Drivers of Skills Accumulation in Singapore

Findings from the Skills Accumulation Study

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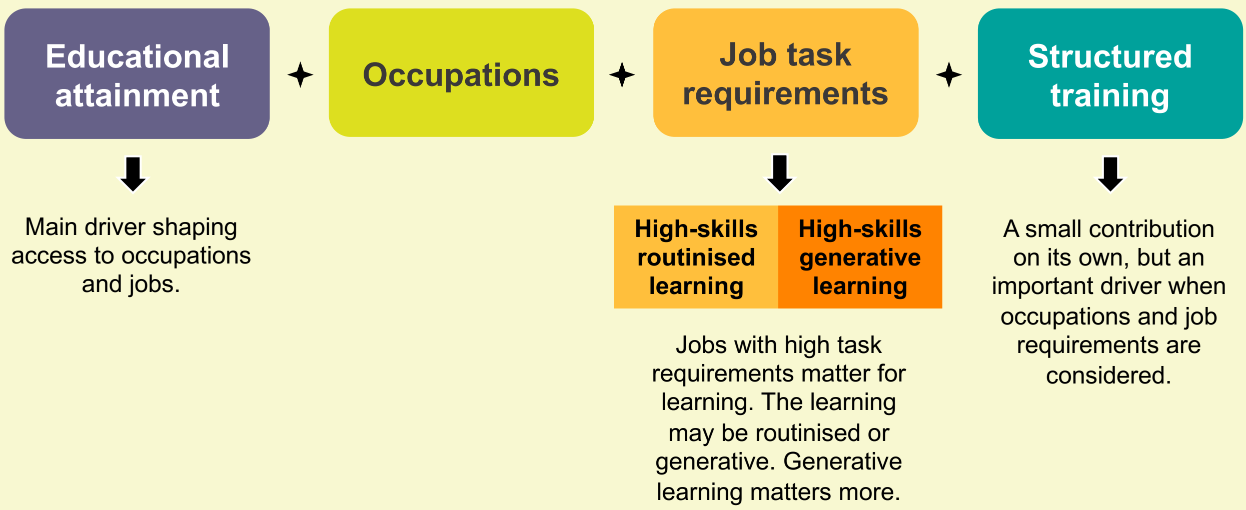
Executive summary

This study on skills accumulation in Singapore explores the key factors that shape an individual's career capital over the life course. By examining the role of formal educational attainment, occupations, job design and structured training, it highlights how these elements interact to influence workforce outcomes over time. The findings offer valuable insights into how Singapore can further strengthen its skills development efforts and better support its workforce amid ongoing economic and labour market transformations.

The key takeaway is the need for a more holistic approach to skills accumulation – one that goes beyond initial educational attainment and structured training – to foster value-creating job design and generative learning work environment. Such an approach can advance skills-first pathways and strengthen the role of continuing education and training as a strategic lever for social mobility and economic resilience, capable of altering life-course trajectories and mitigating entrenched disparities.

Key patterns of skills accumulation in Singapore

Four key contributors to skills accumulation



1. Educational attainment and skills demand as key drivers of skills accumulation

Formal educational attainment, occupations and job design strongly influence skills accumulation in Singapore. Degree qualifications provide a significant advantage in accessing high-skilled occupations and explain a substantial portion of wages. In comparison, individuals without such qualifications face more limited career opportunities. To promote more equitable workforce outcomes across the life course, it is important to moderate the strong influence of educational attainment on career trajectories.

2. The impact of structured training on skills accumulation is shaped by educational attainment and skills demand

Structured training alone does not lead to significant wage returns. However, it offers important non-wage benefits, such as higher job security and improved job prospects, particularly for workers without at least a diploma qualification. Despite these benefits, this segment of workers is less likely to participate in training. Crucially, the effectiveness of structured training is heavily shaped by the broader skills ecosystem, including educational attainment, occupations and job design.

3. The importance of job design: encouraging generative learning

Job design is critical in shaping how workers engage with skills development and progression. Generative learning jobs – which encourages new ways of thinking and applying skills – drive higher participation in training, as workers in these roles recognise the ongoing need to utilise and expand their skills.

However, not all high-skilled jobs foster generative learning. Some focus primarily on routinised learning, emphasising memorisation and strict adherence to instructions, and thus limiting skills growth. This highlights the need for job redesign efforts that embed generative learning elements such as decision-making, brokering, and independence, as part of a broader value-creation business strategy – and ensuring such jobs are accessible to a wider range of workers.

Workers in generative learning jobs often see higher wage returns and better overall employment outcomes. Importantly, these benefits extend beyond individuals with high educational levels. Inclusive job design is therefore a key lever for supporting more equitable skills accumulation across all educational levels.

4. Implications: levelling the playing field and driving value-creation

Public policy plays a key role in supporting individuals throughout their skills accumulation journey. First, it can help level the playing field by extending its reach to underserved segments, such as less-credentialled workers, who may otherwise have limited access to training opportunities. Second, policy can support curriculum design and pedagogy training for adult educators, equipping them to better address the unique needs of these underserved groups. Third, beyond direct training support, interventions through the productive system can encourage value creation at the firm-level, fostering the creation of generative learning jobs and aligning training provisions with those that better support generative learning.

1. Introduction

Globally, rapid technological advancements, demographic changes, and structural economic shifts have raised concerns that initial education alone is no longer sufficient to meet evolving skill demands. As skills requirements shift and the pace of skills obsolescence quickens, there is growing recognition that workers must engage in continuous learning and adaptation throughout their careers. Against this backdrop, lifelong learning has moved to the forefront of policy agendas worldwide, positioned as a key lever to sustain employability and support inclusive economic growth.

Singapore has embraced this agenda with sustained and substantial investment in its continuing education and training (CET) ecosystem. Framed as both an economic necessity and a social imperative, these efforts aim to equip workers to remain competitive, relevant, and able to access high-quality, well-paying jobs amid ongoing labour market transformations. The national SkillsFuture movement, launched in 2015, represents the most visible expression of this commitment, aiming to expand opportunities for upskilling and reskilling across the population. These initiatives are unfolding against a backdrop of steadily rising educational attainment in the workforce, underscoring the importance of aligning CET provision not only with changing economic needs, but also with the diverse starting points, career trajectories, and constraints faced by workers at different stages of their lives.

Given the scale of CET investment, it is crucial to assess how effectively such efforts translate into tangible benefits for both individuals and society at large. Monitoring the outcomes not only tests their effectiveness but also informs refinements to strategies and programmes that can further strengthen workforce capabilities.

This report presents findings from the Skills Accumulation Study, which investigates how lifelong skills accumulation impacts employment opportunities and outcomes in Singapore across different workforce segments (see Appendix A for research questions). The central organising theme for this study – skills accumulation – is defined here as the lifelong process through which individuals acquire, develop, and sustain their skills. It encompasses multiple pathways: pre-employment education and training (PET), structured CET programmes, as well as informal learning gained through on-the-job experiences. The interplay between these pathways is critical. CET can complement prior education to deepen expertise, or compensate for earlier gaps in formal learning, thereby shaping both the stock of skills an individual possesses and how these skills are deployed in the labour market. From the demand-side, job design, workplace structures, and organisational practices also play a strategic role in shaping skills accumulation trajectories.

The key takeaway is the need for a more holistic approach to skills accumulation – one that goes beyond initial educational attainment and structured training – to foster value-creating job design and generative learning work environment. Such an approach can advance skills-first pathways and strengthen CET's role as a strategic lever for social mobility and economic resilience, capable of altering life-course trajectories and mitigating entrenched disparities.

The remainder of the report is structured as follows. Chapter 2 outlines the theoretical perspectives that guide the analysis. Chapter 3 describes the data and methods employed. Chapters 4 to 7 present the key findings. Chapter 8 discusses their implications and concludes.

2. Theoretical perspectives

Skills accumulation across the life course

Skills accumulation refers to the lifelong process through which individuals acquire, develop, and adapt their skills over time. This process unfolds through multiple pathways: initial education (PET), structured CET programmes, as well as informal learning gained through on-the-job experiences. While PET builds the foundational stock of skills capital, this base alone is increasingly insufficient to meet evolving labour market demands. CET is thus positioned to play a pivotal role in sustaining and extending skills accumulation over the working life.

To frame the analysis, the study draws on three complementary theoretical perspectives. Together, they illuminate the mechanisms driving skills accumulation, the conditions shaping the effectiveness of CET, and the sources of variation in its returns across worker groups and employment contexts.

Human capital theory

Human capital theory (HCT) (Becker, 1962; Mincer, 1958; Schultz, 1961) – the dominant paradigm in the economics of education and training – conceptualises skills accumulation as an investment in productive capacity. Investments in knowledge and skills are expected to enhance an individual's productivity, which, in competitive labour markets, should yield higher wages and improved employment prospects. Within this framework, CET functions as a mechanism to sustain and expand an individual's human capital, counteracting skills obsolescence and enabling upward mobility over the life course.

In the Singapore context, where manpower planning, workforce development, and economic growth have long been closely intertwined (Ashton & Sung, 1997; Cheung, 1994; Ng, 2012; Sung, 2006), HCT has been a central policy reference point underpinning substantial public investments in CET, most recently through the national SkillsFuture movement (Government of Singapore, 2024; Ministry of Finance Singapore, 2024; 2025). Here, CET is positioned as a strategic lever for supporting lifelong employability and sustaining economic competitiveness. Skills accumulation is thus viewed as a deliberate, policy-supported process of continual human capital enhancement.

Cumulative advantage and the life course perspective

While HCT offers a compelling rationale for CET, it provides only a partial account, where it treats the returns to further training largely as a direct function of the investment itself. The cumulative advantage framework (DiPrete & Eirich, 2006), informed by the life course perspective, adds a critical temporal dimension – that prior educational attainment shapes both access to, and outcomes from, CET.

Skills accumulation is often unevenly distributed: a large body of empirical research demonstrates that individuals with higher initial educational attainment tend to participate in more CET, select higher-quality programmes, and gain greater returns, thereby reinforcing existing labour market advantages over time (Kilpi-Jakonen et al., 2015; Kramer & Tamm, 2018). These disparities may be further reinforced by job characteristics such as task complexity or exposure to technologies, which are themselves more accessible to highly educated workers (Schindler et al., 2011). By contrast, workers with lower educational attainment often encounter more barriers to participation and derive fewer benefits from training opportunities, highlighting the limits of CET in compensating for earlier disadvantages.

This self-reinforcing dynamic, also referred to as the Matthew effect (Merton 1968), raises an important empirical and policy question: Can CET, undertaken later in life, genuinely function in a compensatory capacity – narrowing disparities in skills accumulation trajectories between more and less formally educated workers – or does it primarily operate as a complementary mechanism that amplifies advantages among those already better positioned?

