Skills Pathways and Deep Learning in Singapore's Workforce: Insights from the Skills and Learning Survey 2

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Executive Summary

Singapore's workforce continues to navigate a rapidly changing skills landscape shaped by technological transformation, evolving job demands, and shifting educational participation. This report provides an integrated view of how skills are developed, applied, and valued by examining two interconnected dimensions of the skills ecosystem: **Skills Pathway Opportunities** (the structure of jobs and labour market signals) and **Deep Learning Dispositions** (workers' motivation and skills mastery, shaped by job-learning environments).

Overview

The analysis offers a dual perspective understanding of workforce capability:

- **Skills Pathway Opportunities**: How job structures, task complexity, autonomy, and qualification requirements shape opportunities for workers to utilise and deepen skills.
- **Deep Learning Dispositions**: How workers' motivation and skills mastery interact with workplace environments to influence deep learning and skills transfer.

Together, these two perspectives demonstrate that both job design and learner orientations play essential roles in enabling meaningful skills development and workforce progression.

Key Findings

Skills Pathway Opportunities

- High-task jobs offer richer learning conditions, providing autonomy, complexity, and greater opportunities for capability development.
- Qualification requirements remain influential in shaping access to these roles, with degree-based signals continuing to mediate wage and progression outcomes.
- Skills-based pathway jobs (Type B) show productive potential but currently offer narrower advancement routes compared to degree-requiring roles.
- Training participation is uneven: Workers in high-requirement roles receive substantially more training than those in routine or low-requirement jobs.

Deep Learning Disposition

- Six learner clusters were identified, ranging from disengaged to highly self-driven learners.
- Motivation and skills mastery orientation are the strongest predictors of deep learning and effective skills transfer.
- Workplace conditions matter: Supportive job-learning environments reinforce motivation and mastery, strengthening deeper learning behaviours.

- Equal access does not guarantee equal impact: Workers with lower learning dispositions benefit less from training despite similar participation levels.

Policy and System Implications

Findings point toward the importance of strengthening alignment between job structures and workers' learning dispositions. Jobs create the opportunities for capability use, while workers bring the motivation and mastery orientation needed for meaningful skill development. Singapore's future workforce resilience therefore depends on advancing both sides, improving job-learning environments and enabling workers to grow deeper skills that can be effectively applied and recognised.

Introduction

Background

Singapore's labour market is undergoing significant transformation, driven by technological advancements, global economic restructuring, and demographic change. These forces are reshaping job roles and skill requirements, creating both new opportunities and new vulnerabilities for workers. In this context, workforce skills development has emerged as a national priority.

Through initiatives such as the SkillsFuture movement, Singapore has underscored the importance of enabling all individuals to develop and apply deep skills that sustain employability and support economic adaptability. Skills are recognised as a critical enabler of productivity, resilience, and social progress, underpinning the country's long-term competitiveness and inclusive growth. The ability of the workforce to continually learn, adapt, and innovate is therefore central not only to economic resilience, but also to maintaining access to high-quality, well-paying, and meaningful jobs amid rapid technological change. Sustaining Singapore's investments in workforce and skills development remains vital to navigating an increasingly complex and evolving global landscape.

The Genesis of the Skills and Learning Survey

To response to this policy imperative, the Skills and Learning Survey (SLS) was conceived to generate systematic, evidence-based insights into how skills are developed, utilised and mobilised among Singapore's workforce. The SLS collects data directly from individual job holders, to investigate how workers experience learning in and through work, how they apply their skills, and how these processes shape their career trajectories, opportunities, and outcomes.

Understanding skills development from the individual perspective is crucial, as workers are the ones who directly acquire and apply skills in their jobs and are the intended beneficiaries of Singapore's skills policies and workforce initiatives. The SLS therefore complements establishment-based studies such as the Business and Productivity Skills Survey (BPSS), which focuses on business strategies, workforce planning, and skills demand. Together, these perspectives offer a holistic and nuanced view of Singapore's workforce and skills ecosystem—linking individual learning experiences with organisational practices and structural opportunity conditions.

This report presents findings from the second iteration of the SLS, conducted between October 2021 and August 2022, providing an updated and deeper understanding of how learning and skill use evolve in tandem with labour market changes.

Positioning and Research Objectives

This report situates the investigation of workforce skills development within the broader skills ecosystem, where individual learning capacities/orientations, workplace environments, and labour market structures are mutually reinforcing. Skills are not only personal attributes, but also social and institutional outcomes shaped by the interaction of workers, employers, and policy frameworks.

Against this backdrop, the report addresses two central research questions that correspond to the two analytical strands of the study:

1. Building Deep Learners in the Workforce

- This strand examines workers' motivation and skills mastery—the orientations that underpin deep learning, persistence in skill development, and effective transfer of learning. It investigates how these learning dispositions are shaped by job-learning environments, including autonomy, feedback, challenge, and workplace support.

2. Pathways for Skills Utilisation and Mobilisation

- This strand explores the opportunities embedded in different types of jobs for workers to use, deepen, and be recognised for their skills. It analyses variation in task complexity, autonomy, qualification requirements, and the distribution of training and progression opportunities across job types. Together, these dynamics form the conditions we refer to as Skills Pathway Opportunities.

By bringing these two strands together, the report provides an integrated perspective on how skills are formed, applied, and rewarded across Singapore's labour market, and how job structures and learning dispositions interact to shape capability development.

Research Objectives

SLS2 addresses the following questions:

1. How have the distributions of job types, defined by task requirements and qualification requirements, evolved between 2017 and 2021 in Singapore's resident workforce?
2. How do job entry requirements affect training participation rates across different job types?
3. To what extent do job requirements and qualification demands contribute to wage differentials, and how do these patterns reflect the persistence of a credential-driven wage structure in Singapore?
4. How do workers' motivations and skills mastery orientations interact with job-learning environments to influence deep learning and skills transfer?
5. How well are worker learning dispositions and job opportunity structures aligned, and what does this mean for workforce resilience, productivity, and equitable opportunity?

