomes driven by dynamic transition probabilities. (See Exhibit 5.) The graduates are distributed across four distinct career paths, each associated with a unique skill transformation pathway.

Consider the skill of negotiating as it evolves across the four career paths. Chart 4 presents how average proficiency in negotiating changes from a career path perspective. Based on CaST preliminary results, on average, bachelor's degree graduates enter the workforce with a negotiating skill proficiency of 0.53 out of 5.0. This skill level is carried into the labour market, where it grows through use and atrophies through lack of use.

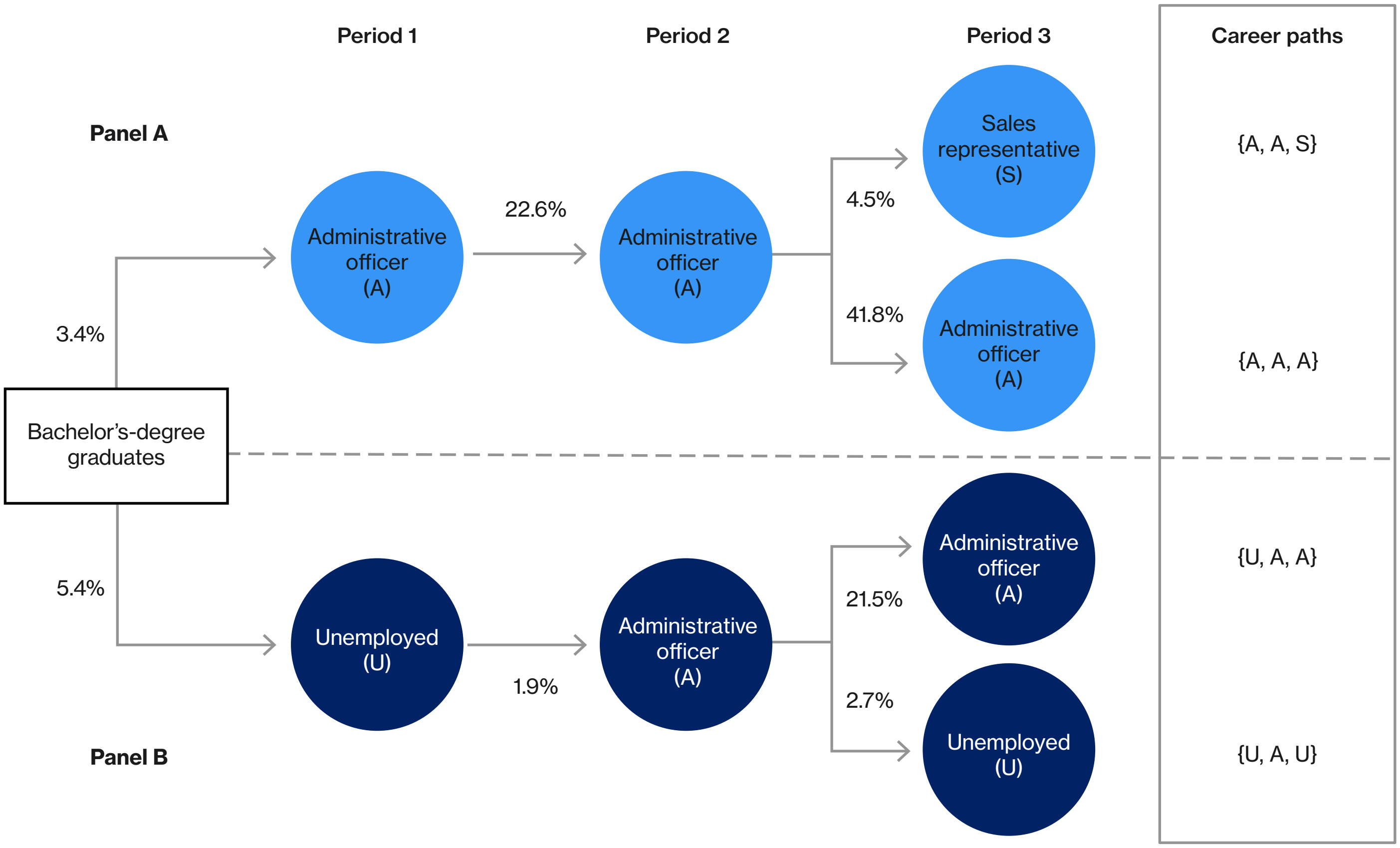
Negotiating is a skill required for administrative officer roles, with an average proficiency level of 3.0 according to the OaSIS framework. As a result, distributions following the {A, A, S} and {A, A, A} career paths experience consistent growth in negotiating skills across all three periods.