Institutional arrangements and organisational design: an alternative lens

The cumulative advantage framework emphasises how prior educational attainment sets enduring trajectories for skills development and career outcomes, but these patterns are not inevitable. An alternative perspective holds that institutional arrangements – policy and organisational design – can actively reshape the opportunities and conditions for skills accumulation.

At the policy level, measures that incentivise investments on the training of lower-skilled and less advantaged segments of the workforce can expand access to skill-building opportunities that might otherwise be limited (Santos et al., 2024). At the organisational level, workplace structures and job design (Avent-Holt et al., 2020a; 2020b) – particularly those that embed inclusive talent management practices (Brown at al., 2019; Sadik at al., 2025) – can create ongoing opportunities for skill development, skills utilisation, and progression. Together, these institutional and organisational levers may equalise the cumulative returns to training, broaden career trajectories, and counteract employer biases or systemic barriers that typically channel high-quality skills development opportunities towards already advantaged workers.

From this perspective, CET is not merely a complementary investment that build on existing human capital. It can also serve as a strategic lever for social mobility – capable of altering life-course trajectories and mitigating entrenched disparities if embedded within supportive institutional frameworks. The subsequent analysis in this report draws on this perspective alongside HCT and cumulative advantage, to examine how skills accumulation in Singapore is shaped by the interaction of educational attainment, occupations, job design and structured training.

3. Data and methods

A multi-data, multi-method research design

This study employs a multi-data, multi-method approach to investigate how lifelong skills accumulation impacts employment opportunities and outcomes in Singapore across different workforce segments. The approach combines a robust empirical base through quantitative analysis – primarily drawing on data from the Skills and Learning Survey (SLS) – with a smaller qualitative component that explores the mechanisms underlying observed patterns (Leech & Onwuegbuzie, 2009; Tashakkori & Creswell, 2007). Findings from both strands are integrated through a triangulation process, which strengthens explanatory power and provides a richer evidence base to inform policy development. This integrated methodology is especially important given the study's aim to guide policymaking.

Conceptual frame

To examine the influence of PET on CET, the conceptual framework treats educational attainment as a key stratifying factor that shapes both access to, and returns from, CET (see Appendix B for an illustration of the conceptual frame). Accordingly, all datasets are analysed by educational attainment categories, enabling systematic comparison of patterns between individuals with different levels of qualifications.

Datasets

Skills and Learning Survey (SLS) 2017 and 2021

The primary dataset for this study is the Skills and Learning Survey (SLS), conducted by the Institute for Adult Learning in 2017 and 2021. These two iterations of the SLS track jobs, skills and learning among the adult working-age resident population (citizens and permanent residents) in Singapore, including both employed and non-employed individuals. Administered face-to-face by trained interviewers, the SLS offers high-quality, reliable, and representative data across a broad range of employment and training-related variables. A key strength of the SLS lies in its comprehensive measures of structured training participation, which distinguishes between job-related and non-job-related training, financing arrangements, training duration, and more. This level of detail enables nuanced analysis of CET participation and outcomes (see Appendix C for definitions of training types).

The survey employs two complementary samples, providing both a broad cross-sectional snapshot and a dynamic longitudinal perspective on workforce trends and training outcomes:

(i) **Cross-sectional sample.** The cross-sectional sample provides a broad view of training and learning trends across different segments of the workforce. It allows identification of associations between variables and interpretation of broad patterns over time. The sample is designed to be representative of the target population, with respondents selected through simple random sampling from a sampling frame drawn from the national registry. This approach ensures that every eligible individual has an equal chance to be selected for participation in the survey, thereby minimising selection bias and enhancing representativeness. For this study, a sub-sample of respondents aged 25 to 70 is extracted and analysed. The achieved sample sizes are 5,724 in 2017 and 5,464 in 2021, respectively.

(ii) **Longitudinal sample.** The longitudinal sample consists of 2,004 individuals who participated in both the 2017 and 2021 iterations of the survey. This sample is essential for estimating the within-individual effect of structured training participation over time. By applying a fixed-effects specification to the repeated observations, the analysis controls for time-invariant, individual-specific characteristics, including unobservable factors. This approach is particularly effective in addressing selection bias related to participation in training, thereby providing a more accurate assessment of the direct impact of training on outcomes.

Matched SLS and administrative training records from SkillsFuture Singapore's database

To examine the contributions of public provisions to the CET landscape, particularly those supported through SkillsFuture, respondent data from the SLS are matched with administrative training participation records from SkillsFuture's Training Grant System database. This matching provides more comprehensive and reliable information on respondents' participation in various types of SkillsFuture-funded training courses, as such details would typically have been difficult for individuals to recall accurately in surveys. However, since the administrative records capture training both prior to and following the SLS survey periods, this limits causal estimation. Instead, the matched data focuses on describing trends and coverage of public training uptake across different education groups.

Semi-structured interviews

To illuminate the mechanisms behind the quantitative findings, eight semi-structured interviews are conducted between May and June 2024. Participants are purposively selected from respondents who have previously completed the SLS, to ensure analytical alignment and enable meaningful linkage across data sources. Recruitment outside this pool is avoided to maintain this coherence. While a larger interview sample is initially targeted, the final number is constrained by the time gap between the last round of SLS data collection and lower respondent willingness to engage in a different mode of data collection (i.e., shifting from personal survey to semi-structured interviews).

The final sample comprises four individuals with diploma qualifications and four with qualifications below the diploma level. This composition enables a comparative examination on how skills accumulation outcomes may differ by prior educational background – a key focus in this study. Despite the small sample size, the interviews yield rich insights into the lived experiences of workers navigating CET opportunities, workplace practices, job design, and career progression, in ways shaped by their educational attainment.

Integration of findings

Findings from the quantitative and qualitative components are then integrated through a triangulation process that cross-validates key patterns and elucidates mechanisms and pathways. This mixed-method integration enriches the study's explanatory power and informs nuanced, evidence-based policy recommendations.

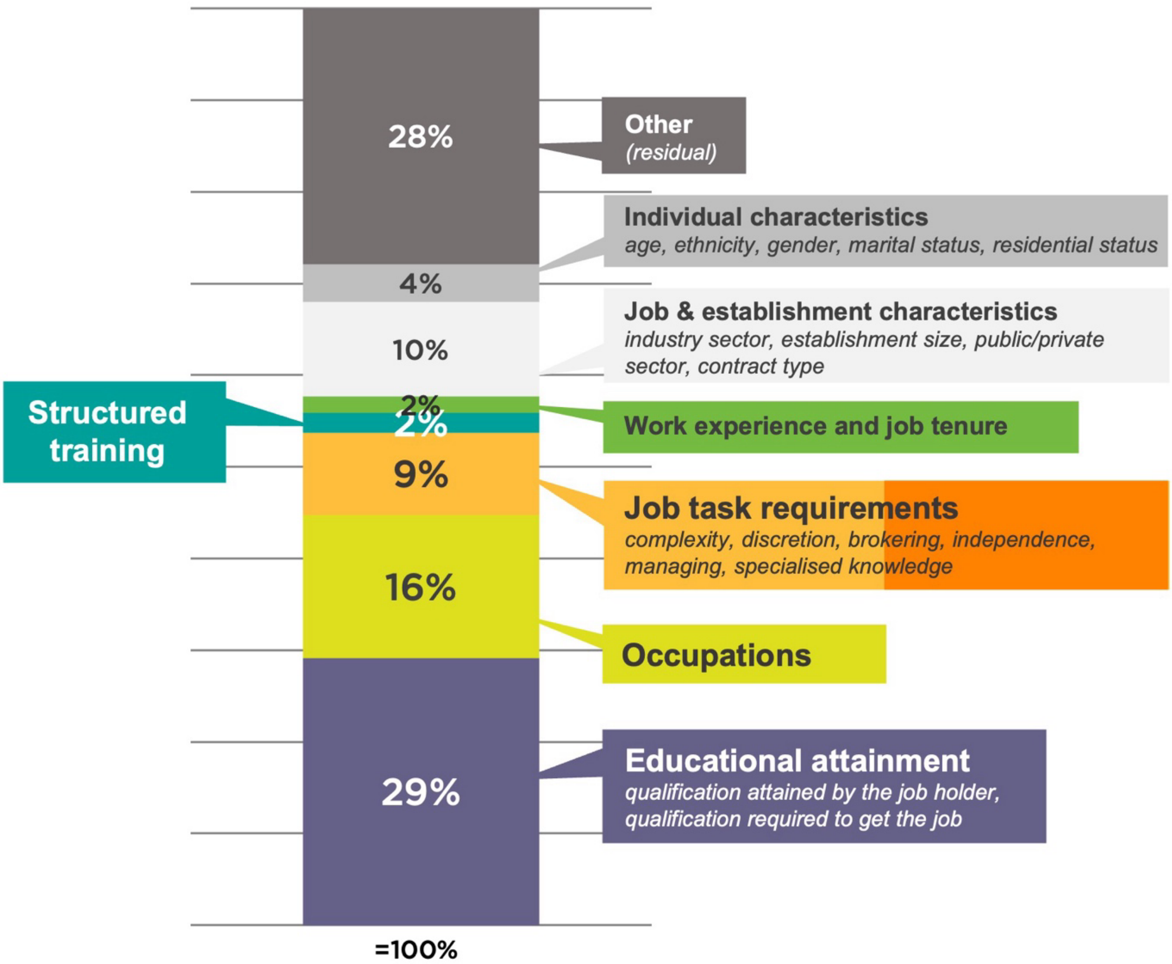
The next four chapters present the key findings from the analysis.

4. Skills accumulation in a highly credentialled society

The premium placed on educational attainment

In Singapore, educational attainment is a key determinant of an individual's career capital. The findings show that qualifications – both those held by job holders and those required by their jobs – explain a significant proportion (29 percent) of the wage variation (see Figure 1). This indicates the strong value employers place on formal qualifications. Notably, this contribution has remained largely constant, even as the proportion of degree holders in the workforce increased steadily between 2017 and 2021[1].

Figure 1. What explains wage variation in Singapore?



