Drivers of Skills Accumulation in Singapore

Findings from the Skills Accumulation Study

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May 2025

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This publication should be attributed as Institute for Adult Learning. (2025). *Drivers of Skills Accumulation in Singapore: Findings from the Skills Accumulation Study.* Chia Ying, Bryan Ang, Jamie Lee.

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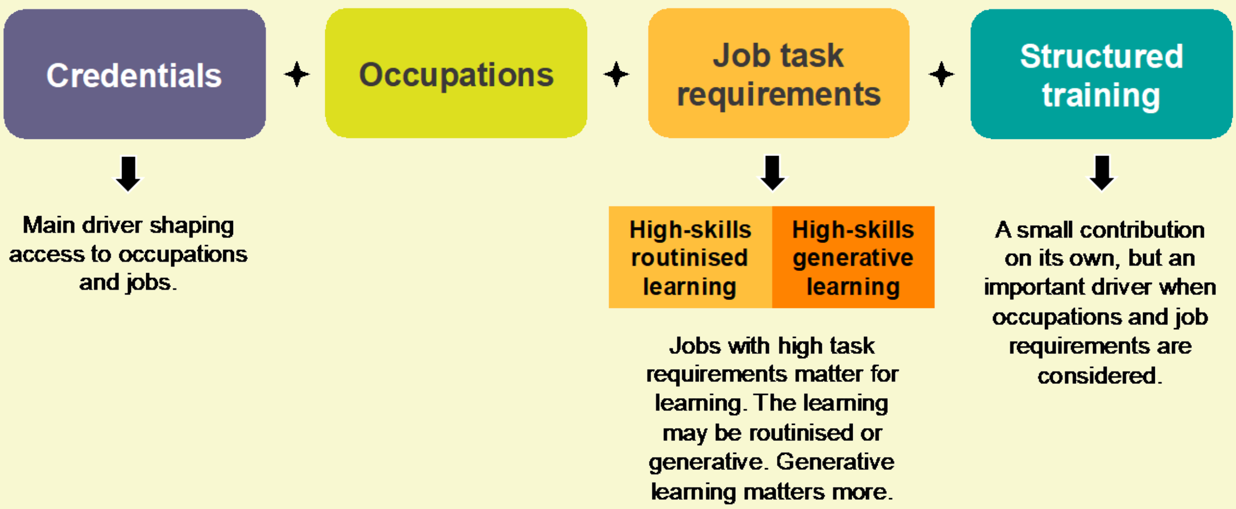
Executive summary

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 credentials, 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 that moves beyond the traditional credentials and structured training. It underscores the critical role of fostering value-creating job design and generative learning workplaces to advance skills-first pathways and support the development of a more inclusive and future-ready workforce.

Key patterns of skills accumulation in Singapore

Four key contributors to skills accumulation



1. Credentials and skills demand as key drivers of skills accumulation

Formal credentials, occupations and job design strongly shape skills accumulation in Singapore. Degree qualifications provide the best head-start in accessing high-skills occupations and explain a substantial portion of wages. In comparison, individuals without such credentials face limitations in their career opportunities. To enhance opportunities across the workforce and throughout working life, it is important to moderate the influence of credentials on life chances.

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

On its own, structured training does not generate significant wage returns. However, it provides 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 also less likely to participate in training. Quite crucially, the effectiveness of structured training is also heavily shaped by the broader skills ecosystem, including credentials, occupations and job design.

3. The importance of job design: encouraging generative learning

Generative learning jobs – those which learning encourages new ways of thinking and applying skills – drive higher participation in training, as workers in such roles recognise the need to continuously utilise and expand their skills. These jobs offer a critical pathway for skills accumulation and the growth of individual career capital.

However, not all jobs promote this kind of learning. Some high-skills jobs focus solely on routinised learning, which emphasises memorisation and strict adherence to instructions and thus limits skills growth. This underscores the need for job redesign efforts that prioritise generative learning, by including elements such as decision-making, brokering, and independence, as part of a value-creation business strategy.

Workers in generative learning jobs often see higher wage returns and better overall employment outcomes, compared to those in routinised learning roles. Importantly, these benefits extend to workers without degree qualifications, emphasising that job design plays a key role in advancing skills-first practices in the workplace.