In Period 3, those who transition into sales representative roles show a sharper increase in average negotiating proficiency compared to those who remain in administrative roles, reflecting the higher skills demands of sales representative positions (level 4.0 according to OaSIS).

In contrast, the distribution of bachelor's degree graduates who are unemployed immediately after graduation—following the {U, A, A} and {U, A, U} paths—initially experience a decline in negotiating skills due to lack of use. Once employed in Period 2, their negotiating skills begin to improve, although the growth is more modest compared to peers who have been employed as administrative officers for longer. For those who continue working as administrative officers into Period 3 (the {U, A, A} path), negotiating skills continue to develop steadily.

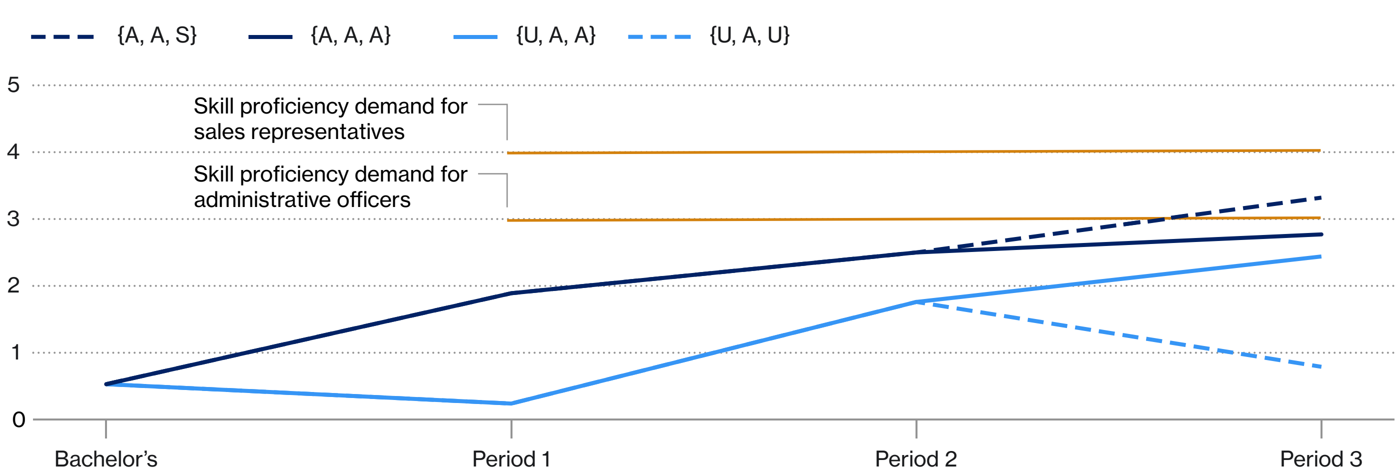
CaST fosters our understanding of skill development in the labour market. It captures the dynamic realities of how individuals enter, exit, and progress through jobs—revealing how prior experiences shape future work opportunities and how skills grow or decay depending on use.

Exhibit 5
CaST transition probabilities and the resulting career paths



Note: The percentages represent transition probabilities that change over time shaped by work history. These percentages are based on the estimated transition probabilities for the 2022 school leaver cohort shown in charts 2 and 3. They are based on preliminary work and are used in this report solely to illustrate how CaST skills differ from standard approaches.
Sources: Signal49 Research; CaST model preliminary estimates; Statistics Canada.

Chart 4
Negotiating skills are uniquely transformed along different career paths
(average negotiating skill proficiency)



Note: Negotiating skill refers to the capability to participate in or facilitate communication between parties, in order to resolve differences and reach a mutually acceptable or viable agreement (Employment and Social Development Canada, "About the Occupational and Skills Information System"). Proficiency levels range from 0 to 5, in which 0 indicates that the skill has not been developed, and values from 1 to 5 reflect increasing proficiency levels. The average negotiating skill proficiency levels in the table are based on preliminary work and is used in this report solely to illustrate how CaST skills differ from standard approaches.
Sources: Signal49 Research; CaST model preliminary estimates.

What we can do with this new approach

The Career Paths and Skills Transformations model offers a new approach to understanding skills supply by capturing the dynamic nature of skill evolution across individual career paths. By modelling skill distributions within each occupation, CaST supports detailed skill gap analyses, allowing career development practitioners, training institutions, and policy-makers to identify where upskilling efforts are most needed. It also opens further opportunities for empirical study.