Source: Skills and Learning Survey, 2021

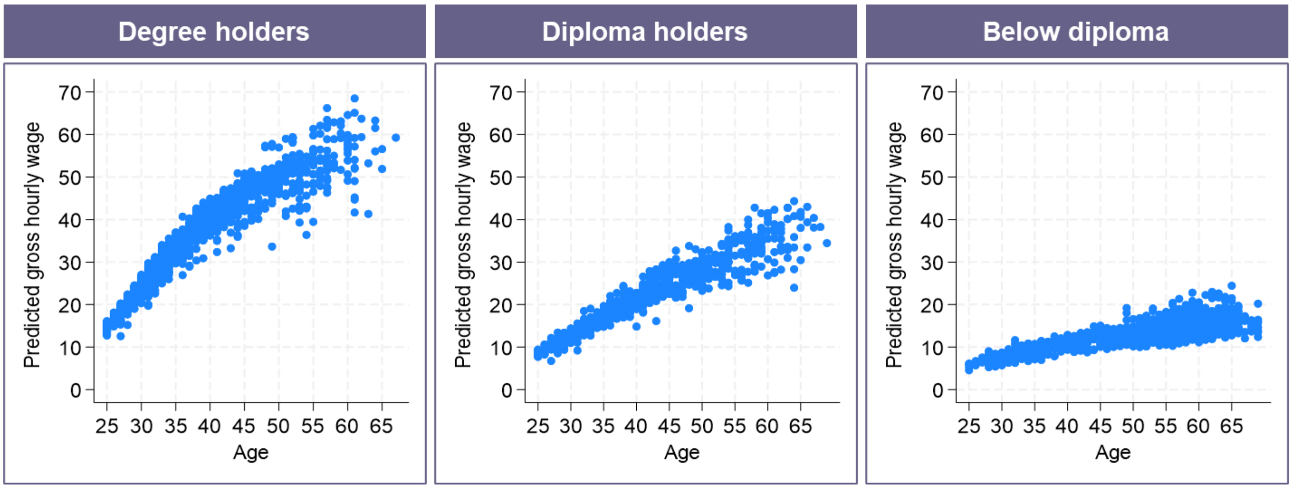
The sample includes only full-time employees. Results are based on a cross-sectional regression decomposition, following Fields (2003).

Beyond educational attainment, wage differences are also shaped by skills demand at work. Specifically, occupations account for 16 percent and job task requirements account for 9 percent of the variation. Establishment- and job-related characteristics such as establishment size, sector type and contract type account for another 10 percent. In comparison, other forms of skills accumulation have a smaller direct effect, with both work experience and structured training[2] each explaining less than 2 percent of wage variation.

The education premium over the life course

The influence of educational attainment extends well beyond initial labour market entry, and has a cumulative effect on wage trajectories over the course of an individual's career (see Figure 2). Degree holders, in particular, benefit from greater access to high-skilled occupations and roles with higher job task requirements, positions that are generally associated with higher wages. Some of these opportunities are also available to diploma holders. In contrast, individuals without the requisite formal qualifications face limited pathways into high-skilled roles and tend to experience comparatively flat wage growth over time. Crucially, this finding highlights that in Singapore's labour market – where educational attainment continues to play a dominant role – work experience and skills acquired on the job may not be sufficient to fully compensate for the absence of formal qualifications.

Figure 2. Age-wage profile, by educational attainment



Source: Skills and Learning Survey, 2017 & 2021

The sample includes only full-time employees. Results are based on fixed-effects regressions of log hourly wages on age and its powers. The models include controls for highest qualification attained by the job holder, qualifications required by the job, training participation, job task requirements, years of work experience, job tenure, establishment size and marital status. Distribution of hourly wages is trimmed to include only the 1st to 99th percentile.

Recalibrating the influence of educational attainment

Overall, the findings point to the need to recalibrate the weight placed on educational attainment in shaping life chances. An over-reliance on formal qualifications may limit opportunities for capable individuals who have accumulated skills through alternative, skills-based routes. A more balanced approach that recognises diverse forms of learning and validates practical work experiences will be most crucial to building a more inclusive and resilient workforce.

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[1] According to data from the Ministry of Manpower's Comprehensive Labour Force Survey, the proportion of degree holders among the resident workforce increased steadily from 35.7% in 2017 to 41.3% in 2021.

[2] In this cross-sectional regression model, structured training explains slightly less than 2 percent of the variation of wages, and its effect on wages is found to be significant. However, when using fixed-effects regression – a method that better accounts for time-constant unobservable individual factors influencing selection into the training – no significant contribution from training is found.

5. Benefits of structured training participation

High levels of training participation, but strongly shaped by education

There is, overall, a high level of training participation in Singapore. According to data from the Skills and Learning Survey, the overall rate of training participation rose from 56.3 percent in 2017 to 61.7 percent in 2021, an increase of 5.5 percentage points (see Figure 3). The rise in training participation may largely be attributed to the increasing proportion of degree and diploma holders in the resident population. Job-related training increased by 3.5 percentage points. However, most of the growth occurred in to non-job-related training, which increased by 5.4 percentage points.

Certain segments saw notable shifts in training participation. Mid-career individuals aged 40 to 49 years old saw a substantial increase of 9.2 percentage points in job-related training participation, but this was largely driven by the growing proportion of degree and diploma holders in this age group. Additionally, non-working individuals (i.e., unemployed or out of the labour force) also saw increased training participation, although this was primarily in non-job-related training.

Figure 3. Incidence of training participation (%), 2017 and 2021

	All structured training			Job-related structured training			Non-job-related structured training		
	2017	2021	∆	2017	2021	∆	2017	2021	∆
Overall	56.3	61.7	**+5.5*** **	51.2	54.7	**+3.5*** **	25.1	30.6	**+5.4*** **
Age group									
25 to 29 years old	75.8	82.4	**+6.5*** **	70.7	73.8	+3.1	38.2	46.9	**+8.7*** **
30 to 39 years old	74.6	76.4	+1.8	71.4	71.7	+0.3	33.5	37.1	**+3.6***
40 to 49 years old	62.7	72.9	**+10.2*** **	58.9	68.1	**+9.2*** **	25.7	34.4	**+8.7*** **
50 to 59 years old	47.1	51.9	**+4.8** **	42.0	43.9	+2.0	18.8	24.3	**+5.5*** **
60 to 70 years old	28.4	34.5	**+6.1*** **	20.2	24.4	**+4.2** **	15.1	18.1	**+3.0***
Education attainment									
Degree	81.9	84.7	**+2.8*** **	77.9	78.9	+1.0	37.0	43.6	**+6.6*** **
Diploma	69.5	75.4	**+5.9** **	64.1	65.4	+1.2	31.6	39.6	**+7.9*** **
Post-secondary	50.5	50.1	-0.4	44.7	42.4	-2.3	23.0	23.2	+0.3
Secondary	41.0	39.6	-1.4	34.9	32.1	-2.7	18.3	17.2	-1.1
Below secondary	23.3	24.0	+0.7	18.2	18.5	+0.3	9.2	8.8	-0.4
Labour force status									
Employed	65.9	68.8	**+2.9*** **	62.7	64.1	+1.5	27.6	31.9	**+4.3*** **
Unemployed	44.5	60.3	**+15.8*** **	35.2	41.4	+6.2	25.3	40.5	**+15.2*** **
Out of labour force	16.7	27.5	**+10.8*** **	4.5	10.2	**+5.7*** **	14.3	22.7	**+8.4*** **

Source: Skills and Learning Survey, 2017 & 2021

Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For further analysis by other training types, refer to Table D1 in Appendix D.

Training participation is also shaped by job skills demand

The findings from a regression analysis of individual, job, and establishment-related characteristics highlight educational attainment as a key determinant of training participation. Even after accounting for factors such as age, gender, occupation, job requirements, and establishment factors, employees without a tertiary education (i.e., those without at least a diploma qualification) are less than half as likely to take part in job-related structured training compared to degree holders (see Figure 4). This pattern reflects the Matthew Effect in further training – where those who are already better educated are more likely to access subsequent learning opportunities – underscoring the importance of accounting for cumulative advantage in understanding training disparities.

Apart from educational attainment, the findings also highlight other groups of workers who are less likely to participate in training. These include production and related workers, employees on temporary contracts or informal work arrangements, as well as those working in small- and medium-sized establishments or private organisations. The findings suggest the need for targeted support for these groups to ensure they are not disadvantaged in accessing training opportunities.

Additionally, training participation is also influenced by skills demand at work. Employees are more likely to engage in training when their jobs require them to continuously update or expand their skill sets. This is evident from the findings, which show that employees who lack opportunities to use their knowledge and skills at work, who lack opportunities to learn new things, or who have not experienced recent technological changes are also less likely to participate in training. This underscores the importance of job design in driving higher levels of training participation (Ehlert, 2020).

Figure 4. Determinants of training: Who are less likely to participate in training?

		Job-related structured training	Non-job-related structured training
Individual	Educational attainment	**Non-tertiary-educated**	**Non-tertiary-educated**
	Age	*No significant difference*	*No significant difference*
	Gender	**Females**	*No significant difference*
	Race	*No significant difference*	*No significant difference*
	Individual motivation for learning	*No significant difference*	**Individuals who report lower levels of intrinsic motivation for learning**
Job/establishment	Occupation	**Production and related workers**	**Production and related workers**
	Job tenure	**Longer job tenures**	**Longer job tenures**
	Contract type	**Temporary contracts or informal arrangements**	*No significant difference*
	Job requirements	**Lack opportunities to use knowledge and skills, lack opportunities to learn new things at work, no recent technological changes at work**	**No recent technological changes at work**
	Establishment size	**Small and medium establishments**	*No significant difference*
	Public/private sector	**Private sector**	*No significant difference*

Source: Skills and Learning Survey, 2021

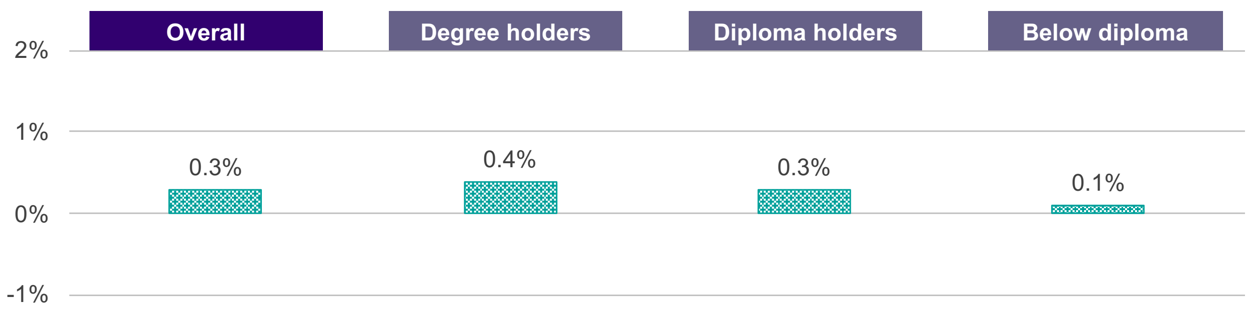
The sample includes only full-time employees. Results are based on logistic regressions of structured training participation on various individual-, job-, and establishment-related factors.