Report Structure

The remainder of this report is organised as follows. Chapter 2 outlines the theoretical perspectives that inform the study, while Chapter 3 describes the data sources and methodological approach. Chapters 4 and 5 present the key findings from the analysis. Chapter 6 provides the discussion, and Chapter 7 sets out the implications for policy and practice. Chapter 8 concludes the report.

Theoretical Framework

This chapter sets out the theoretical foundations of the Skills and Learning Study. It synthesises insights across economics, sociology, psychology, and skills ecosystem research to provide an integrated lens for analysing skills development, utilisation, and mobility in Singapore's workforce.

The meaning of skill: An interdisciplinary approach

What is "skill"? Despite its importance as a concept and centrality to debate on workforce development, there is yet still no consensus on its meaning across disciplines. Skills have been conceptualised variously as individual capabilities, job requirements, credentials, or socially recognised attributes (Green F. , 2011). This research acknowledges the interdisciplinary nature of the discourse surrounding skills. For practical purposes, rather than to delineate by to disciplinary boundaries, it instead seeks to extract what is salient and useful from various academic traditions to guide the conceptual and analytical approaches. (See Green, 2011, for a detailed explanation and critique). Below is a summary of the key points that inform this research's approach to skills.

Three Interlocking Perspectives on Skills

Economics Perspective

From an economics perspective, skills are most commonly conceptualised through the lens of human capital theory (Becker, 1964), where skills are treated as individual investments that enhance productivity and are rewarded through higher wages. This perspective has been highly influential in shaping education and training policy and sees skills as investments that improve performance and generate returns for individuals and employers. This perspective highlights that developing deep skills is essential for building a resilient and high-performing workforce. However, human capital theory has also been critiqued for underplaying the institutional and organisational processes that mediate how skills are recognised and rewarded in practice (Brown, Lauder, & Ashton, 2011). In particular, it tends to assume a relatively direct link between skills and wages, an assumption that this study empirically interrogates through its analysis of job task requirements, qualification demands, and wage outcomes.

Sociological Perspective

Sociological theories emphasise the influence of social structures, occupational institutions, and labour market signalling. From this viewpoint, what counts as "skill" is shaped by occupational norms, credentialing systems, and employer practices, rather than by task content alone (Rigby & Sanchis, 2005). Qualifications continue to play an important signalling role in Singapore's labour market, shaping access to certain jobs and career pathways. At the same time, skills-based pathways are emerging in selected domains. This perspective helps explain why opportunities for advancement may differ across job types and sectors, and is especially relevant for understanding the frequent conflation of skills and qualifications in practice, and for analysing phenomena such as skill under-use, where workers' capabilities exceed what their jobs allow them to deploy or be rewarded for (Felstead, Gallie, Green, & Zhou, 2007).

Psychological Perspective

Psychological theories situate skills within cognitive, behavioural, and motivational processes. Skills encompass not only technical competencies but also the cognitive and behavioural habits that influence how individuals learn and perform (Ryan & Deci, 2000; Illeris, 2003). Motivation and mastery orientation are central to skill acquisition and transfer, and these are shaped by the job-learning environment, including feedback, autonomy, and opportunities to apply learning.

The Skills Ecosystem: A Contextualised and Systemic Approach to Skills Development

Building on these perspectives, this study adopts a skills ecosystem approach that situates skills within the broader socio-economic system. Skills are shaped by the active and interdependent role of employers, policymakers, educational and training institutions, and the workers themselves. The skills ecosystem concept originates from the work of Finegold and others (Finegold, 1999; Anderson & Warhurst, 2012), who emphasised that skill formation and utilisation depend not only on individual effort or firm-level decisions, but on the coordination and complementarities across multiple actors within an economic system. It reflects a dynamic interplay between individual learning capacities, the structural conditions of work, workplace learning affordances as well as credential structures. Recognising these interdependencies highlights that all stakeholders share the responsibility for helping workers grow and ensuring that skills development creates fair and useful opportunities that lead to productive outcomes.

Two Core Constructs in this Study

Within this ecosystem, the study focuses on two interrelated constructs that capture both the demand-side and individual dimensions of skills development: skills pathway opportunity and deep learning disposition. Our analysis examines how job structure, defined through skills pathway opportunities and workers deep learning dispositions, reflected in deep learning dispositions, interact to shape overall skill development and utilisation.

Skills Pathway Opportunities

Skills pathway opportunities describe the job conditions that enable workers to apply, deepen, and develop their skills. Drawing on research on workplace learning and job quality, skills pathway opportunities are shaped by task complexity, autonomy, opportunities for problem-solving, and access to informal learning and feedback at work (Eraut, 2004; Alan, Duncan, Francis, & Golo, 2019). This demand-side view underscores that effective skills development requires workplaces that provide meaningful opportunities for skill application and recognise workers' skills beyond formal credentials.

In conceptualising skills pathway opportunities, this study focuses on high cognitive, non-routine task dimensions that are most directly linked to learning, autonomy, and progression, consistent with prior work emphasising the role of task complexity and discretion in shaping skills utilisation and development (Green & Henseke, 2021). While the survey also captures physical task demands, these are not included in the present analysis. This reflects an analytical choice rather than a data limitation. In the Singapore policy and labour-market context, workforce development initiatives place particular emphasis on adaptability, continuous learning, and progression, outcomes that are more closely associated with non-routine cognitive and social aspects of work. Physical skills remain essential in many occupations but are not the primary focus of the skills pathway framework examined in this report.

Deep Learning Dispositions

Deep learning dispositions capture workers' inclination to engage deeply with learning, going beyond surface understanding to make connections, reflect, and apply their skills in new contexts (Biggs & Tang, 2011). These dispositions are influenced by motivational factors such as autonomy, and the inclination towards mastery, which together shape how individuals approach learning tasks and respond to challenges. This perspective highlights that meaningful skill development depends not only on training access, but also on the learner's underlying motivation and orientation toward continuous improvement.

The deep learning construct is operationalised through three component dimensions that are grounded in prior research:

Motivation to learn reflects individuals' willingness to invest effort in learning and is shaped by perceptions of autonomy, relevance, and support (Ryan & Deci, 2000).