By examining career paths, we can identify which skills are most vulnerable to atrophy, and which are likely to persist or grow. This nuanced view enables career development practitioners and training institutions to design more targeted interventions, such as re-skilling programs, unemployment support, and career guidance services.

CaST could inform workforce development strategies by highlighting the importance of skill usage over time. For example, it can help identify occupations in which skill decay is common due to underutilization, guiding investments in training to maintain proficiency or work-integrated learning to build base capacity.

Beyond current assessments, CaST can be used to forecast how skills supply will evolve in response to education policy changes. For example, increasing seats in fields linked to specific occupations allows policy-makers to anticipate how the overall skill profile of the workforce will shift over time—supporting more proactive and evidence-based planning for future labour market needs.[29]

CaST provides a more accurate picture of the skill base among unemployed individuals and those not in the labour force—groups that standard models often overlook. By recognizing that skills do not vanish during periods of unemployment, CaST challenges the assumption that jobless individuals lack usable skills. This insight is especially valuable during economic disruptions like the COVID-19 pandemic, when many workers lost jobs but retained some valuable skills.

CaST helps policy-makers better assess true skills supply, avoid misdiagnosing skill shortages, and better understand skill mismatches between the unemployed population and job vacancies.

In addition to practical implications, CaST opens rich avenues for empirical research across multiple domains. In labour economics, it could enable studies on the relationship between skill trajectories and wage progression, offering insights into how skill growth or decay influences earnings over time. It also supports investigations into skill mismatch and its impact on productivity, allowing researchers to quantify the economic costs of underutilized or misaligned skills within firms and industries.

CaST also facilitates research on the return on skill investment, helping to evaluate which skills yield the greatest economic benefits across different career paths and sectors. This knowledge can inform education and training policy by aligning curricula with evolving labour market demands.

Finally, CaST's ability to simulate future skills supply in various labour market scenarios—such as technological disruption, demographic shifts, or economic shocks—makes it a valuable tool for forecasting and strategic planning. Its power to expand to a greater number of job types and skills (beyond the 45 occupations and 33 skills in CaST 1.0) makes it an adaptable tool to conduct research in varying levels of granularity.

CaST is a new approach to forecasting skills supply that can support researchers and policy-makers in areas of interest such as anticipating skill shortages, designing responsive training systems, and building a more resilient and adaptive workforce.

29 The Conference Board of Canada's *From Shortages to Solutions: Tackling Canada's Critical Gaps in Healthcare, Trades, and Tech* (2025) identifies targeted increases in graduates by field of study as a strategy to address labour market imbalances. CaST can be leveraged to forecast how such policy changes would affect the future supply of skills across the Canadian workforce.

Appendix A

CaST model schematic diagram

What makes up a cohort?

The supply of workers in the labour market comprises many cohorts of school leavers, each entering the labour market at different times. For each cycle, CaST tracks the career paths of only a single cohort of school leavers who enter the workforce at the same time regardless of their level of education.[1] (See Appendix A Exhibit 1.) For instance, a high school graduate and a master's degree graduate are part of the same cohort if they both enter the workforce in the same year.

Each cohort is represented by a distribution of educational profiles, a measure independent of cohort size. Because we are constructing the distribution for a single cohort, we use graduation data for the same year. We source data on high school graduates from the Elementary-Secondary Education Survey (ESES),[2] data on post-secondary graduates from the Postsecondary Student Information System (PSIS),[3] and data on registrations from the Registered Apprenticeship Information System (RAIS).[4]

CaST is built at the cohort level. To capture the entirety of the labour market, CaST layers multiple cycles into the model, looping across different cohorts who graduated at the same time.[5] (See Appendix A Exhibit 2.)

1 Many high school, college, and university students work during their studies and have already entered the labour force prior to graduation. A simplification of the model is to consider "labour market entry" to be that point in time in which formal education is complete and the individual works full time. Nonetheless, CaST accounts for the average skills gained from part-time work prior to labour market entry.