No direct impact of structured training on wages; broader context matters

The study examines the wage returns to assess the impact of participation in training. However, accurate estimation must account for potential selection bias, as individuals with certain characteristics may be more likely to participate in training. In particular, given that individuals with higher levels of education are more likely to engage in training, this could lead to an overestimation of the impact of training on wages if not properly accounted for.

To address this bias, the study applies fixed-effects regression to a longitudinal sample of respondents who participated in two waves of the Skills and Learning Survey. This is a more robust method which allows for the control of time-constant unobservable individual factors such as inherent ability or personal motivation that may influence both the likelihood of participating in training and wage outcomes, thereby providing a more accurate estimate.

Figure 5. The effect of structured training participation on log hourly wages, estimated using fixed effects models



Source: Skills and Learning Survey, 2017 & 2021

The sample includes only full-time employees. Results are obtained using fixed effects models of log hourly wages on structured training participation. Models include dummy to control for survey years. Models also include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Distribution of hourly wages is trimmed to include only the 1st to 99th percentile. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For detailed results of different training types, refer to Table D2 in Appendix D.

The findings show that structured training has a minimal and statistically non-significant effect on wages across different types of training. Once key factors such as qualifications, years of work experience, job tenure, and establishment characteristics are controlled for, the direct impact of training on wages disappears (see Figure 5). This suggests that the effect of training is shaped by the broader labour market, job and workplace conditions rather than on training alone. Similar studies in other labour markets that have similarly applied more sophisticated methods to control for selection into training have tended to yield consistent findings (Pischke, 2001; Ehlert, 2017).

Notable non-wage benefits of structured training, particularly among low-credentialled groups

While structured training does not directly increase wages, it has notable non-pecuniary labour market and organisational-related benefits. Fixed-effects estimations reveal that structured training enhances job security, job prospects, work engagement, organisational commitment, and job satisfaction (see Figure 6).

Figure 6. The effect of job-related and employer-required training on non-wage outcomes

	Labour market outcomes			Organisational-related outcomes		
	Job security	Internal job prospects	External job prospects	Work engagement	Organisational commitment	Job satisfaction
Overall						
Job-related	◇	◇	◆	◆	◆	◆
Employer-required	◆	◆	◆	◆	◆	◆
Degree holders						
Job-related	◇	◇	◆	◇	◇	◇
Employer-required	◇	◇	◆	◇	◇	◇
Diploma holders						
Job-related	◇	◇	◇	◇	◇	◇
Employer-required	◇	◇	◇	◇	◇	◇
Below diploma						
Job-related	◇	◆	◇	◆	◆	◆
Employer-required	◆	◆	◆	◆	◆	◆

◆ Positive effect | ◆ Negative effect | ◇ No significant effect

Source: Skills and Learning Survey, 2017 & 2021

The sample includes only full-time employees. Results are obtained using fixed effects models of structured training participation on respective non-wage outcomes. Models include dummy to control for survey years. Models also include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For detailed results of different training types, refer to Tables D3 – D12 in Appendix D.

These benefits are most evident among non-tertiary-educated workers – those without a degree or diploma. Given their weaker initial position in the labour market, training offers them a crucial pathway to improving job stability and career prospects. However, this group is also the least likely to participate in training. In contrast, highly educated workers already hold stronger position in the labour market. They have greater access to job opportunities and a wider range of learning resources. While training is still necessary for them to keep up with evolving job demands, it does not significantly enhance their perceived job security, career prospects or job satisfaction, as they already enjoy these advantages.

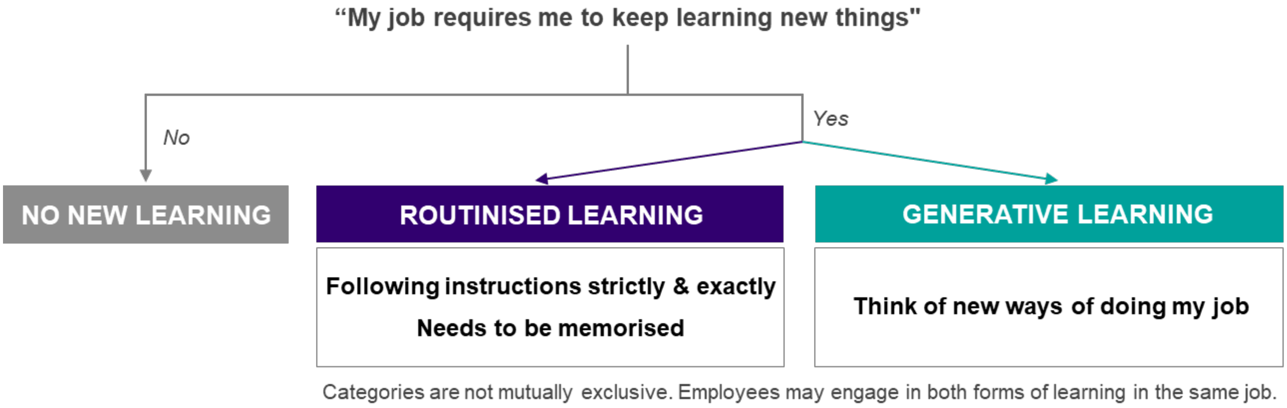
The findings reveal a paradox: those who stand to gain the most from structured training are also the least likely to engage in it. This underscores the need for targeted interventions to increase training participation among low-credentialled workers, ensuring they can fully benefit from skills development opportunities.

6. Extending skills accumulation through generative learning jobs

Learning requirements and job design matter

Skills demand, shaped in large part by how jobs are designed, plays a critical role in determining learning opportunities at work. Drawing on data from the Skills and Learning Survey, the study explores how jobs differ in their learning requirements and how these requirements are embedded within the design of the job. It first identifies whether a job involves learning requirements, then categorises the nature of the learning requirements into two broad types: routinised learning or generative learning (see Figure 7).

Figure 7. Routinised and generative learning requirements of jobs



Source: Skills and Learning Survey, 2021

Routinised learning jobs are characterised by rote learning and memorisation. In contrast, generative learning jobs involve learning that encourages new ways of thinking and doing the job. This distinction highlights the importance of enhancing the generative capacity of the workforce – not only to meet evolving skills demands but also to support innovation and value creation within organisations.

Job tasks linked to generative learning are associated with higher wages

Both generative and routinised learning jobs are associated with job task complexity, suggesting that both are linked to high-skilled jobs, a finding that may seem surprising (see Figure 8). However, these two job types differ significantly in how other aspects of their tasks are structured and designed.

Routinised learning jobs are typically tied to repetitive, routine tasks that emphasise attention to detail, adherence to established procedures and strict compliance with guidelines. These roles offer limited scope for skill expansion, often focusing more on efficiency and consistency rather than innovation.

In contrast, generative learning jobs are more expansive and dynamic. They are linked to tasks designed to provide opportunities for decision-making, brokering and independence. Interestingly, these roles also foster environments where vertical trust – that is, trust between different levels of the organisational hierarchy – is prioritised. Such environments promote collaboration and creative problem-solving, which not only enhances personal growth but also drives innovation within the organisation.

Figure 8. Factors associated with routinised and generative learning jobs and effect on wages

	Routinised learning jobs [i]	Generative learning jobs [i]	Wage effect [ii]
Job task requirements			
Complexity: Complex problem solving	◆	◆	◆
Discretion: Decision-making latitude	◇	◆	◆
Brokering: Persuading others	◇	◆	◆
Independence: Planning own work	◇	◆	◇
Managing: Managerial responsibilities and supervisory duties	◇	◆	◆
Knowledge: Product knowledge	◆	◇	◇
Knowledge: Specialised knowledge	◆	◆	◆
Routine: Task repetition	◆	◇	◆
Routine: Paying attention to details	◆	◇	◇
Job environment			
Horizontal trust: Trust among work peers	◇	◇	◇
Vertical trust: Trust between subordinates and supervisors	◇	◆	◇

◆ Positive effect | ◆ Negative effect | ◇ No significant effect

Source: Skills and Learning Survey, 2021

The sample includes only full-time employees.

[i] Results of logistic regressions of routinised learning and generative learning, respectively, on job task requirements and job environment.

[ii] Results of logistic regression of log hourly wages on job task requirements and job environment.

Models include controls for age, gender, ethnicity, highest qualification attained by the job holder, occupation, residential status, establishment size and sector type (public/private), structured training participation and individual motivation for learning. Distribution of hourly wages is trimmed to include only the 1st to 99th percentile.

More importantly, the findings reveal that job tasks linked to generative learning are also positively associated with higher wages (see Figure 8). This highlights the value that employers place on tasks that require employees to actively engage in learning, demonstrate innovation, and contribute to broader business strategies. The wage premium also reflects the value-added outcomes that this type of job design offers to both individuals and organisations.

Generative learning jobs are associated with improved non-wage labour market and organisational-related outcomes

Moreover, the findings show that, overall, generative learning jobs also contribute to improved non-wage labour market and organisational-related outcomes (see Figure 9). Generative learning jobs are associated not only with improved job security and better job prospects but also with greater organisational commitment, work engagement and job satisfaction, above and beyond what is observed in routinised learning jobs. Crucially, these benefits extend beyond individuals with high educational levels.

Figure 9. Non-pecuniary labour market and organisational-related outcomes associated with routinised and generative learning jobs

	Labour market outcomes			Organisational-related outcomes		
	Job security	Internal job prospects	External job prospects	Work engagement	Organisational commitment	Job satisfaction
Overall						
Routinised learning jobs	◇	◆	◆	◆	◆	◇
Generative learning jobs	◆	◆	◆	◆	◆	◆
Degree holders						
Routinised learning jobs	◇	◆	◆	◆	◇	◇
Generative learning jobs	◇	◆	◆	◆	◇	◆
Diploma holders						
Routinised learning jobs	◇	◇	◇	◆	◇	◇
Generative learning jobs	◆	◇	◆	◆	◇	◆
Below diploma						
Routinised learning jobs	◇	◇	◆	◆	◇	◆
Generative learning jobs	◇	◇	◆	◆	◆	◇

◆ Positive effect | ◆ Negative effect | ◇ No significant effect

Source: Skills and Learning Survey, 2021

The sample includes only full-time employees. Results are based on a series of logistic regression of outcomes on routinised and generative learning jobs. Models include controls for age, gender, ethnicity, highest qualification attained by the job holder, occupation, residential status, establishment size and sector type (public/private), structured training participation, individual motivation for learning, job tasks and job environment.