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 targeting 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.

Introduction

Over the last decade, in response to the growing demand for highly skilled manpower driven by rapid technological advancements and structural shifts in the economy, the Singapore government has made significant and sustained public investments to strengthen lifelong skills development as both an economic and social lever. This commitment is reflected in substantial funding injections and flagship programmes in the national SkillsFuture movement launched in 2015. Notably, these investments take place alongside a steady rise in educational attainment within the workforce over the same period. The overarching goal is to ensure that the workforce remains competitive, relevant, and equipped to access high-quality, well-paying jobs amid ongoing economy and labour market transformations.

Given these substantial policy efforts, it is crucial to assess the extent to which investments in skills accumulation – that is, the lifelong process through which individuals acquire and develop their skills – translate into tangible benefits for individuals and society. Monitoring the impact of these investments helps to determine their effectiveness and informs refinements to policies, strategies and programmes that further strengthen Singapore's workforce capabilities.

To this end, this report presents findings from the Skills Accumulation Study, which examines how lifelong skills accumulation impacts employment opportunities and workforce outcomes in Singapore. Employing a multi-data, multi-method approach – including robust quantitative analysis using data from the Skills and Learning Survey 2017 and 2021, triangulated with qualitative insights on individual learning and career pathways – the study provides a systematic evidence base to support policy decision-making and guide the future direction of workforce development initiatives.

The study takes a broad perspective on skills accumulation, considering how individuals acquire and develop their skills through multiple pathways at across the life course. This includes not only formal education, but also participation in training courses and, more critically, learning gained through on-the-job experiences. It examines how these pathways interact to shape an individual's career capital over time. Importantly, the study also adopts a job requirements lens, analysing how the demands of specific roles and workplace contexts influence both skills development and broader workforce outcomes.

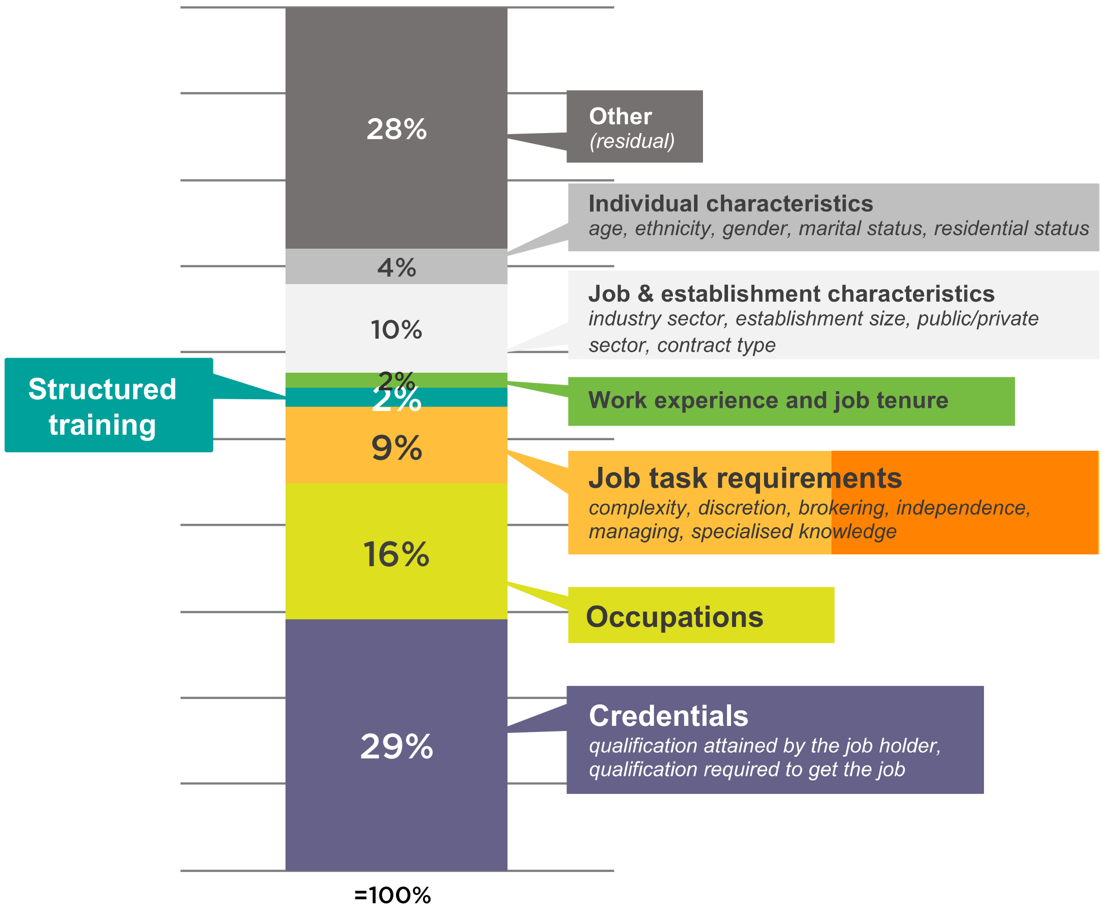
The key takeaway is the need for a more holistic approach to skills accumulation that moves beyond the traditional credentials and structured training. It underscores the critical role of fostering value-creating job design and generative learning workplaces to advance skills-first pathways and support the development of a more inclusive and future-ready workforce.