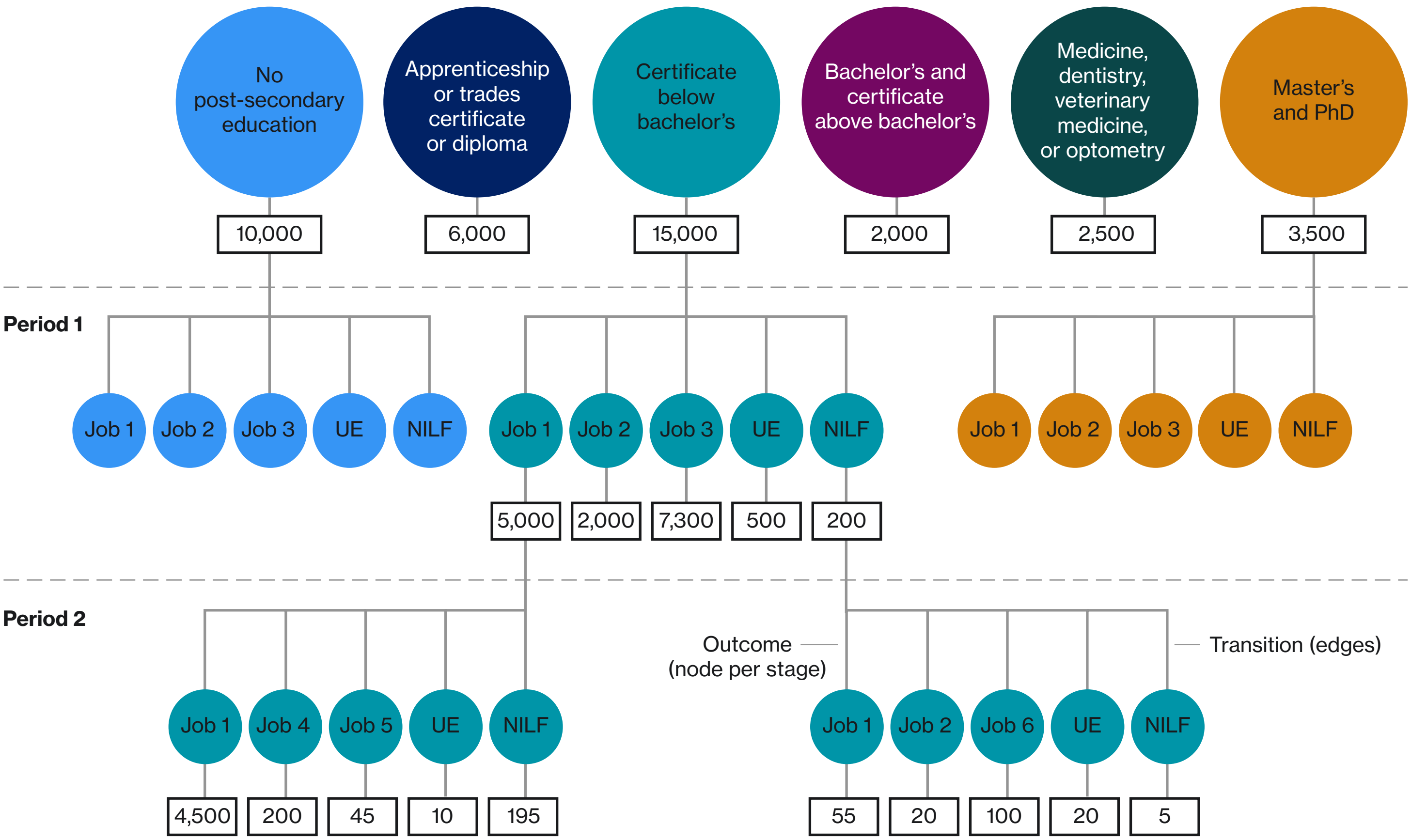
2 Only high school graduates who do not pursue post-secondary education are included in the "no post-secondary education" profile of school leavers. Ideally, this profile would also include individuals with less than a high school education entering the labour force, but their impact is not considered substantial due to Canada's strong high school graduation rates—84 per cent for on-time and 91 per cent for extended graduation rates as of the school year 2021–22. See Statistics Canada, Table 37-10-0176-01, "Number of Graduates From Regular Programs for Youth, Private or Independent Secondary Schools"; and Statistics Canada, Table 37-10-0008-01. "Number of Graduates From Regular Programs for Youth, Public Secondary Schools."

3 Post-secondary graduates are assumed to enter the labour force upon graduation. See Statistics Canada, Table 37-10-0276-01, "Postsecondary Graduates."

4 Registered apprentices are considered to enter the labour force upon registration, even while enrolled in post-secondary education, as they spend the majority of their time gaining supervised work experience in their chosen trades. See Statistics Canada, Table 37-10-0219-01, "Apprenticeship Programs."