Skills mastery orientation captures an individual's focus on developing competence and improving performance through learning, rather than solely achieving external rewards (Dweck, 1986).

Job learning environment refers to the extent to which workplace conditions—such as feedback, support, task variety, and opportunities for experimentation—facilitate learning through work (Marsick & Watkins, 1990; Eraut, 2004).

Why Deep Learning Matters

Deep learning is used in this study because it captures the type of learning that leads to sustainable and transferable skills.

From a lifelong learning perspective, skills develop through continuous, self-directed engagement, shaped by cognitive, emotional, and social factors (Illeris, 2003). Deep learning dispositions reflect these longer-term learning habits where workers' tendencies to seek understanding, reflect, and persist through challenge.

From the learning outcomes perspective, deep learning is associated with deeper understanding, better retention, and stronger transfer to real work situations (Makransky, Terkildsen, & Mayer, 2019; Mayer, 2002). Learning that involves reflection and cognitive effort consistently leads to higher achievement (Hattie, 2009).

From the corporate learning perspective, most skill development occurs through real work, challenging tasks, problem-solving, collaboration, and feedback, not mainly through formal training. The widely cited 70–20–10 model reflects this pattern, suggesting that roughly 70 per cent of learning occurs through work-based experience, 20 per cent through social interaction, and 10 per cent through formal instruction (Lombardo & Eichinger, 2000). Studies of workplace learning show the importance of everyday experience in capability growth (Marsick & Watkins, 1990; Eraut, 2004).

From a human–AI collaboration perspective, deep learning is increasingly critical as AI automates routine tasks. Workers need higher-order abilities such as judgement, sense-making, and problem-framing. Research shows that effective human–AI collaboration depends on these deeper cognitive skills, not only on technical competencies (Gašević, Siemens, & Sadiq, 2023).

Together, these perspectives reinforce deep learning as a meaningful indicator of long-term employability, adaptability, and workforce resilience.

Taken together, these theoretical perspectives establish the foundations for analysing skills within Singapore's workforce. By integrating economic, sociological, and psychological views of skill with a wider skills ecosystem lens, this study recognises that skill development is both an individual and structural process. Skills Pathway Opportunities and deep learning dispositions are therefore examined as interconnected components of the same system, which operationalise how skills are embedded in jobs and expressed through learners. This framework provides the basis for interpreting the findings and for understanding how skills can be better developed, recognised, and utilised across the workforce.

The next chapter outlines how these concepts were operationalised in the study, detailing the learning and job constructs used, the underlying theoretical models, and the analytic strategies applied to examine skill opportunity structures and deep learning dispositions across Singapore's workforce

Data and Methods

Study Design

The Skills and Learning Study (SLS) was designed as a dual-perspective investigation into how Singapore's workforce learns, adapts, and progresses in a changing labour market. It combines two complementary perspectives within a single skills ecosystem:

- Skills Pathway Opportunities, which examines whether the labour market provides skills-based pathways that are accessible, progressive, and fairly rewarded; and
- Deep learning disposition, which explores deep learning through individual motivation, mastery orientation, and workplace environments influence participation in and benefits from learning.

Together, these perspectives provide a holistic understanding of how labour market structures and learning behaviours jointly shape skills development and workforce outcomes.

The study was implemented through a large-scale national survey of 5,996 Singapore Citizens and Permanent Residents aged 20 to 70 years. Respondents were randomly selected from the national population registry and representativeness by age, gender, and education were ensured during data collection. The survey achieved a response rate of over 60 per cent, which is high for a large-scale national survey and supports the robustness of the dataset. Data collection was conducted between August 2021 and April 2022 using computer-assisted personal interviewing (CAPI), administered in face-to-face sessions of approximately 90 minutes.

The survey instrument covered multiple domains, including skills use in jobs, employment context, job content, attitudes to lifelong learning, training participation, workplace learning conditions, and career progression. In addition to providing descriptive insights, the survey enabled advanced analytical approaches to examine both structural and behavioural dimensions of skills development.

Participants and Sampling

The dataset used for analysis comprises a representative sample of Singapore residents aged 25–65. This age range was selected to focus on the core working-age population with sustained labour market attachment and this sub sample is representative of Singapore's resident workforce. Table 1 summarises the demographic composition of the survey cohort, which is broadly aligned with the national profile. The sample includes balanced representation by gender (48.5% male, 51.5% female) and age cohorts (approximately 18–21% in each decade group). Educational attainment ranges from lower-secondary qualifications (16.8%) to university degrees (34.8%).

Data Collection Procedure

All fieldwork was conducted by a vendor appointed by IAL. Prior to data collection, interviewers underwent structured training sessions to familiarise themselves with the survey instrument, ethical guidelines, and respondent engagement procedures. Data were collected via CAPI to ensure accuracy and consistency, with built-in validation checks for skip patterns and missing values.

Table 1 Breakdown of sample collected

Sample listing	Proportion (%)
Gender	
Male	48.5
Female	51.5
Age	
20- 29	18.6
30- 39	20.6
40- 49	20.5
50- 59	21.0
60- 70	19.3
Highest Qualification	
Lower secondary and below	16.8
Secondary	14.1
Post- secondary	11.6
Diploma	22.7
Degree and above	34.8
Employment status	
Employed	79.6
Unemployed	3.1
Out of labour force	17.3
Out of labour force	6.41

Conceptual Foundations of Job and Learner Constructs

This study operationalises two main sets of constructs, job constructs and learner constructs, to examine how job structures and individual learning orientations interact to shape skills development. We begin with the job constructs, which capture the opportunities and constraints embedded in the design of work, before turning to learner constructs that describe how individuals engage with learning within these job conditions.

Job Constructs: Skills Pathway Opportunities

Skills Pathway Opportunities refer to job conditions that support workers in using, deepening, and advancing their skills. These constructs recognise that skills development depends not only on worker motivation but also on whether jobs provide meaningful opportunities to apply and grow skills.