1. Skills accumulation in a highly credentialled society

The premium placed on credentials

In Singapore, credentials are a key determinant of an individual's career capital. The findings show that a significant proportion (29 percent) of the wage variation is explained by credentials. This includes both the qualifications attained by the job holder, as well as those required to get the job, with the latter as an important indication of the value that employers place on formal educational qualifications. Notably, this contribution from credentials 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

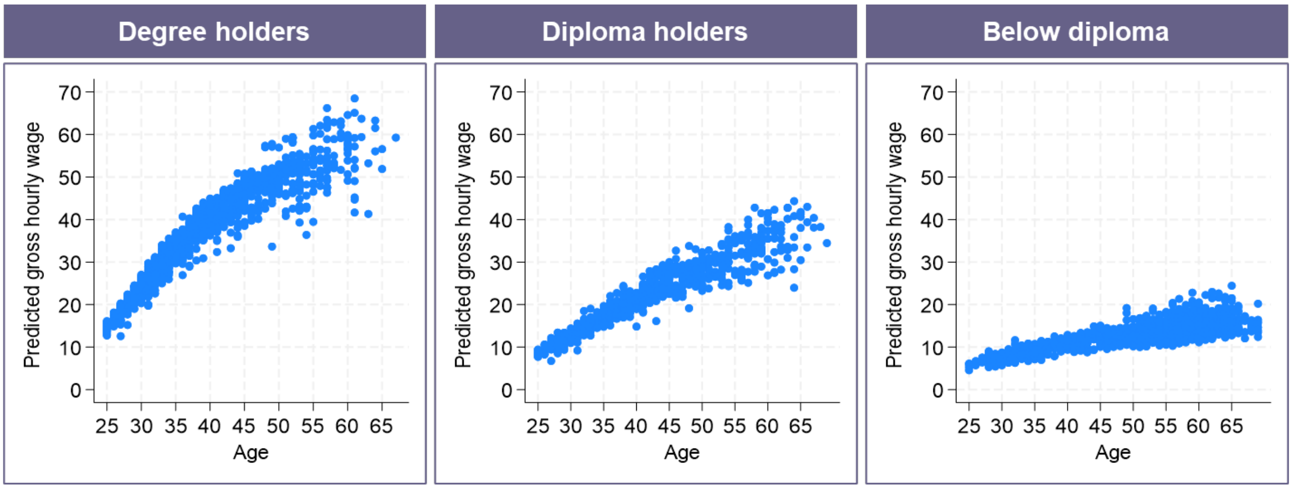
The sample includes only full-time employees. Results are based on a cross-sectional regression decomposition, following Fields (2003).

Beyond credentials, wage variation is 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 much smaller effect, with both work experience and structured training[2] each explaining less than 2 percent of wage variation.