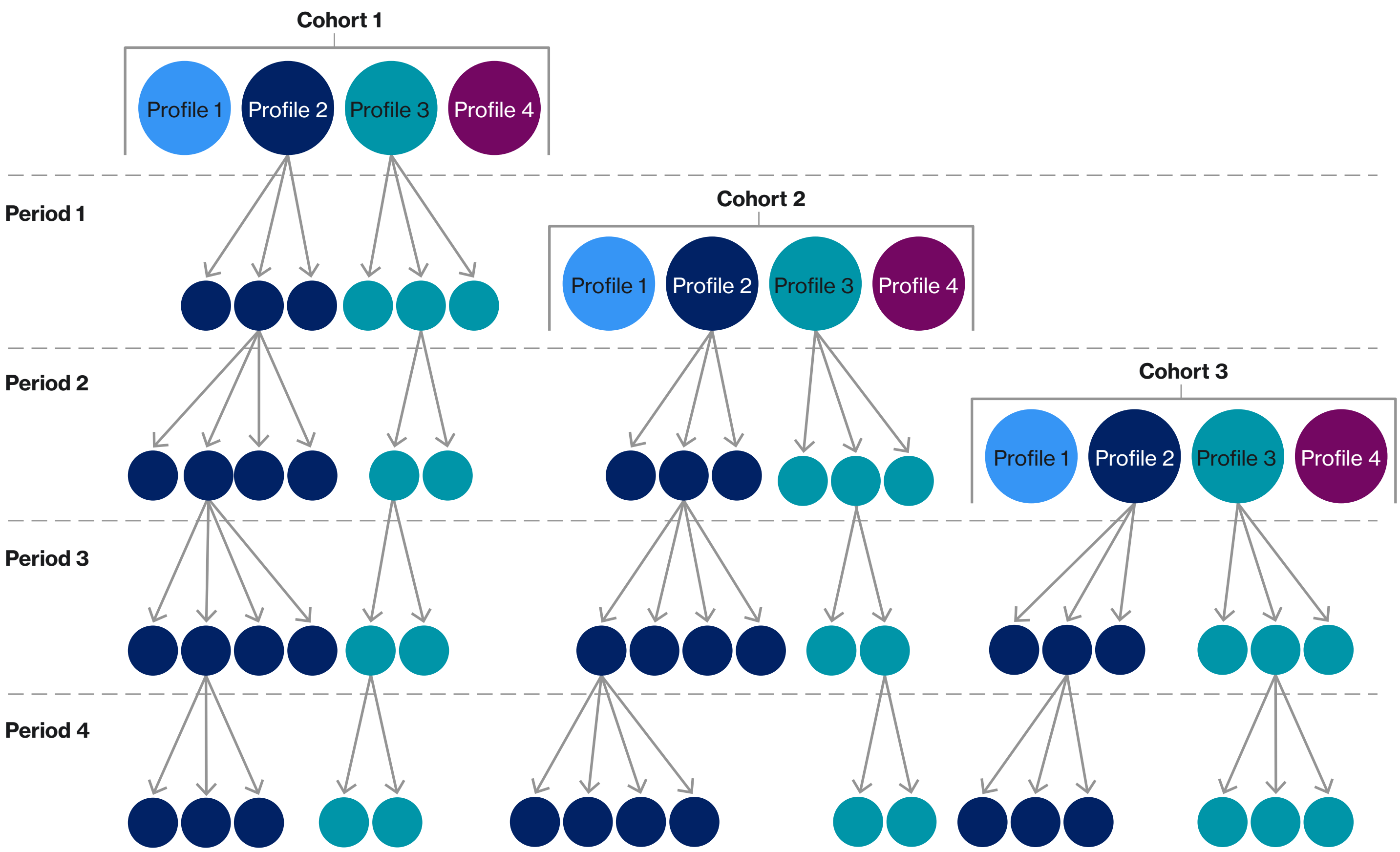
5 Over time, CaST lumps labour market attrition coming from emigration, deaths, retirements, and school re-enrollees into one category of individuals who are not returning to the labour market. School re-enrollees will be captured as part of a new cohort when they graduate from their new program.

Exhibit 1
Structure for a single cohort



UE = unemployed
NILF = not in the labour force
Note: The figures presented are hypothetical and are provided for illustrative purposes only.
Source: Signal49 Research.

Exhibit 2
Structure for multiple cohorts



Source: Signal49 Research.