Skills-based pathways: understanding 'parity of esteem'

A defining principle of viable skills-based pathways is 'parity of esteem', where there is equality in status between academic and skill-based vocational routes. Based on the related academic literature, we identified four criteria to reflect 'parity of esteem' of skills-based pathway jobs, that we use for our investigation. We describe the four criteria in Table 2 below.

Table 2 Criteria for skills-based pathway jobs

Do	**Challenging** Jobs are complex and have high task content.
Get	**Inclusive** Jobs do not require the degree qualification to get.
Progression	**Coherent** Jobs provide a pathway from entry-level to deep specialisation.
Reward	**Fair** Jobs pays equitable wages as those that require the degree qualification.

Setting up the investigation

The analytical distinction between the skills required to *get* a job and those required to *do* a job has a longer lineage in the skills literature, reflecting enduring concerns about access, utilisation, and recognition of skills in labour markets. This study builds on and operationalises this distinction following the methods developed by Green and Henseke (2021). We categorise the jobs into based on their 'do' and 'get' requirements.

'Do' requirement: whether the job has high task requirements

The Skills and Learning Survey uses the Job Requirement Approach to measure task requirements. This approach asks job holders about the importance or frequency of a series of different types of tasks performed at work. The approach has been tested for reliability and validity and is used in similar type of surveys internationally. Table 3 describes the list the task variables that we have identified from the survey to reflect jobs that involve high-level, non-routine cognitive and interpersonal tasks, such as those requiring literacy, numeracy, problem solving, interpersonal and computer requirements.

Further, to distinguish between jobs with low and high task requirements, we first estimate the task variables with the job degree requirement as the dependent variable. Next, we predict an overall task requirement score as the probability of the job degree requirements conditional on job task requirements and then dichotomise the overall task requirement score into a low and high value range. The cut-off value is optimised by maximising the sum of sensitivity and specificity.

To aid interpretation, we use factor analysis to group the task variables into 4 key tasks dimensions. Where the task variables load across dimensions, we reflect the dimension with the highest loading.

Table 3 Key task dimensions and related task variables

Key task dimensions	Related task variables
Cognitive	Reading and writing, numeracy, analysing, planning own work, paying attention to details
Social	Dealing with people, persuading or influencing others, giving speeches and presentations
Task complexity	Complex problem solving, digital complexity, continuous learning, task variety, managerial and supervisory duties
Task discretion	Deciding how hard to work, what tasks to do, how to do the tasks, and quality standards of work outputs

'Get' requirement: whether the job requires a degree to get

The Skills and Learning Survey ask job holders about the qualifications that a person applying today would need to get the same type of job. Based on the responses, we distinguished between jobs that require and do not require a degree to get. We note that this is meant to reflect the qualification requirements of the job, which may or may not be a match with the qualification of the job holder.

Four types of jobs

Accordingly, we identify four types of jobs, as described in Figure 1.

Given that Type B jobs have high task requirements yet do not require the degree qualification to gain access, it might suggest that a category of jobs that offer skills-based pathway. We shall examine this in more details in the subsequent sections.

	Low task requirements	High task requirements
Degree required	*C* ***Low task requirements, degree required***	*A* ***High task requirements, degree required***
No degree required	*D* ***Low task requirements, no degree required***	*B* ***High task requirements, no degree required***

Figure 1 Four types of jobs

This typology enabled an assessment of the extent to which skills-based jobs (Type B) provide genuine alternatives to degree-driven pathways (Type A). Analytical techniques included:

- **Factor analysis** to construct composite task dimensions.
- **Logistic regression models** to estimate the probability of high/low task requirements.
- **Cross-tabulations and regressions** to examine training participation across job types.
- **Mincer-type wage regressions** to evaluate wage returns, controlling for qualifications and demographic characteristics.

This approach allowed the study to investigate whether skills-based pathways exist in practice, and how they compare to credential-based routes in terms of progression, training, and rewards.

Learner Constructs: Deep Learning Disposition

The learner constructs examined how psychological and workplace factors shape deep learning among workers. A deep learning approach is characterised by intrinsic motivation, curiosity, and a desire to understand complex ideas (Trigwell, Prosser, & Ginns, 2005; Biggs & Tang, 2011). Workers who adopt deep learning actively connect new knowledge to prior knowledge, apply it in real-world situations, and engage meaningfully with their learning experience. This leads to better skill retention, greater transferability, and stronger adaptability (Folaranmi, 2024), all of which are essential in a fast-changing economy. By contrast, a surface approach to learning is motivated by outside demands or a need to meet requirements with minimal effort (Biggs & Tang, 2011). Surface learners often rely on memorisation and show minimal interaction with content, which leads to less effective training outcomes (Ellström, 2001). Table 4Table 4 Pro and cons of deep and surface approach to learning below presents the key characteristics of deep and surface approach to learning and their pros and cons.

Table 4 Pro and cons of deep and surface approach to learning

Approach	Key Characteristics	Pros	Cons
Deep	Intrinsic motivation, conceptual understanding, critical thinking	Promotes long-term learning, adaptability, and innovation	May be time-consuming; dependent on learner's environment and support

Approach	Key Characteristics	Pros	Cons
Surface	Memorisation, minimal engagement, extrinsic motivation	Quick to implement; efficient for short-term goals	Poor retention, limited problem-solving capacity, less effective in dynamic contexts

This analysis examines three connected components, namely, motivation to learn, skills mastery and job-learning environment, that influence workers' learning process to better understand what encourages or impedes deep learning.