The credential premium over the life course

The influence of credentials extends well beyond initial entry into employment and has a cumulative effect over the course of an individual's career. Degree holders, in particular, benefit from greater access to high-skills occupations and roles with higher job task requirements, which are typically 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-skills roles and tend to experience comparatively flat wage growth over time. Crucially, the finding highlights that, in Singapore's labour market where credentials continue to play a dominant role, work experience and skills acquired on the job may not be sufficient to offset the absence of formal educational 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 role of credentials

Overall, the findings point to the need to recalibrate the weight placed on credentials 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.

2. 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. The rise in training participation largely corresponds with an 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 may be attributed 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 E1 in Appendix E.

Training participation is also shaped by job skills demand

The findings from a regression analysis of various individual, job, and establishment-related characteristics on training participation emphasise education attainment as a key determinant. 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.

Apart from education 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	Education 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

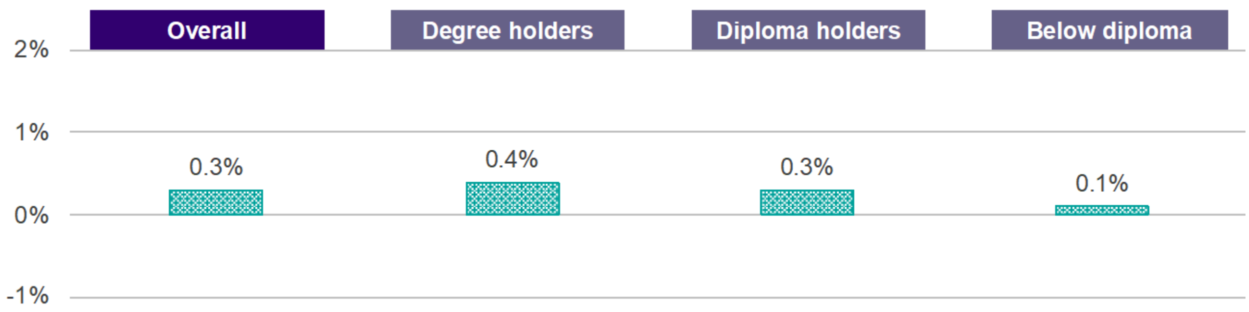
The sample includes only full-time employees. Results are based on logistic regressions of structured training participation on various individual-, job-, and establishment-related factors.

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. For instance, individuals with higher levels of education are more likely to engage in training, which 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, providing a more accurate estimate of the wage impact of training.

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 E2 in Appendix E.

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. 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.

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 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 E3 – E11 in Appendix E.

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.

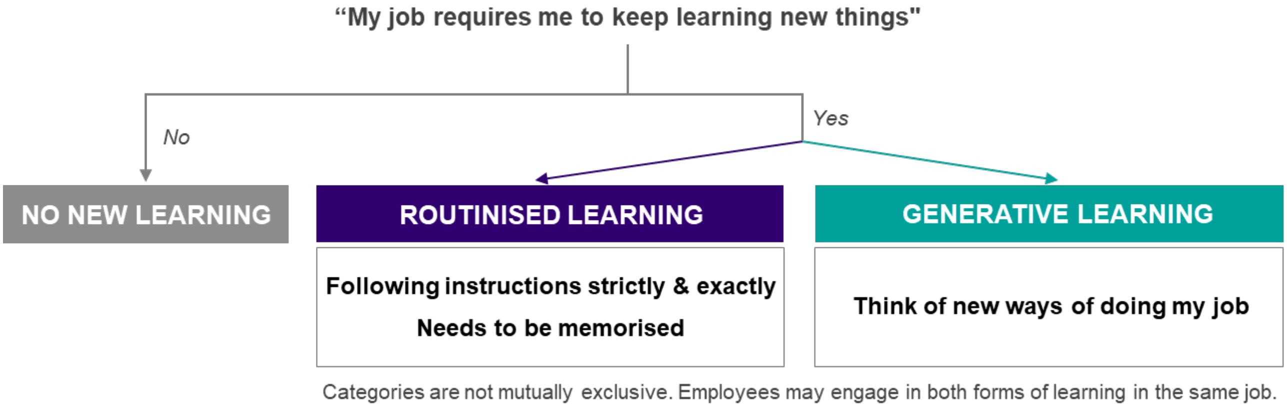
The findings reveal a paradox: those who stand to gain the most from structured training are also the least likely to engage in it. This underscores the need for targeted interventions to increase training participation among low-credentialled workers, ensuring they can fully benefit from skills development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

3. 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.