Appendix B

Methodology

We define a Markovian model, in which the outcome at a certain period depends on the previous outcome and the individual's profile. This structure allows the simulation of longitudinal labour market trajectories for a given cohort of school leavers.

Block 1: Educational profiles

A distribution of educational profiles is calculated for each cohort of school leavers when they first enter the labour market.

Let:

- C denote an identifier of the cohort of school leavers entering the labour market in a given period
- N_C be the total number of school leavers in cohort C
- $P = \{P_1, P_2, \ldots, P_K\}$ be the set of educational profiles, where K is the total number of profiles
- n_k be the number of school leavers contained in profile k, such that $\sum_{k=1}^{K} n_k = N_C$

The distribution of educational profiles is defined by the following probability mass function, describing the likelihood that a randomly selected school leaver from a cohort belongs to profile P_k.

$$\Pr(\mathcal{P}_k) = \frac{n_k}{N_C}, \text{for } k = 1,2,\ldots,K$$

Block 2: Labour market outcomes

Different labour market outcomes characterize the career paths of a school leaver cohort. In CaST, a career path is conceptualized as a time-ordered sequence of labour market activities that a school leaver engages in after exiting the education system.

Let:

- $\mathcal{O} = \{o_1, o_2, \ldots, o_M\}$ be the set of labour market outcomes (e.g., employed in NOC j, unemployed, not in labour force)
- $\mathcal{O}_t \in \mathcal{O}$ be the labour market outcome at period t, $t = \{1,2,\ldots,T\}$
- $\mathcal{P}_k \in \mathcal{P}$ be the profile assigned to a group of school leavers

The **profile-to-outcome transition** defines the probability of entering a specific labour market outcome immediately after leaving school, conditional on the educational profile.

$$\Pr(\mathcal{O}_1 = o_m | \mathcal{P}_k), \qquad \text{for } o_m \in \mathcal{O}, \mathcal{P}_k \in \mathcal{P}$$

The **outcome-to-outcome transition** defines the probability of transitioning between labour market outcomes over time, conditional on the current state and the educational profile.

$$\Pr(\mathcal{O}_{t+1} = o_{m'} | \mathcal{O}_t = o_m, \mathcal{P}_k), \qquad \text{for } o_m, o_{m'} \in \mathcal{O}, \mathcal{P}_k \in \mathcal{P}$$

The full career journey of a distribution with profile P_k is characterized by the sequence $\{O_1, O_2, \ldots, O_T\}$ with the following joint probability:

$$\Pr(\mathcal{O}_1, \mathcal{O}_2, \ldots, \mathcal{O}_T | \mathcal{P}_k) = \Pr(\mathcal{O}_1 | \mathcal{P}_k) \prod_{t=1}^{T} \Pr(\mathcal{O}_{t+1} | \mathcal{O}_t, \mathcal{P}_k)$$

For example, in a three-period career path, $\Pr(O_1, O_2, O_3 \,/\, P_k)$ gives us the probability that the distribution follows a $\{O_1, O_2, O_3\}$ career sequence.

Block 3: Skill transformations

The skill transformation block describes how an individual's skill level changes over time depending on how much the skill is needed and used in their job, with past experiences further shaping future growth, decline, or loss of that skill.

Let:

- V_{spot} be the proficiency value in skill s for an individual with profile p in outcome o at period t
- V_{spot-1} be the proficiency value at period $t-1$
- o_t be the labour market outcome at period t
- o_{t-1} be the labour market outcome at period $t-1$
- V^*_{sot} be the reference maximum proficiency for skill s in outcome o_t
- $\bar{V}_{sot}$ be the mean proficiency requirement for skill s in outcome o_t
- GF_{spot} be the growth factor, $GF \geq 1$
- AF_{spot} be the atrophy factor, $0 < AF < 1$
- DF_{spot} be the decay factor, $0 < DF < 1$
- τ be the decay condition threshold

The **skill treatment function** is defined as follows:

$$V_{spot} = \begin{cases} V_{spot-1} \cdot AF_{spot}, & \text{if } V_{spot-1} > 0 \text{ and } \bar{V}_{so_t} = 0 \text{ (i.e., skill not required)} \\ V_{spot-1} \cdot DF_{spot}, & \text{if } V_{spot-1} > 0, \bar{V}_{so_t} > 0, \text{and } \frac{V_{spot-1} - \bar{V}_{so_t}}{V_{spot-1}} > \tau \text{ (i.e., skill underutilized)} \\ V_{spot-1} + GF_{spot} \cdot \max\left(0, V^*_{so_t} - V_{spot-1}\right), & \text{otherwise (i.e., skill used and growing)} \end{cases}$$

We show path dependency of the skill treatment function through recursive skill accumulation. That is, the skill proficiency at time t is recursively dependent on the value at period $t-1$. This structure means that the entire history of labour market outcomes up to period $t-1$ is embedded in V_{spot-1}. In the current period, the labour market outcome, o_t, influences the reference values V^*_{sot} and $\bar{V}_{sot}$ that guide skill growth, decay, or atrophy.