Measures

The main objective of this analysis is to identify the key characteristics of individuals who adopt a deep approach to learning. To achieve this, the analysis included multiple indicators, including:

- **Motivation to learn (MtL)** constructs are based on the Self-Determination Theory (Ryan & Deci, 2000), which distinguishes between intrinsic motivation, extrinsic regulation, and amotivation, offering insights into the quality of the learner's motivation. The MtL scale was developed conceptually from the Behavioural Regulation in Exercise Questionnaire (BREQ/BREQ-2) (Markland & Tobin, 2004), which are grounded in Self-Determination Theory and have been widely validated in physical activity settings. Items were adapted to reflect learning behaviour rather than exercise behaviour while maintaining alignment with SDT's regulation continuum. Respondents indicated their agreement on a four-point Likert scale (1 = strongly disagree to 4 = strongly agree). Items captured the extent to which learning was perceived as externally pressured (e.g. expectations from others), internally regulated through guilt or obligation, personally valued, integrated with life goals and identity, or intrinsically enjoyable. Variables include:

SDT dimensions	Example items
Amotivation	I don't see why I should have to learn
External regulation	I learn because other people say I should
Somewhat external regulation	I feel guilty when I don't learn
Somewhat internal regulation	I value the benefit of learning; Learning is consistent with my life goals
Intrinsic motivation	I enjoy my learning sessions

- **Skills Mastery (SM)** reflects a personal commitment to developing expertise and using one's capabilities to grow. This mindset is a key driver of deep learning orientation. SM was measured using items adapted from the technical/functional competence dimension of Schein's Career Anchors framework. This dimension reflects individuals' intrinsic orientation towards developing expertise, applying specialised skills, and deriving fulfilment from mastery and competence in their work (Schein, 1990).

Respondents indicated how true each statement was of them on a four-point Likert scale (1 = always true of me to 4 = never true of me). Items captured aspiration towards recognised expertise and fulfilment derived from using and developing one's skills. For analytic purposes, items were coded such that higher scores indicate a stronger orientation towards skills mastery. The SM measure consists of the following two questions:

- I aspire to be so good at what I do so that my expert advice will be sought continually
- I am most fulfilled in my work when I am able to use my skills and talents.

- **Job Learning Environment (JLE)** refers to the presence of informal, continuous, and collaborative learning opportunities at work. It influences how learning unfolds in everyday work settings and determines whether learning can be effectively supported. The JLE consist of multiple learning-related items available in the survey. This reflects that workplace learning opportunities are multi-dimensional and embedded in everyday work activities rather than captured by a single instrument (Marsick & Watkins, 1990; Eraut, 2004).

The scale incorporates interrelated aspects of the learning environment: initial learning demands, continuous learning, task discretion, and informal learning and peer learning opportunities. Specifically, items capture whether jobs require workers to learn new things, support learning at job entry and over time, provide discretion over how tasks are carried out, and create opportunities for informal learning and helping others learn.

These dimensions align with research on expansive learning environments and skills utilisation, which emphasises task variety, autonomy, feedback, and social learning as core conditions for learning through work (Fuller & Unwin, 2004).

JLE variables	Example items
Initial learning at work	How long did it take for you, after you first started doing this type of job, to learn to do it well?
Continuous learning at work	How much continuous learning is normally expected in this job every year?
Learning new things at work	How often does your job require you to keep learning new things
Helping others to learn at work	My job requires that I help my colleagues to learn new things
Informal learning opportunities at the workplace	Learn new work-related things from co-workers or supervisors
Task discretion	How much influence do you personally have on deciding how hard you work?

It should be noted that for the cluster analysis, learning environment components were represented using individual survey items to preserve variation across dimensions, with the exception of autonomy, which was operationalised as a composite measure derived from four task discretion items.

Together, these three components offer a holistic view of the psychological and work environment that influence learning approaches. Rather than treating all learners as a single group, this analysis uses cluster analysis to identify distinct learner profiles based on how these components interact. This person-centred approach allows us to uncover meaningful subgroups within the workforce, compare their learning outcomes, and design targeted strategies to support deeper learning engagement across different learner types.

By combining these insights, the study contributes to a better understanding of how learning orientation and work environments shape the workforce's readiness for continuous development and lifelong learning.

Deep learning capability

In addition to the measures used for the cluster analysis, the study includes a measure of deep learning capability that is used exclusively in the structural equation modelling (SEM) analysis. This construct captures individuals perceived ability to engage in self-directed, adaptive, and exploratory learning, including seeking out information, learning independently, and generating novel approaches to tasks.

Deep learning capability was measured using a set of self-report items adapted from the Programme for the International Assessment of Adult Competencies (PIAAC), capturing individuals perceived ability to engage in self-directed learning, information seeking, and adaptive problem-solving. Items reflect confidence in learning independently, identifying information needs, and generating new approaches to tasks.

Respondents indicated how true each statement was of them using a four-point response scale ranging from “Always true of me” to “Never true of me”, with higher scores indicating stronger perceived deep learning capability. This measure was used exclusively in the structural equation modelling (SEM) analysis.

Outcomes variables

In addition to the core constructs of deep learning disposition and skills pathway opportunity, the study examines a set of outcome measures to characterise and interpret the learner clusters identified in the analysis. These outcomes are not treated as independent explanatory variables but are used to examine how different learner profiles are associated with distinct patterns of workplace experience and broader developmental outcomes.

Specifically, the cluster analysis is examined in relation to three outcome domains: (i) organisational and job-related factors, including communication, trust, and job content; (ii) training participation and training transfer; and (iii) personal and social development outcomes, such as life satisfaction, personal growth, exposure to new ideas and cultures, and participation in community and voluntary activities.

Analysing these outcome measures alongside the learner clusters enables the study to assess how differences in learning dispositions and job learning environments are reflected in both workplace outcomes and wider individual development, thereby strengthening the interpretive value of the cluster-based profiling.

Internal consistency analysis indicated that all multi-item dimensions used in the study demonstrated acceptable reliability (Cronbach's $\alpha \geq 0.70$).

Analytical Approach

To examine how the three components influence learning approaches, or more specifically, deep learning in the workplace, this analysis employed Structural Equation Modelling (SEM) as the analytical approach. SEM was chosen for its ability to estimate both direct and indirect relationships between the three key components. This method allowed us to test a theory-driven model of learning behaviour while accounting for complex relationships between variables. By using SEM, the analysis provided a comprehensive view of how JLE and psychological drivers, together, shape deep learning strategy among workers.

Following the SEM analysis, a cluster analysis was conducted to identify distinct learner profiles based on MtL, drive for SM, and their JLE. The clustering was conducted using Ward's linkage method, which is a form of agglomerative hierarchical clustering. This method was chosen for its robustness in generating clusters that are relatively homogeneous within but distinct between, as it minimises the total within-cluster variance during the formation of clusters. The squared Euclidean distance (L2squared) was selected as the distance measure, which is appropriate for continuous, standardized variables.