Generative learning jobs are associated with higher levels of training participation

Across all education groups, generative learning jobs are linked to higher levels of training participation as compared to routinised learning jobs see Figure 10). This reflects a reciprocal relationship between training and generative learning (Ellström, 2010; Støren, 2016). On the one hand, individuals in generative learning jobs are more likely to seek out or be offered training opportunities, because their roles demand continuous learning, regular skills development and innovation. On the other hand, engaging in training can deepen workers' capacity for generative learning by equipping them with new ideas, perspectives, and skills that can feedback into their day-to-day innovation efforts. Moreover, the finding also reinforces that the design of the job itself – such as whether it fosters creativity or learning – plays a key role in training participation, rather than the individual's educational or occupational background alone.

Figure 10. The likelihood of training participation and training transfer among routinised and generative learning jobs

	Likelihood of training participation *compared to non-learning jobs* [i]	**Likelihood of training transfer** *compared to non-learning jobs* [ii]
Overall		
Routinised learning jobs	**1.3 times** **	**1.3 times** ***
Generative learning jobs	**1.6 times** ***	**2.1 times** ***
Degree holders		
Routinised learning jobs	1.4 times	1.2 times
Generative learning jobs	**1.5 times** ***	**2.1 times** ***
Diploma holders		
Routinised learning jobs	1.0 times	**1.5 times** **
Generative learning jobs	**2.0 times** ***	**3.0 times** ***
Below diploma		
Routinised learning jobs	**1.5 times** ***	**1.5 times** ***
Generative learning jobs	**1.6 times** ***	**2.0 times** ***

Source: Skills and Learning Survey, 2021

The sample includes only full-time employees.

[i] Results of logistic regressions of structured training participation on routinised and generative learning jobs.

[ii] Results of logistic regressions of training transfer on routinised and generative learning jobs.

Models include controls for age, gender, ethnicity, highest qualification attained by the job holder, occupation, residential status, establishment size and sector type (public/private), individual motivation for learning, job tasks and job environment. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The nature of training matters

The type and characteristics of the training itself also plays a critical role in this relationship. When examining different types of training, the findings indicate that as opposed to those that are mandated by the employer, ground-up training opportunities that are self-initiated by the employee are more strongly linked to generative learning roles (see Figure 11). This self-directed engagement reflects and reinforces the proactive, exploratory orientation that generative learning jobs require.

Furthermore, the time spent on training is also important. The findings indicate that longer training durations, such as those involving ongoing development rather than short, one-off sessions, are more likely to have a stronger connection to generative learning jobs. The longer training period allows more time for reflection, experimentation, and interaction between experiences from the workplace and the learning process, creating a dynamic learning loop.

Figure 11. Training types associated with routinised and generative learning jobs

Types and characteristics of structured training	Routinised learning jobs	Generative learning jobs
Job-related training	◆ (positive)	◆ (positive)
Non-job-related training	◆ (negative)	◆ (negative)
Employer-required training	◆ (positive)	◆ (positive)
Non-employer-required training	◆ (negative)	◇
More than 40 hours of training per year	◇	◆ (positive)
More than 80 hours of training per year	◇	◆ (positive)

◆ Positive effect | ◆ Negative effect | ◇ No significant effect

Source: Skills and Learning Survey, 2021

The sample includes only full-time employees. Results are based on a series of logistic regression of routinised learning and generative learning, respectively, on each training type or characteristics. Models include controls for age, gender, ethnicity, highest qualification attained by the job holder, residential status, establishment size and sector type (public/private) as well as factors related to individual motivation for learning, job tasks and work environments. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Generative learning jobs are associated with higher levels of training transfer

Finally, the findings also show that, as compared to routinised learning jobs, generative learning jobs are generally associated with higher levels of training transfer – that is, the extent to which the skills gained during training can be effectively applied in the workplace (see Figure 10). This is largely due to the value-creating orientation of generative learning roles, which provides more opportunities to integrate what they learn into their daily tasks and makes them more receptive to applying newly acquired skills.

Four profiles

Sketches of how workers in generative learning jobs experience extended pathways for skills accumulation, as compared to routinised learning jobs

ALEX

Diploma holder, mid-thirties

Manufacturing Associate, MNC

Job learning requirements: Routinised

In his role, Alex operates sophisticated machineries, but performs primarily routine, execution-based tasks. Allocation of job tasks is stratified by education attainment, with degree holders entrusted with system ownership and process innovation:

> *“[Degree holders will become] process owners... They also will be system owners. They are in charge of the system.”*

Despite operating in a technically demanding environment, Alex’s exposure to higher-level learning opportunities is much more limited:

> *“But for me, I just need to execute it. As long as there's no new process, no new equipment, there won't be any more training.”*

Insight: Restrictive job design limits opportunities for skills expansion and career progression.

BENJAMIN

Diploma holder, early forties

Senior Engineer, mid-sized foreign enterprise

Job learning requirements: Generative

Benjamin's job demands high level of technical mastery, involving continuous learning and regular skill validation:

> *"Every quarterly (sic) we have a skill level check… When your skill level is there, the boss will eventually choose you to travel overseas to support the installation or the troubleshooting."*

Benjamin rose from technician level and has potential to progress to a principal engineer role that involves increased levels of planning and strategic contribution.

Insight: The role integrates continuous learning with regular skills checks and international exposure.

CHARLES

Diploma holder, mid-thirties

Executive Education Programme Manager, Institute of Higher Learning

Job learning requirements: Generative

Despite not having a degree, Charles was hired into a degree-qualified role through a recommendation. The job offers decision-making latitude and alignment with broader organisational goals:

> "*I get to plan what I do… there's autonomy for [me] to decide on what [I] want to do… I feel that my current role right now is very important for the success of the department and the organisation, because [I am] carrying [the] organisation's brand."*

Charles has been promoted twice in six years.

Insight: Roles offering professional discretion allow non-degree holders to demonstrate value and achieve upward mobility.

DOUGLAS

NITEC holder, mid-thirties

Head of Commercial and Sales, SME

Job learning requirements: Generative

Douglas has built his expertise through over a decade of hands-on industry experience. His role demands brokering, independent decision-making, and client understanding:

> *"[We] have to make decisions depending on how the conversation is leading and the situation for that customer they are speaking with. It's [about] acting and doing what's fair, and then also trying to listen to understand. [When hiring] I mind very little about education. I mind more about their attitude, and their job history profile."*

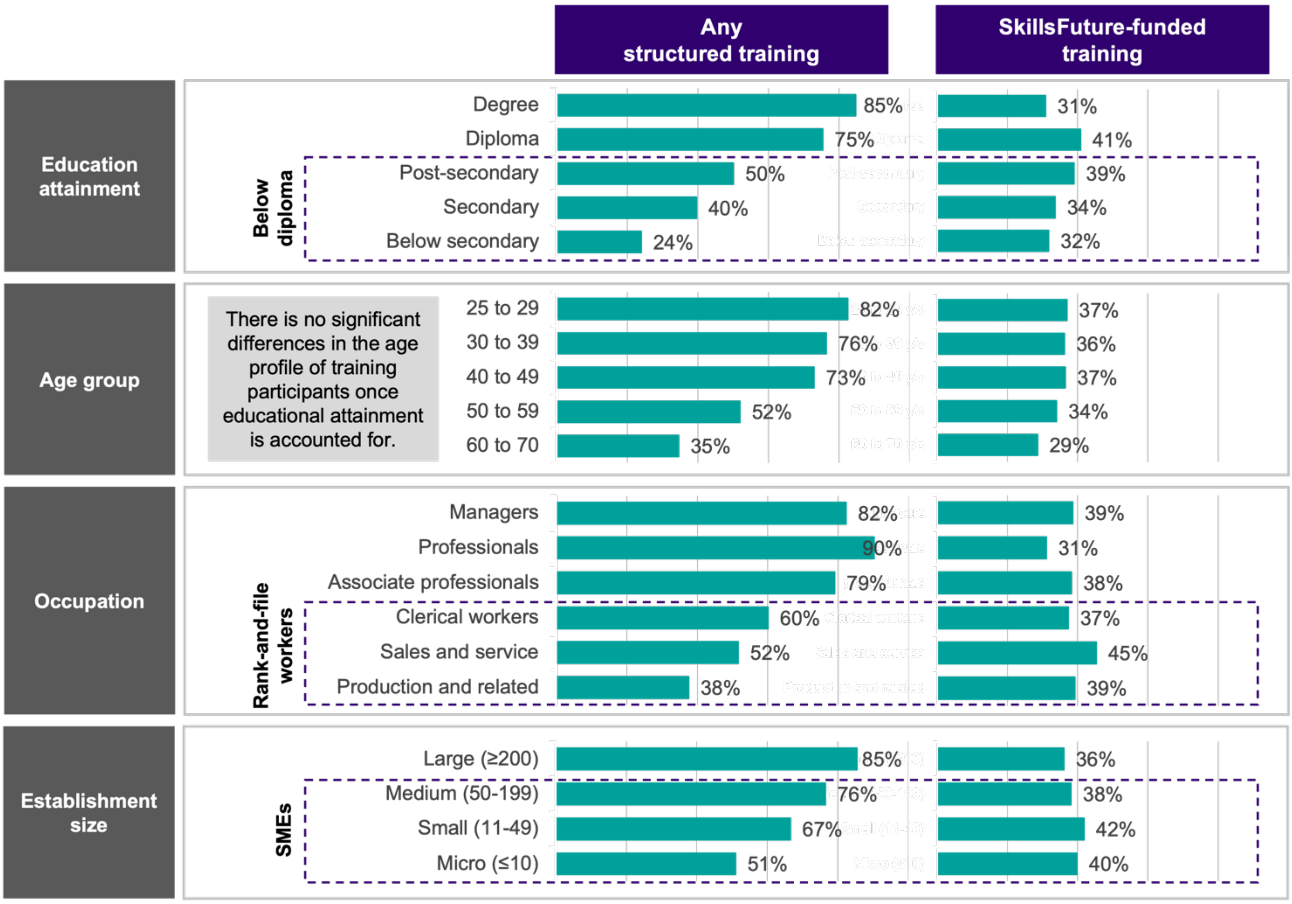
Insight: Even without high credentials, strategic roles that value initiative can foster long-term skills growth and leadership development.

7. Enhancing access through public investments in training

Higher participation rates in SkillsFuture-funded training among low-credentialled and rank-and-file workers

Using matched data of respondents from the Skills and Learning Survey and administrative training records from SkillsFuture Singapore's database, the study examines the profile of individuals who participated in SkillsFuture-funded training programmes, compared to general patterns of training participation.

Figure 12. Incidence of Skills-Future-funded training participation (%)



Source: Skills and Learning Survey, 2021 & administrative training records from SkillsFuture Singapore

The proportion is calculated based on the sample of respondents who completed the Skills and Learning Survey in 2021. Some SkillsFuture-funded training may have taken place outside of the survey data collection period, so responses may not fully align. Respondents may also have participated in both SkillsFuture-funded and non-SkillsFuture-funded training courses.