In this iteration of the CaST model (CaST 1.0), our goal is to support a viable, scalable model. As such, we keep the dimensions of each block's components minimal.

Appendix C

The Occupational and Skills Information System

The Occupational and Skills Information System (OaSIS) is a comprehensive database developed by Employment and Social Development Canada (ESDC) that links competencies to detailed occupational profiles. Originally adapted from the U.S. Department of Labor's O*NET to suit Canadian needs, OaSIS aligns with Canada's National Occupational Classification (NOC) system. It expands the 516 five-digit NOC unit groups (NOC 2021) into 900 seven-digit occupational profiles (OaSIS 2023 Version 1.0), maintaining the same high-level structural breakdown as the NOC.

The OaSIS framework is structured around a Skills and Competencies Taxonomy (SCT), which introduces a standardized competency lexicon for the world of work. The SCT comprises over 300 competency descriptors organized into eight categories: five based on individual characteristics and three reflecting the contextual features of the work environment in which occupations are performed. (See Appendix C Table 1.)

Table 1
OaSIS SCT categories

Individual characteristics	Work environment
Skills (43 descriptors)	Work activities (56 descriptors)
Abilities (56 descriptors)	Work context (73 descriptors)
Personal attributes (32 descriptors)	Tools and technologies
Knowledge (46 descriptors)	
Interests (6 descriptors)	

SCT = Skills and Competencies Taxonomy
Sources: Signal49 Research; Employment and Social Development Canada, "About the Occupational and Skills Information System."

For the purposes of the CaST model, we focus on the "skills" category within the SCT. Although this category includes 43 descriptors, only 33 are accompanied by proficiency ratings on a scale from 0 to 5. Accordingly, our skill treatment is limited to these 33 descriptors. (See Appendix C Table 2.)

ESDC regularly updates the OaSIS framework to ensure alignment between the NOC and the SCT, reflecting evolving labour market and occupational information. Although an update schedule has not been formally published by ESDC, the first version of the OaSIS was released in 2022 and subsequently updated in 2023.

Find out more information on the OaSIS framework.

Table 2
OaSIS skills

Foundational

1. Oral communication: Active listening
2. Oral communication: Oral comprehension
3. Oral communication: Oral expression
4. Reading comprehension
5. Writing
6. Numeracy
7. Digital literacy

Analytical

8. Critical thinking
9. Learning and teaching strategies
10. Decision making
11. Evaluation
12. Systems analysis
13. Problem solving

Technical

14. Equipment and tool selection
15. Preventative maintenance
16. Setting up
17. Operation and control
18. Operation monitoring of machinery and equipment
19. Troubleshooting
20. Repairing
21. Quality control testing
22. Product design
23. Digital production

Resource management

24. Management of financial resources
25. Management of material resources
26. Management of personnel resources
27. Time management
28. Monitoring

Interpersonal

29. Coordinating
30. Instructing
31. Negotiating
32. Persuading
33. Social perceptiveness

OaSIS = Occupational and Skills Information System
Sources: Signal49 Research; Employment and Social Development Canada, "About the Occupational and Skills Information System."

Appendix D

National Occupational Classification

The National Occupational Classification (NOC) is Canada's national reference for organizing occupations. It offers a structured system that classifies all types of occupational activity across the country, supporting the collection, analysis, and sharing of labour market information.

The 2021 NOC, jointly developed by ESDC and Statistics Canada, follows a five-level hierarchical structure. At the top level are 10 broad occupational categories, followed by 45 major groups. These are further divided into 89 sub-major groups, which break down into 162 minor groups and, finally, 516 unit groups at the most detailed level. The 2021 NOC is also associated with a six-tiered training, education, experience, and responsibilities (TEER) category, identified by the second digit of any NOC code.

For ease of application in CaST 1.0, we use the 45 NOC major groups as our employment outcomes. (See Appendix D Table 1.)

Find out more information on the 2021 NOC.