The resulting clusters were reviewed to identify patterns that differentiate deep learners from other groups. An initial six-cluster solution was retained to capture underlying variation in learner profiles. However, subsequent analysis showed that two of the clusters were substantively similar and differed only marginally in intensity rather than orientation. For interpretive clarity and policy relevance, the six clusters were therefore consolidated into three broader learner types, but the six-cluster solution is retained as the primary analytical representation of learner profiles. Typically, individuals characterised by high intrinsic motivation, strong inclination towards SM, more learning opportunities at work were grouped into the "deep learning cluster". In contrast, other clusters reflected varying combinations of lower MtL, weaker inclination towards SM, and less supportive workplace environment, seems more likely to be disengaged from learning.

This approach complements the variable-centred view commonly used in workplace learning research, offering a richer and more nuanced understanding of the diversity of learning profiles present in Singapore's workforce.

Linking Job Structures and Deep Learning Dispositions

Although analysed separately for clarity, job structures and learner dispositions are interdependent components of the same skills ecosystem:

- Jobs shape learning possibilities through autonomy, task complexity, and opportunities for practice.
- Learners' dispositions shape how effectively they take advantage of workplace opportunities.

This integrated approach allows the study to examine not just who learns deeply, but whether the labour market provides sufficient opportunities to support such learning.

Findings on Skills Pathway Opportunities

Introduction

This section presents findings from the job perspective of the Skills and Learning Study (SLS), which examines the structure and characteristics of work in Singapore's labour market. Using the Job Requirement Approach, the analysis explores the types of tasks that define different jobs, the extent to which these jobs rely on formal qualifications, and how such features shape access to training, skill utilisation, and wage outcomes. By identifying patterns of "skills-based" and "credential-based" pathways, this perspective provides insights into how the organisation of work supports or constrains opportunities for learning and progression.

Findings

Growth in share of Type A jobs between 2017 and 2021, but Type D jobs still dominate among the resident workforce

	Low task requirements	High task requirements
Degree required	***C*** ***Low task requirements, degree required*** 2017 **7.9%** vs. 2021 **8.3%** (non-sig change)	***A*** ***High task requirements, degree required*** 2017 **29.0%** vs. 2021 **32.0%** (↑3.0pp)
No degree required	***D*** ***Low task requirements, no degree required*** 2017 **43.0%** vs. 2021 **39.9%** (↓3.1pp)	***B*** ***High task requirements, no degree required*** 2017 **20.1%** vs. 2021 **19.7%** (non-sig change)

Figure 2 Distribution of jobs by type, 2017 and 2021

Note: The percentages across job types add up to 100% for the respective years.

Considerably higher task complexity requirements among Type A jobs

Next, we examine the requirements by each task dimension. We find that while generally comparable in most task dimensions, Type A jobs have considerably higher task complexity requirements than Type B (see Figure 3). We note that the task complexity dimension as captured here describes the design of job tasks, rather than the skills or capabilities of the job holder.

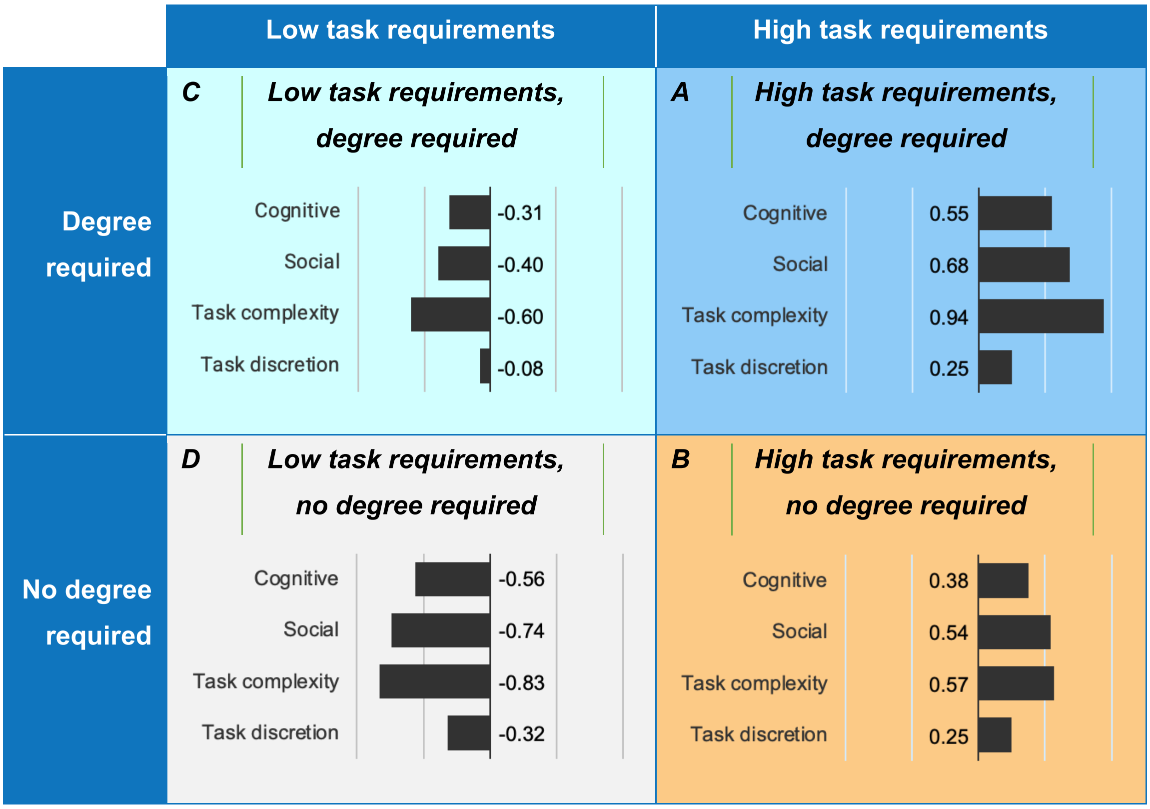

Figure 3 Mean task dimension scores by job type, 2021

Note: The respective task dimension score reflected in the figure has been standardised to obtain a sample mean of zero and a sample standard deviation of one. A higher task dimension score suggests a higher requirement by the job.