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-skills jobs, a finding that may seem surprising. 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	◆	◇	◆ (negative)
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. 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. 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 education 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. This reflects a reciprocal relationship between training and generative learning (Ellstrom, 2010; Storen, 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. 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	◆	◆
Non-job-related training	◆	◆
Employer-required training	◆	◆
Non-employer-required training	◆	◇
More than 40 hours of training per year	◇	◆
More than 80 hours of training per year	◇	◆

◆ 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. 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."*

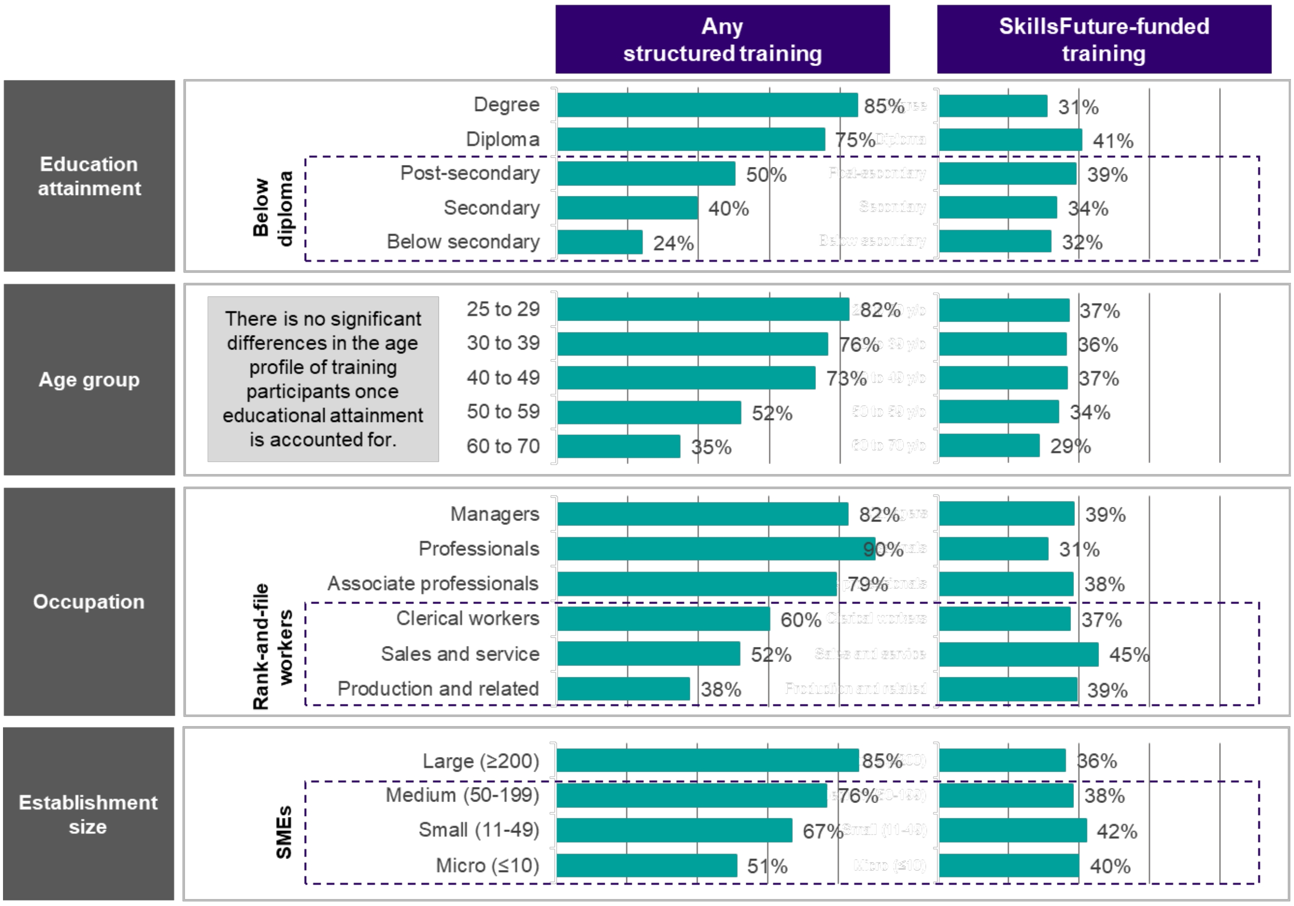
Insight: Even without high credentials, strategic roles that value initiative can foster long-term skills growth and leadership development.