Table 1
NOC major occupational groups

NOC code	Occupational group
0	Legislative and senior managers
10	Specialized middle management occupations in administrative services, financial and business services and communication (except broadcasting)
11	Professional occupations in finance and business
12	Administrative and financial supervisors and specialized administrative occupations
13	Administrative occupations and transportation logistics occupations
14	Administrative and financial support and supply chain logistics occupations
20	Specialized middle management occupations in engineering, architecture, science and information systems
21	Professional occupations in natural and applied sciences
22	Technical occupations related to natural and applied sciences
30	Specialized middle management occupations in health care
31	Professional occupations in health
32	Technical occupations in health
33	Assisting occupations in support of health services
40	Managers in public administration, in education and social and community services and in public protection services
41	Professional occupations in law, education, social, community and government services
42	Front-line public protection services and paraprofessional occupations in legal, social, community, education services
43	Assisting occupations in education and in legal and public protection
44	Care providers and legal and public protection support occupations
45	Student monitors, crossing guards and related occupations
50	Specialized middle management occupations in art, culture, recreation and sport
51	Professional occupations in art and culture

(continued ...

Table 1 (cont'd)
NOC major occupational groups

NOC code	Occupational group
52	Technical occupations in art, culture and sport
53	Occupations in art, culture and sport
54	Support occupations in sport
55	Support occupations in art and culture
60	Middle management occupations in retail and wholesale trade and customer services
62	Retail sales and service supervisors and specialized occupations in sales and services
63	Occupations in sales and services
64	Sales and service representatives and other customer and personal services occupations
65	Sales and service support occupations
70	Middle management occupations in trades and transportation
72	Technical trades and transportation officers and controllers
73	General trades
74	Mail and message distribution, other transport equipment operators and related maintenance workers
75	Helpers and labourers and other transport drivers, operators and labourers
80	Middle management occupations in production and agriculture
82	Supervisors in natural resources, agriculture and related production
83	Occupations in natural resources and related production
84	Workers in natural resources, agriculture and related production
85	Harvesting, landscaping and natural resources labourers
90	Middle management occupations in manufacturing and utilities
92	Processing, manufacturing and utilities supervisors and utilities operators and controllers
93	Central control and process operators and aircraft assembly assemblers and inspectors
94	Machine operators, assemblers and inspectors in processing, manufacturing and printing
95	Labourers in processing, manufacturing and utilities

NOC = National Occupational Classification
Sources: Signal49 Research; Employment and Social Development Canada, "National Occupational Classification."

Appendix E

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Acknowledgements

This research was prepared with financial support provided through the Government of Canada's Future Skills Program. We are proud to serve as a research partner in the Future Skills Centre consortium.

It takes a team to deliver great research. We thank the many staff whose expertise and contributions helped to bring this research to life.

Tony Bonen, Executive Director, PhD, conceived of this research project and provided overall project direction and oversight. Jahm Mae Guinto, Economist, MA, wrote this report. Brittany Feor, Senior Economist, MA; Jahm Mae Guinto, Economist, MA; and Khurram Makhdumi, Economist, MA, executed the research.

We thank Michael Burt, Vice-President, MA; Alan Chaffe, Associate Director, PhD; Anne-Lore Fraikin, Associate Director, PhD; Erin Macpherson, Manager, MSc; Michael Bassett, Director, MA; and Leslie Twilley, Chief Research Officer, PhD, for providing feedback on drafts of this research.

This output was designed by Sarah Casselman, Senior Graphic Designer

We also wish to thank the members of the Research Advisory Board who supported this research:

- **Brendon Bernard**, Senior Economist, Indeed
- **Robert Carlyle**, PhD, VP, HR Analytics, Systems and Risk Management, Sun Life Financial
- **Ken Chatoor**, Director, Research and Strategic Foresight, Labour Market Information Council
- **Christopher Chevrier**, Director, Employment and Social Development Canada
- **Sonny Hedge**, Dean, Engineering Technology, College of the North Atlantic
- **Pari Johnston**, President and Chief Executive Officer, Colleges and Institutes Canada
- **Dr. Patrick Rouble**, Past President and Board Chair, Skills/Compétences Canada
- **Lisa Taylor**, Founder and Chief Executive Officer, Challenge Factory

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Signal49 Research

To cite this research: Research, Signal49. *From Jobs to Journeys: Enhancing Forecasts With the Career Paths and Skill Transformations Model.* Ottawa: Signal49 Research, 2026.

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PUBLICATION P-01867-J1K4G9
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