Overall, slightly more than three in ten adult residents in Singapore have participated in SkillsFuture-funded training courses (see Figure 12). When compared to general training trends, however, there are systematic differences in the profiles of SkillsFuture-funded trainees. The findings show that SkillsFuture-funded trainees are more likely to be low-credentialled workers without at least a diploma qualification, rank-and-file employees – particularly those in less complex or low-discretion jobs – and individuals working in small- and medium-sized establishments. These results suggest that publicly funded training through SkillsFuture has effectively reached underserved segments of the workforce. They highlight the important role of public investments in bridging opportunity gaps for individuals who may otherwise lack access to employer-funded or self-funded training, while also addressing market failures in training provision.

Publicly funded training as a lever to promote generative learning in the workplace

The findings underscore the critical role of generative learning jobs in supporting ongoing skills accumulation. At present, workers in both routinised and generative learning roles are equally likely to have participated in SkillsFuture-funded training (see Figure 13). This points to an untapped opportunity, where public training investments could be more intentionally directed to promote and enable generative learning in the workplace.

Figure 13. The association of participation in SkillsFuture-funded training with routinised and generative learning jobs

Types and characteristics of structured training	Routinised learning jobs	Generative learning jobs
SkillsFuture-funded training	◇	◇

◆ Positive effect | ◆ Negative effect | ◇ No significant effect

Source: Skills and Learning Survey, 2021

The sample includes only full-time employees. Results of logistic regressions of routinised learning and generative learning, respectively, on participation in SkillsFuture-funded training. Models include controls for age, gender, ethnicity, highest qualification attained by the job holder, residential status, establishment size and sector type (public/private) as well as factors related to individual motivation for learning, job tasks and work environments.

8. Discussion and conclusion

Dominance of prior educational attainment on lifelong skills accumulation

This study affirms that formal qualifications remain a central driver of skills accumulation and career capital in Singapore. Educational attainment significantly influence access to CET, high-skilled occupations, wages, and overall career opportunities. Workers with higher educational attainment disproportionately participate in CET, while low-credentialled groups face barriers that limit their engagement. Moreover, job characteristics, such as opportunities for use of knowledge and skills at work, and exposure to technological changes, are also more prevalent among the highly educated. The cumulative impact of educational attainment over the life course underscores their role as anchors for employability and career progression. Importantly, after adjusting for selection bias, the minimal wage returns to structured training suggest that CET alone is not a sufficient substitute for initial educational attainment. These findings challenge traditional HCT assumptions and reinforce the cumulative advantage framework, highlighting how prior educational attainment continues to shape labour market outcomes despite ongoing CET efforts.

The pivotal role of job design and generative learning

Beyond credentials and training participation, the study highlights job design as a critical factor in skills accumulation. Generative learning jobs – characterised by decision-making autonomy, innovation, and value-creation – are linked to higher wages, increased training participation, and improved non-wage outcomes. These roles extend pathways for skills development and help to mitigate cumulative advantage effects. This perspective shifts responsibility beyond individuals to broader organisational and job-level factors, reinforcing the need for inclusive job redesign that fosters generative learning environments and maximises skills utilisation across the workforce.

Institutional moderation: pathways to greater equity

From an institutional perspective, disparities in skills accumulation and training outcomes are neither predetermined nor immutable. Institutional arrangements – including targeted outreach and generative job design – can influence both the supply and demand sides of CET participation. Public investments through initiatives like SkillsFuture have shown promise in expanding training access among underserved, low-credentialled, and rank-and-file workers, addressing market failures and employer biases. Nevertheless, stronger alignment between training initiatives with workplace practices that foster generative learning roles is necessary to maximise both the effectiveness and equity of skills development.

Policy implications

Building on these insights, a more holistic approach to skills development is needed – one that goes beyond traditional credentials and structured training to address the broader conditions under which learning occur. This can move CET beyond merely complementing existing human capital into a mechanism that actively promotes social mobility and labour market inclusivity. The following outlines key priorities:

- **Extend training reach to better serve at-risk workforce segments.**
  Publicly funded training programmes through SkillsFuture have shown promise in reaching groups typically underserved by employer-financed or self-initiated training. Continued investment is essential, with outreach efforts intentionally expanded and programmes designed strategically to better meet the needs of these segments. This includes adapting course formats and content to align with their learning contexts, preferences, and constraints.

- **Strengthen adult educator capabilities to meet diverse learner needs.**
  The quality and effectiveness of training hinges heavily on the capabilities of adult educators. Thus, strengthening their professional development should be a priority. This entails a focus on equipping adult educators with stronger pedagogical skills and curriculum design capabilities so they can more effectively engage adult learners from diverse backgrounds, particularly those who are less-credentialled or have had negative prior learning experiences. In addition, adult educators should be equipped to facilitate generative forms of learning that foster critical thinking and problem-solving, helping workers remain adaptable and resilient in a changing work environment.

- **Intervene through the productive system to promote generative learning jobs.**
  Beyond direct training support, the findings highlight a strong impetus to intervene through the productive system to promote firm-level strategies that focus on value creation. Such strategies are found to be closely linked to the presence of generative learning jobs that support skill development through meaningful, complex tasks. Incentivising job redesign that expands worker decision-making, independence, and brokering responsibilities is a critical lever for advancing skills-first pathways and creating more inclusive opportunities.

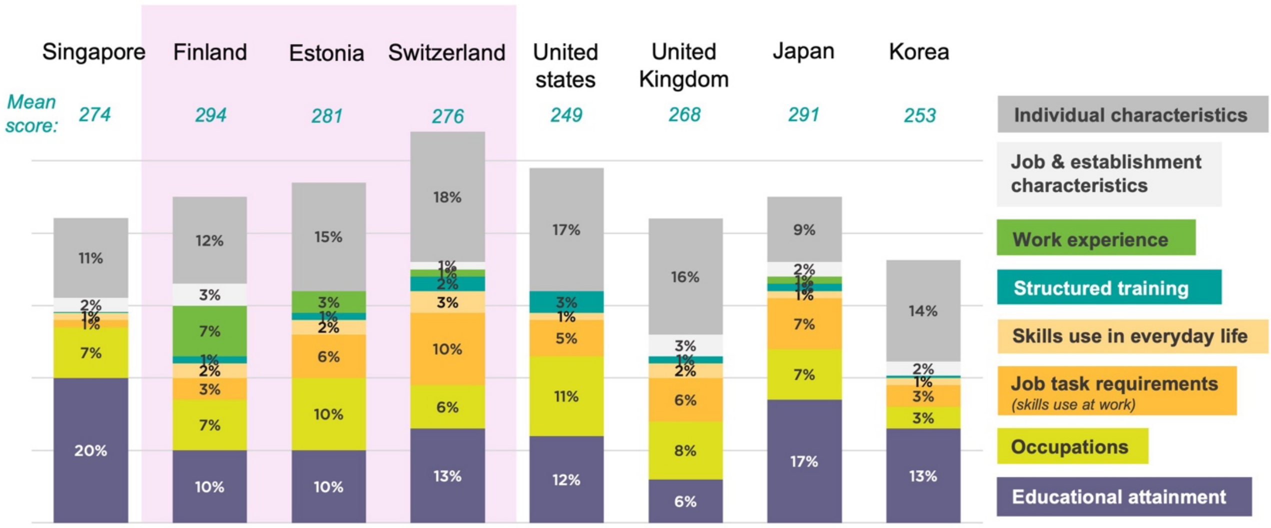
Areas for future research

This study advances understanding of skills accumulation in Singapore while identifying important avenues for further investigation:

- **Contributions of skills accumulation to patterns of job mobility.**
  Additional longitudinal data points would allow for a deeper analysis of how lifelong skills accumulation affects job transitions and mobility across the life course. This includes examining employment changes such as movements in and out of work and shifts between different types of roles. Such research can offer a more nuanced understanding between long-term mobility trends and those driven by cohort or period effects.

- **Comparative studies of other economies and labour markets.**
  Comparative research can reveal alternative models of skills accumulation beyond Singapore's strong emphasis on formal educational attainment. For instance, data from the Survey of Adult Skills (PIAAC) Cycle 2 conducted between 2022 and 2023 show that in coordinated market economies like Finland, Estonia and Switzerland, job task design and work experience are key determinants of adult skills proficiency – contrasting with the dominance of educational attainment in Singapore (see Figure 14) Notably, these workforces have performed comparatively well in the PIAAC study. Nordic countries, in particular, are found to be effective at mitigating social and educational inequalities (Scandurra & Calero, 2020; Sulkunen et al., 2021) through inclusive lifelong learning policies. This suggest that Singapore could benefit from an exploration of broader, more inclusive and practice-oriented approaches to skills development beyond formal qualifications.

Figure 14. Cross country comparison: What explains numeracy proficiency scores?



Source: Survey of Adult Skills (PIAAC) Cycle 2, 2022-2023

PIAAC is an initiative of OECD that measures the distribution of key information-processing skills proficiency, namely literacy, numeracy, and adaptive problem-solving skills, among the adult population. In PIAAC, proficiency is considered as a continuum of ability involving the mastery of information-processing tasks of increasing complexity. The results are represented on a 500-point scale. The sample includes only full-time employees. Results are based on cross-sectional regression decompositions following Fields (2003). Each bar summarises the results from one regression and its height represents the R-squared of that regression. The component of each bar shows the contribution of each factor (or set of regressors) to the total R-squared. Similar patterns are observed for literacy and adaptive problem-solving proficiency scores.

Conclusion

Concluding, this study underscores that while formal educational attainment remains a strong determinant of skills accumulation and career capital in Singapore, rethinking job design to foster generative learning and widening inclusive access to CET can unlock greater value and equity, enabling lifelong skills accumulation to serve as a genuine vehicle for social mobility and economic resilience.

Technical Appendix

Appendix A.

Research objectives

The Skills Accumulation Study investigates how different forms of skills accumulation across the life course impact employment outcomes, within the context of Singapore's evolving work, employment and education landscape.

Research questions

RQ1: How do the following factors influence the impact of skills accumulation on employment outcomes for different population segments in Singapore?