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

Recommendations and future research

Policy implications

Drawing on key findings from this study, several policy implications emerge that are critical to strengthening Singapore's workforce capabilities and supporting more inclusive skills development. Together, they call for a more holistic approach to skills development that goes beyond traditional credentials and structured training, addressing the broader conditions under which learning and upskilling occur.

Extend the reach of training to better serve at-risk workforce segments

Publicly funded training programmes, such as those funded by SkillsFuture, have shown promise in reaching less-credentialled, rank-and-file workers, or those working in small- and medium-sized establishments – groups that are typically underserved by employer-financed or self-initiated training. Continued investment is essential, with more targeted outreach and intentional programme design 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 policy 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, there is 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 and complex tasks. Policies can play a more active role in shaping these dynamics, for example by incentivising job redesign that expands worker decision-making, independence, and brokering responsibilities. This is a critical lever for advancing skills-first pathways and creating more inclusive opportunities.

Areas for future research

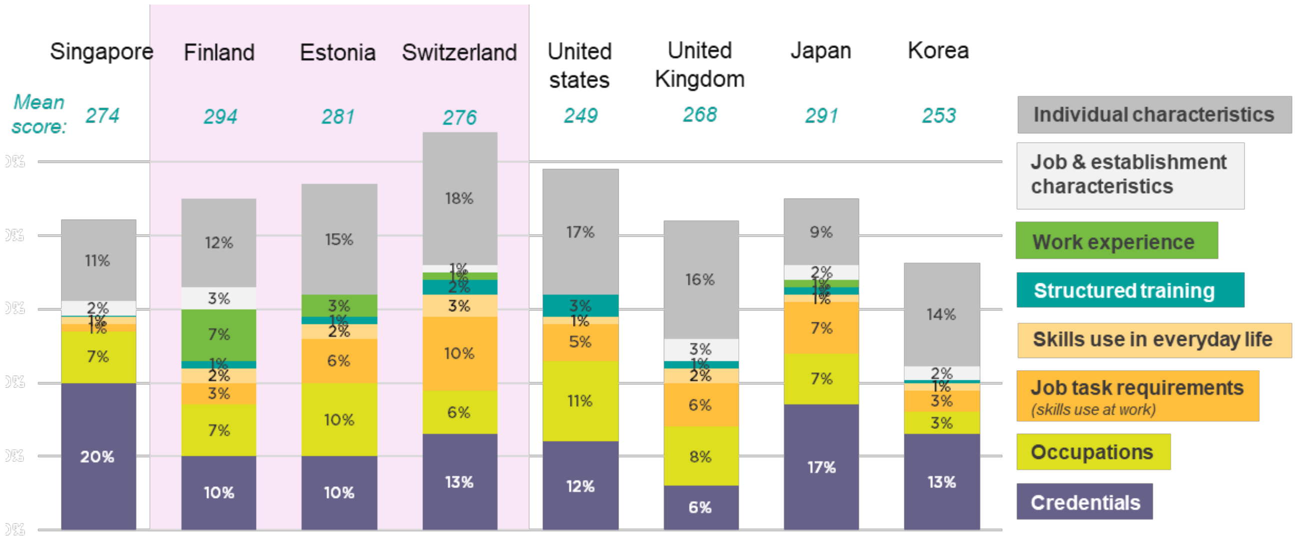
Contributions of skills accumulation to patterns of job mobility

Future research, especially with additional longitudinal data points, can explore how skills accumulation shapes patterns of job transitions and mobility across the life course. Adopting a life-course approach to learning – combined with a deeper analysis of employment transitions, including movements in and out of employment and shifts between different types of roles – can offer richer insights. Such an approach also enables 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

There is value in conducting comparative research to identify alternative models of skills accumulation and draw relevant lessons for Singapore. For instance, an analysis of the determinants of numeracy proficiency scores using data from the Survey of Adult Skills (PIAAC) Cycle 2 conducted between 2022 and 2023 finds that job task design and work experience are strong drivers of adult skills proficiency in Finland, Estonia and Switzerland – three coordinated market economies whose workforces performed comparatively well in the study. This contrasts with the dominant role of credentials in Singapore, highlighting the need to explore broader drivers of skills development.