Exceedingly high entry requirements for Type A jobs: degree plus work experience

When we further unpack the entry requirements of different job types by the years of relevant work experience required to do the job well, we find Type A jobs to have exceedingly high entry requirements. On top of requiring the degree to gain access, a significantly larger share (65%) of Type A jobs also require three years or more of work experience to do, especially when compared to other job types (see Figure 4). This finding suggests a phenomenon that can be described as ‘degree-plus’, with intensification of entry requirements among a certain segment of top jobs in the labour market.

In comparison, only 36% of Type B jobs require three years or more of relevant work experience to do, suggesting that most of the jobs in this category are entry-level jobs. This finding suggests the scarcity of progression opportunities for Type B jobs beyond entry-level requirements and highlights a limitation of existing skills-based pathway opportunities in Singapore’s labour market. For more equitable skill-based progression pathways, we would expect a more even distribution of work experience requirements between Type A and Type B jobs.

Further, we also note that Type B can be characterised as diploma jobs, where 66% of them require a diploma to get. This compares with only 31% of Type D jobs that require a diploma to get.

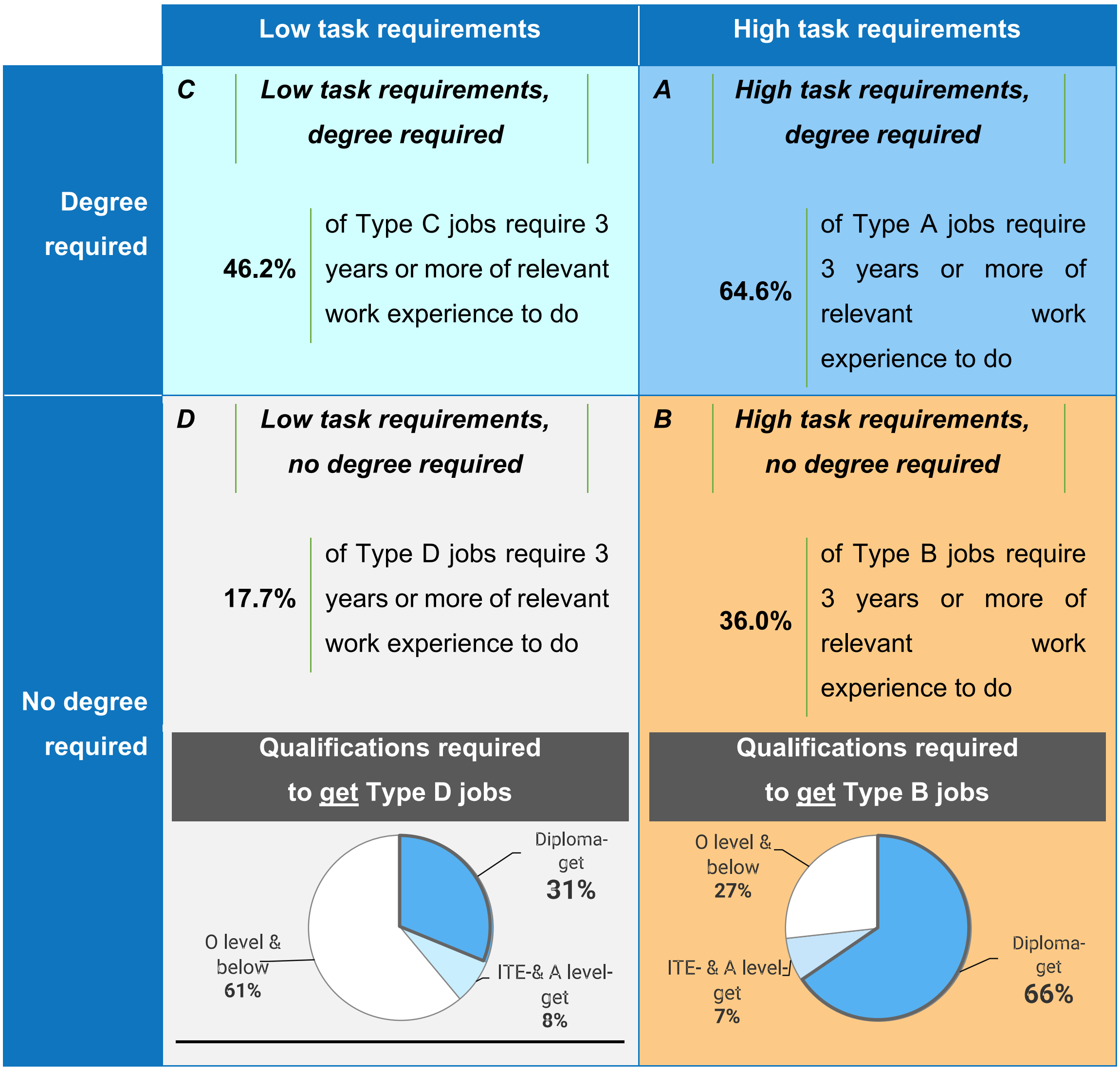

Figure 4 Share of jobs that require 3 years or more of relevant work experience to do by job type, 2021

Uneven incidence of training participation among job holders in different job types, driven by differences in job requirements

Examining the incidence of having participated in job-related training in the last 12 months, we find that training participation is uneven across different job types. Job holders working in jobs with higher job requirements are significantly more likely to have participated in training. In 2021, while an overwhelming majority – nine in 10 (90.2%) – of the job holders in Type A jobs participated in training in the last 12 months, only slightly more than four in 10 (43.2%) of the job holders in Type D jobs did so over the same period (see Figure 5).

Controlling for various individual background characteristics including highest qualification attained, gender, age group, and marital status, we find this difference in training participation across different job types to be even more evident. The likelihood of a job holder in a Type A job having participated in training in the last 12 months is 4.5 times that of a job holder in a Type D job, while the likelihood of a job holder in Type B job and one in Type C job having participated in training is 1.8 times and 1.6 times that of a job holder in a Type D job respectively.