- Individual characteristics
- Training type and characteristics
- Job characteristics

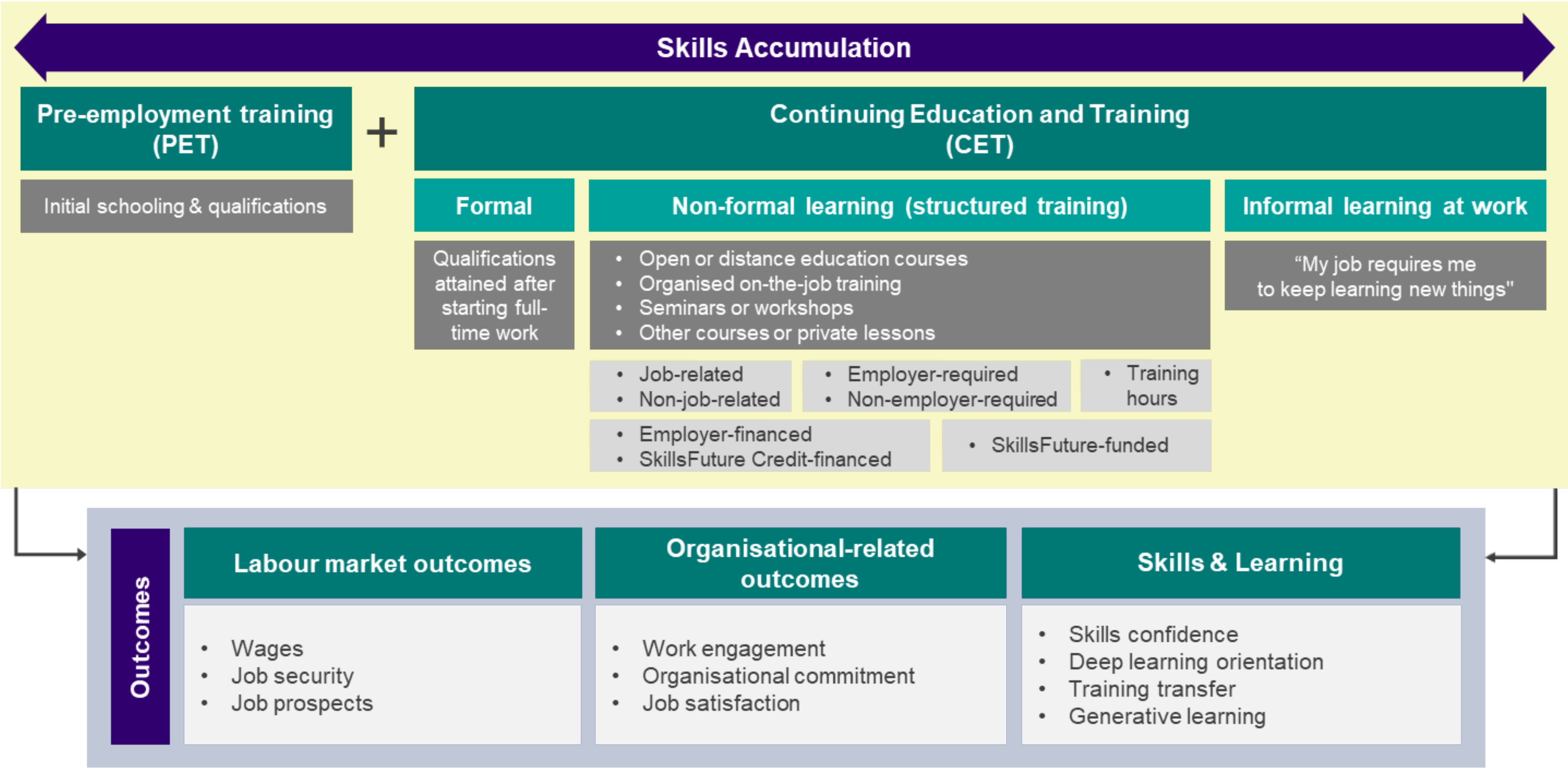
RQ2: To what extent does continuous education and training (CET) impact employment outcomes, over and beyond the contributions of pre-employment training (PET)?

RQ3: What is the profile of the resident population who is less likely to participate in CET?

RQ4: How, when and why do employers reward skills accumulation?

Appendix B.

Conceptual frame



Appendix C.

Definitions of types of training

Definitions of the types of structured training used in the study

Structured training	Participation in organised learning activities in the 12 months preceding the survey: • Courses conducted through open or distance education. • Organised sessions for on-the-job training or training by supervisors or co-workers. • Seminar or workshops. • Other courses or private lessons.
Job-related	Structured training that is related to current or future job.
Non-job-related	Structured training that is not related to current or future job.
Employer-required	Structured training that is required or mandated by the employer.
Non-employer-required	Structured training that is not required or mandated by the employer.
Employer-financed	Structured training that is funded or partially funded by the employer.
SkillsFuture Credit-financed	Structured training that is funded or partially funded using SkillsFuture Credit.
Training hours	Total time in the last 12 months preceding the survey that is spent on any form of structured training. Excludes time spent on homework or travel.
SkillsFuture-funded training	Training course that is funded or partially funded by SkillsFuture Singapore.

Appendix D.

Additional data tables

Table D1. Incidence of training participation (%) for selected training types and characteristics, 2017 & 2021

	Employer-required structured training[i]			Non-employer-required structured training[i]			Employer-financed structured training[i]			More than 40 hours of training per year			More than 80 hours of training per year		
	2017	**2021**	**Δ**	**2017**	**2021**	**Δ**	**2017**	**2021**	**Δ**	**2017**	**2021**	**Δ**	**2017**	**2021**	**Δ**
Overall	61.5	61.6	0.0	31.7	37.9	**+6.2*** **	54.1	53.2	-0.9	24.1	32.7	**+8.6*** **	13.3	21.2	**+7.9*** **
Age group															
25 to 29 years old	72.0	72.0	0.0	39.1	48.2	**+9.1*** **	63.5	61.9	-1.6	38.2	49.7	**+11.4*** **	24.6	38.9	**+14.3*** **
30 to 39 years old	73.1	72.2	-1.0	40.7	46.9	**+6.2*** **	64.0	62.9	-1.1	36.1	43.6	**+7.5*** **	18.8	28.7	**+9.8*** **
40 to 49 years old	64.3	68.4	**+4.2***	33.3	42.5	**+9.2*** **	56.8	59.5	+2.7	25.3	40.0	**+14.6*** **	13.5	23.6	**+10.4*** **
50 to 59 years old	53.8	53.5	-0.2	23.7	29.2	**+5.6** **	47.5	45.0	-2.5	18.2	24.9	**+6.7*** **	9.8	15.7	**+5.9*** **
60 to 70 years old	32.9	34.0	+1.1	14.3	18.0	+3.7	27.6	29.5	+1.9	8.1	13.3	**+5.2*** **	4.5	8.0	**+3.4*** **
Education attainment															
Degree	79.7	78.5	-1.2	48.5	55.1	**+6.6*** **	72.4	70.5	-2.0	43.1	52.6	**+9.5*** **	23.5	33.9	**+10.3*** **
Diploma	69.3	68.0	-1.3	33.7	42.8	**+9.1*** **	59.5	56.8	-2.7	29.0	40.4	**+11.5*** **	17.1	27.6	**+10.5*** **
Post-secondary	56.2	49.9	**-6.4***	23.0	22.8	-0.2	48.9	41.5	**-7.4***	15.2	20.7	**+5.6** **	8.8	13.2	**+4.5** **
Secondary	46.7	44.4	-2.3	17.2	18.8	+1.6	37.0	37.0	0.0	11.6	13.2	+1.7	5.7	7.5	+1.8
Below secondary	28.7	25.9	-2.7	10.1	7.5	-2.6	25.4	19.4	**-6.1** **	6.5	5.8	-0.7	3.4	3.8	+0.4
Labour force status															
Employed										28.5	36.1	**+7.6*** **	15.5	22.7	**+7.2*** **
Unemployed										18.1	36.2	**+18.1*** **	13.7	29.3	**+15.6*** **
Out of labour force										5.9	15.6	**+9.8*** **	3.7	13.1	**+9.3*** **

Source: Skills and Learning Survey, 2017 & 2021

Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[i] Employees only.

Table D2. The effect of training participation on log hourly wages, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Wage premium:									
Overall	0.3%	2.3%	0.5%	0.7%	-0.6%	2.3%	1.4%	1.8%	1.2%
R^2 (within)	0.2737	0.2748	0.2738	0.2738	0.2738	0.2737	0.2752	0.2746	0.2740
n (obs)	*2,546*	*2,546*	*2,546*	*2,546*	*2,546*	*2,539*	*2,192*	*2,546*	*2,546*
Wage premium:									
Degree holders	0.4%	3.8%	3.2%	-0.5%	0.5%	4.0%	-1.3%	3.2%	0.2%
Diploma holders	0.3%	3.1%	-2.3%	1.6%	-0.6%	1.6%	3.2%	-1.0%	0.5%
Below diploma	0.1%	1.0%	-3.1%	1.3%	-3.7%	1.0%	3.9%	1.5%	6.3%
R^2 (within)	0.2731	0.2744	0.2758	0.2734	0.2741	0.2763	0.2744	0.2747	0.2743
n (obs)	*2,546*	*2,546*	*2,546*	*2,546*	*2,546*	*2,539*	*2,192*	*2,546*	*2,546*

Source: Skills and Learning Survey, 2017 & 2021

The sample includes only full-time employees. Results are obtained using fixed effects models of log hourly wages on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Distribution of hourly wages is trimmed to include only the 1st to 99th percentile. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D3. The effect of training participation on perceived job security, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Job security (standardised coefficient):									
Overall	0.093	0.093	-0.056	**0.146 ****	-0.015	0.059	-0.038	-0.013	0.021
R^2 (within)	0.0259	0.0259	0.0252	0.0291	0.0243	0.0242	0.0247	0.0243	0.0243
n (obs)	*2,687*	*2,687*	*2,687*	*2,687*	*2,687*	*2,677*	*2,318*	*2,687*	*2,687*
Job security (standardised coefficient):									
Degree holders	0.063	0.031	-0.005	0.166	0.023	-0.050	-0.118	-0.087	-0.006
Diploma holders	0.012	0.044	-0.124	0.076	-0.082	0.014	0.026	0.079	0.055
Below diploma	0.143	0.152	-0.105	**0.160 ***	-0.038	**0.204 ****	0.076	0.075	0.082
R^2 (within)	0.0259	0.0261	0.0255	0.0288	0.0244	0.0270	0.0249	0.0255	0.0241
n (obs)	*2,687*	*2,687*	*2,687*	*2,687*	*2,687*	*2,677*	*2,318*	*2,687*	*2,687*

Source: Skills and Learning Survey, 2017 & 2021

Perceived job security: “How likely is it that you will lose your job in the next 12 months?”.