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.

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

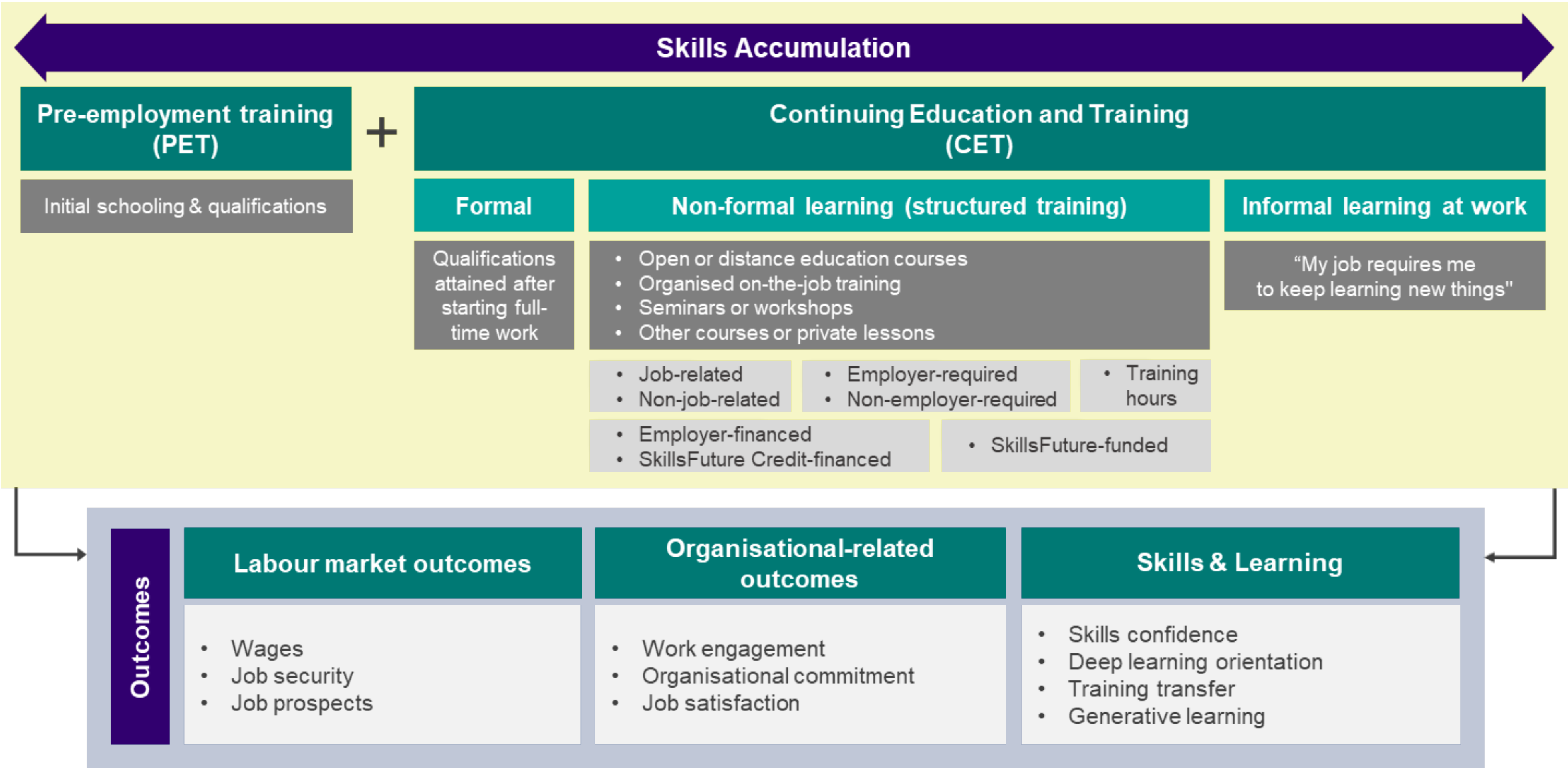
RQ2: To what extent does continuous education and training (CET) impact employment outcomes, over and beyond the contributions of pre-employment training (PET)?