The sample includes only full-time employees. Results are obtained using fixed effects models of perceived job security on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D4. The effect of training participation on perceived internal job prospects, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Internal job prospects (standardised coefficient):									
Overall	0.079	0.096	0.030	**0.105 ***	0.012	**0.109 ****	0.089	0.064	0.076
R^2 (within)	0.0344	0.0351	0.0333	0.0359	0.0331	0.0354	0.0342	0.0343	0.0344
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Internal job prospects (standardised coefficient):									
Degree holders	-0.058	0.000	-0.007	0.043	-0.035	0.069	**0.177 ***	0.003	0.090
Diploma holders	0.150	0.099	0.098	0.051	0.044	0.159	0.119	0.036	-0.037
Below diploma	0.113	**0.144 ***	0.043	**0.179 ****	0.103	0.116	-0.090	**0.274 ****	0.180
R^2 (within)	0.0346	0.0348	0.0330	0.0360	0.0331	0.0348	0.0352	0.0364	0.0345
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Perceived internal job prospects: “Over time, my job provides opportunities for: increases in pay / increases in managerial responsibility / increases in job scope.”

The sample includes only full-time employees. Results are obtained using fixed effects models of perceived internal job prospects on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D5. The effect of training participation on perceived external job prospects, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
External job prospects (standardised coefficient):									
Overall	0.086	**0.109 ***	-0.015	**0.149 ****	-0.035	**0.141 ****	-0.018	**0.139 ****	0.041
R^2 (within)	0.0356	0.0366	0.0342	0.0395	0.0345	0.0396	0.0360	0.0395	0.0345
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
External job prospects (standardised coefficient):									
Degree holders	0.192	**0.255 ****	0.014	**0.241 ****	0.012	**0.230 *****	-0.013	**0.182 ****	0.086
Diploma holders	-0.114	-0.123	-0.099	-0.115	**-0.244 ****	-0.103	-0.106	0.039	-0.074
Below diploma	0.113	0.127	0.006	**0.199 ****	0.088	**0.199 ****	0.070	0.163	0.036
R^2 (within)	0.0364	0.0389	0.0334	0.0427	0.0376	0.0430	0.0361	0.0390	0.0339
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Perceived external job prospects: “Your job provides work experiences that make you more marketable.” / “Your job provides educational experiences that make you more marketable.” / “Your resume improved as a result of having this job.”

The sample includes only full-time employees. Results are obtained using fixed effects models of perceived external job prospects on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D6. The effect of training participation on work engagement, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Work engagement (standardised coefficient):									
Overall	**0.207 *****	**0.194 *****	-0.017	**0.127 ****	0.054	0.071	**0.105 ***	0.010	0.025
R^2 (within)	0.0416	0.0410	0.0336	0.0373	0.0344	0.0339	0.0337	0.0335	0.0336
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Work engagement (standardised coefficient):									
Degree holders	0.117	0.051	-0.078	-0.052	0.052	-0.014	-0.0159	-0.021	0.023
Diploma holders	0.116	0.183	-0.082	0.156	-0.054	-0.022	0.059	-0.009	0.018
Below diploma	**0.288 *****	**0.281 *****	**0.231 ****	**0.266 *****	0.190	**0.222 ****	**0.238 ****	0.136	0.049
R^2 (within)	0.0429	0.0428	0.0381	0.0420	0.0361	0.0374	0.0372	0.0343	0.0334
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Work engagement: “How much effort do you put into your job beyond what is required?”.

The sample includes only full-time employees. Results are obtained using fixed effects models of work engagement on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D7. The effect of training participation on organisational commitment, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Organisational commitment (standardised coefficient):									
Overall	0.076	**0.138 ****	-0.049	**0.142 ****	-0.052	**0.162 *****	-0.081	**0.094 ***	0.006
R^2 (within)	0.0318	0.0348	0.0313	0.0358	0.0315	0.0381	0.0360	0.0332	0.0306
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Organisational commitment (standardised coefficient):									
Degree holders	0.000	0.084	-0.015	0.082	-0.055	**0.235 *****	0.022	0.072	0.026
Diploma holders	-0.009	0.081	-0.107	0.137	-0.094	0.006	**-0.381 *****	0.062	**-0.199 ***
Below diploma	0.140	**0.189 ****	-0.067	**0.191 ****	0.002	**0.173 ****	0.104	0.192	0.233
R^2 (within)	0.0318	0.0344	0.0309	0.0353	0.0308	0.0392	0.0413	0.0328	0.0341
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Organisational commitment: “I am willing to work harder than I have to in order to help this organisation succeed?” / “This organisation really inspires the very best in me in the way of job performance.” / “I am proud to be working for this organisation.”

The sample includes only full-time employees. Results are obtained using fixed effects models of organisational commitment on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D8. The effect of training participation on job satisfaction, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Job satisfaction (standardised coefficient):									
Overall	0.124	**0.214 *****	-0.040	**0.204 *****	-0.081	**0.181 *****	**-0.127 ***	**0.096 ***	-0.044
R^2 (within)	0.0234	0.0294	0.0210	0.0300	0.0225	0.0283	0.0271	0.0229	0.0210
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Job satisfaction (standardised coefficient):									
Degree holders	0.052	0.065	0.017	0.123	-0.077	**0.178 ***	-0.015	0.096	0.015
Diploma holders	-0.115	0.117	**-0.226 ****	0.156	**-0.195 ***	-0.042	**-0.366 *****	-0.016	**-0.358 *****
Below diploma	**0.252 *****	**0.339 *****	0.025	**0.297 *****	0.045	**0.322 *****	-0.043	**0.259 ****	0.203
R^2 (within)	0.0266	0.0317	0.0236	0.0307	0.0234	0.0324	0.0305	0.0243	0.0276
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Job satisfaction: "All in all, how satisfied are you with your job?".

The sample includes only full-time employees. Results are obtained using fixed effects models of job satisfaction on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D9. The effect of training participation on literacy skills confidence, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Literacy skills confidence (standardised coefficient):									
Overall	0.004	0.019	-0.055	0.030	-0.032	0.035	**-0.121****	0.048	0.005
R^2 (within)	0.0378	0.0379	0.0392	0.0381	0.0383	0.0399	0.0437	0.0387	0.0378
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Literacy skills confidence (standardised coefficient):									
Degree holders	-0.085	-0.052	-0.007	0.003	-0.004	-0.004	-0.097	0.057	0.048
Diploma holders	-0.179	-0.077	**-0.215 *****	-0.053	**-0.178 ****	-0.039	**-0.204 ***	-0.001	-0.142
Below diploma	0.131	0.109	0.018	0.101	0.071	**0.132 ***	-0.078	0.116	0.083
R^2 (within)	0.0384	0.0354	0.0387	0.0347	0.0371	0.0367	0.0397	0.0346	0.0354
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Literacy skills confidence: "How confident are you in performing tasks/activities that require reading and writing?".

The sample includes only full-time employees. Results are obtained using fixed effects models of literacy skills confidence on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D10. The effect of training participation on numeracy skills confidence, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Numeracy skills confidence (standardised coefficient):									
Overall	0.015	0.020	-0.006	0.019	-0.011	0.084	0.005	0.047	**0.109 ****
R^2 (within)	0.0264	0.0265	0.0264	0.0265	0.0264	0.0286	0.0258	0.0272	0.0300
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Numeracy skills confidence (standardised coefficient):									
Degree holders	-0.060	-0.037	0.020	-0.044	0.032	0.017	-0.014	-0.017	**0.140 ****
Diploma holders	-0.092	-0.059	0.014	-0.053	-0.117	0.025	0.052	**0.156 ***	0.035
Below diploma	0.104	0.093	-0.111	0.115	0.005	**0.204 *****	-0.034	0.094	0.117
R^2 (within)	0.0239	0.0232	0.0227	0.0240	0.0232	0.0273	0.0222	0.0248	0.026
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Numeracy skills confidence: “How confident are you in performing tasks/activities that require calculations of numbers, decimals, percentages or fractions?”

The sample includes only full-time employees. Results are obtained using fixed effects models of numeracy skills confidence on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D11. The effect of training participation on digital skills confidence, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Digital skills confidence (standardised coefficient):									
Overall	**0.085 ** **	**0.078 ** **	0.011	0.041	-0.005	0.046	0.039	0.000	0.031
R^2 (within)	0.0539	0.0533	0.0492	0.0505	0.0491	0.0503	0.0501	0.0491	0.0498
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Digital skills confidence (standardised coefficient):									
Degree holders	-0.035	-0.012	0.014	-0.057	-0.006	-0.019	-0.006	0.008	0.057
Diploma holders	-0.003	-0.001	-0.031	-0.041	-0.042	-0.018	0.014	-0.007	-0.068
Below diploma	**0.178 *** **	**0.164 *** **	0.060	**0.160 *** **	0.043	**0.153 *** **	**0.151 * **	-0.013	0.079
R^2 (within)	0.0592	0.0573	0.0489	0.0584	0.0486	0.0551	0.0501	0.0478	0.0509
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Digital skills confidence: "How confident are you in performing tasks/activities that require general use of the computer, for purposes such as to communicate with others using email, or software like Word, PowerPoint, or Excel?"

The sample includes only full-time employees. Results are obtained using fixed effects models of digital skills confidence on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D12. The effect of training participation on deep learning orientation, estimated by fixed-effects models

	Structured training								
	Any structured training	Job-related	Non-job-related	Employer-required	Non-employer-required	Employer-financed	SkillsFuture Credit-financed	More than 40 hours per year	More than 80 hours per year
Deep learning orientation (standardised coefficient):									
Overall	0.023	0.046	-0.015	0.040	0.006	0.024	-0.029	0.019	0.027
R^2 (within)	0.0416	0.0421	0.0415	0.0420	0.0414	0.0414	0.0458	0.0416	0.0417
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*
Deep learning orientation (standardised coefficient):									
Degree holders	0.122	0.093	0.007	0.086	-0.010	0.052	0.026	0.092	**0.135 ****
Diploma holders	-0.125	-0.052	-0.041	-0.111	0.057	-0.124	-0.020	**-0.170 ****	-0.168
Below diploma	0.031	0.060	-0.054	-0.079	-0.013	0.094	-0.150	0.091	-0.118
R^2 (within)	0.0362	0.0355	0.0344	0.0369	0.0344	0.0379	0.0391	0.0398	0.0407
n (obs)	*2,697*	*2,697*	*2,697*	*2,697*	*2,697*	*2,687*	*2,319*	*2,697*	*2,697*

Source: Skills and Learning Survey, 2017 & 2021

Deep learning orientation: “When I hear or read about new ideas, I try to relate them to real life situations to which they might apply.” / “When I come across something new, I try to relate it to what I already know.” “I like to get to the bottom of difficult things.” / “I like to figure out how different ideas fit together.” / “If I don’t understand something, I look for additional information to make it clearer.”

The sample includes only full-time employees. Results are obtained using fixed effects models of deep learning orientation on structured training participation. Models include dummy to control for survey years. Models include controls for highest qualification attained by the job holder, qualifications required by the job, job task requirements, years of work experience, job tenure, establishment size and marital status. Statistical significance denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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