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.
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 workforce outcomes in Singapore. It includes a robust quantitative analysis, complemented by qualitative insights to support the interpretation of the quantitative findings. This is followed by a holistic triangulation process to synthesise findings across datasets. This methodological integration strengthens the explanatory power of the study, thus increasing confidence in use of the findings for informing relevant policy directions and strategies. This approach is especially important because the findings are intended to guide policymaking.

This section outlines the datasets employed and their respective uses in the study.

Skills and Learning Survey (SLS) 2017 and 2021

The primary source of data for this research is the Skills and Learning Survey (SLS) 2017 and 2021, conducted by Institute for Adult Learning. 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. The survey provides comprehensive individual-level data on training and learning, alongside other employment- and job-related topics. It is administered face-to-face by trained interviewers to ensure high-quality and representative data.

The dataset comprises two complementary samples, designed to provide both a broad snapshot and a dynamic view of workforce trends:

(i) **Cross-sectional sample.** The cross-sectional sample provides a broad view of key trends in training and learning across different segments of the workforce. It allows researchers to identify associations between variables and interpret broad patterns of change. 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 used to estimate the within-individual effect of structured training participation. By applying a fixed-effects specification to the repeated observations, researchers can control for time-invariant, individual-specific characteristics, including unobservable factors. This approach is particularly valuable for assessing whether training directly contributes to various outcomes, as it better accounts for selection bias – specifically, the factors influencing who chooses to participate – and thus more accurately isolates the effect of training.

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

To examine the contributions of SkillsFuture to the training landscape, data of respondents 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.

Semi-structured interviews

Following the preliminary analysis of quantitative data, semi-structured interviews are carried out to enrich and deepen the interpretation of findings. The interviews focus on exploring the underlying mechanisms that may explain the relationship between skills accumulation and employment outcomes.

A total of eight interviews are conducted between May and June 2024, with participants drawn from the SLS sample using purposive sampling. The group includes four individuals with diploma qualifications and four with qualifications below the diploma level. This sampling method enables meaningful linkages between the qualitative and quantitative datasets.

The interviews explore participants' broader work experiences, with particular emphasis placed on how organisational structures and mechanisms – such as the firms' training and talent management practices, as well as job design – influence who is selected for training. They also examine how these factors, in turn, shape skills accumulation and employment outcomes.

Appendix D.

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 E.

Additional data tables

Table E1. Incidence of training participation (%) for selected training types and characteristics, 2017 & 2021

	Employer-required structured training[1]			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	△	2017	2021	△	2017	2021	△	2017	2021	△	2017	2021	△
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 E2. 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 E3. 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 E4. 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 E5. 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 E6. 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 E7. 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 E8. 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 E9. 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 E10. 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 E11. 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 E12. 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 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

References

Ehlert, M. (2017). Who benefits from training courses in Germany? Monetary returns to non-formal further education on a segmented labour market. *European Sociological Review, 33*(3), 436–448.

Ehlert, M. (2020). No future, no training? Explaining cross-national variation in the effect of job tasks on training participation. *Kölner Zeitschrift für Soziologie und Sozialpsychologie, 72*(Suppl 1), 483–510.

Ellström, P. E. (2010). Practice-based innovation: A learning perspective. *Journal of Workplace Learning, 22*(1), 27–40.

Fields, G. S. (2003). Accounting for income inequality and its changes: A new method with application to the distribution of earnings in the United States. *Research in Labor Economics, 22*, 1–38.

Pischke, J. S. (2001). Continuous training in Germany. *Journal of Population Economics, 14*, 523–548.

Støren, L. A. (2016). Factors that promote innovativeness and being an innovative learner at work – Results from PIAAC. *European Journal of Education: Research, Development and Policy, 51*(2), 176–192.