This finding shows that job requirements are a strong driver of training participation. More importantly, it also highlights that job holders performing low-skilled work – crucially, a group of workers who requires more targeted support for reskilling and upskilling – are less likely to have access to training opportunities at work.

	Low task requirements	High task requirements
Degree required	***C*** ***Low task requirements, degree required*** **74.6%** of job holders in Type C jobs participated in training in the last 12 months	***A*** ***High task requirements, degree required*** **90.2%** of job holders in Type A jobs participated in training in the last 12 months
No degree required	***D*** ***Low task requirements, no degree required*** **43.2%** of job holders in Type D jobs participated in training in the last 12 months	***B*** ***High task requirements, no degree required*** **68.7%** of job holders in Type B jobs participated in training in the last 12 months

Figure 5 Job-related structured training participation incidence by job type, 2021

Credential-driven wage structure

To investigate how job qualification requirements and job task requirements drive differences in pay, we run a series of Mincer-type regression models. First, we model the log gross hourly pay on job type for the sample of degree holders, while controlling for differences in individual characteristics including gender, age group, marital status, as well as self-reported skill confidence level[1]. The result of the estimates is shown in Figure 6.

The finding shows that jobs which employers deem to require the degree qualification command a wage premium, over and beyond task requirements of the job. Among degree holders, those performing Type A jobs earn 1.9 times pay premium over those performing Type D jobs, while those performing Type C jobs – even if these jobs have low tasks requirements – earn 1.5 times pay

[1] The skills confidence measure used in the models is a standardised variable derived from 5 questions asking respondents to self-assess their confidence level in performing tasks related to literacy, numeracy, and computer use.

premium over those performing Type D jobs. In comparison, those performing Type B jobs earn a lower pay premium of 1.3 times as compared to those performing Type D jobs, despite having high task requirements.

	Low task requirements	High task requirements
Degree required	***C*** ***Low task requirements, degree required*** Type C jobs command **1.5× pay premium** over Type D jobs	***A*** ***High task requirements, degree required*** Type A jobs command **1.9× pay premium** over Type D jobs
No degree required	***D*** ***Low task requirements, no degree required*** *Reference group*	***B*** ***High task requirements, no degree required*** Type D jobs command **1.3× pay premium** over Type D jobs

Figure 6 Comparing pay differences of degree holders across job types, 2021

Note: Result of the OLS regression of log gross hourly wage on job types performed by degree holders. The estimates are adjusted for individual characteristics including gender, age group, marital status, and self-reported skill confidence level.

	Low task requirements	High task requirements
Degree required	***C*** ***Low task requirements, degree required*** Type C jobs command **1.4× pay premium** over Type D jobs	***A*** ***High task requirements, degree required*** Type A jobs command **1.4× pay premium** over Type D jobs
No degree required	***D*** ***Low task requirements, no degree required*** *Reference group*	***B*** ***High task requirements, no degree required*** Type B jobs command **1.2× pay premium** over Type D jobs

Figure 7 Comparing pay differences of diploma holders across job types, 2021

Note: Result of the OLS regression of log gross hourly wage on job types performed by diploma holders. The estimates are adjusted for individual characteristics including gender, age group, marital status, and self-reported skill confidence level.

Modelling the log gross hourly pay on job type for the sample of diploma holders (see Figure 7), we observe similar patterns among diploma holders. While they do not possess the requisite qualification, diploma holders performing jobs that require the degree earn a pay premium compared to counterparts performing jobs that do they require the degree qualification. In 2021, the diploma holder performing degree required Types A or C jobs earns a pay premium of 1.4 times compared to those performing non-degree required Type D jobs. In comparison, those performing Type B jobs – which do not require the degree qualification despite high task requirements – earn a lower pay premium of 1.2 times over those performing Type D jobs.

	Low task requirements	High task requirements
Degree required	***C*** ***Low task requirements, degree required*** Degree holders earn a **1.2× pay premium** over diploma holders	***A*** ***High task requirements, degree required*** Degree holders earn a **1.5× pay premium** over diploma holders
No degree required	***D*** ***Low task requirements, no degree required*** **No degree pay premium**	***B*** ***High task requirements, no degree required*** Degree holders earn a **1.3× pay premium** over diploma holders

Figure 8 Pay premium of degree holders over diploma holders in each job type, 2021
Note: Results of the OLS regressions of log gross hourly pay on highest qualification attained, by job types. The estimates are adjusted for individual characteristics including gender, age group, marital status, and self-reported skill confidence level.

Next, we also investigate the implications of qualification attainment on pay. Among degree holders and diploma holders performing the same job type, we model the log hourly pay on the highest qualification attained by job holder, while controlling for differences in individual characteristics including gender, age group, marital status, as well as self-reported skill confidence level. The results of the estimates are shown in Figure 8.

The findings show that degree holders generally earn a premium over diploma holders, even after accounting for different types of jobs performed. In 2021, degree holders performing Type A jobs earn 1.5 times pay premium over diploma holders performing the same job type. Meanwhile, degree holders performing Type B and Type C jobs earn 1.3 times and 1.2 times pay premium respectively over diploma holders performing the same job type.

Notably, however, we find a lack of degree pay premium in Type D jobs. This affirms the earlier discussion that demand-side consideration of what the job requires is an important factor in explaining wages beyond the qualifications of the job holder.

In a further analysis, when we limit the comparison to between degree holders from non-autonomous universities and polytechnic diploma holders, we find similar patterns although the degree premium is smaller.

	Low task requirements	High task requirements
No degree required	***D*** ***Low task requirements, no degree required*** Diploma holders earn a **1.3× pay premium** over ITE graduates	***B*** ***High task requirements, no degree required*** Diploma holders earn a **1.3× pay premium** over ITE graduates

Figure 9 Pay premium of diploma holders over ITE graduates in Type B and Type D jobs, 2021

Note: Results of the OLS regressions of log gross hourly pay on highest qualification attained, by job types. The estimates are adjusted for individual characteristics including gender, age group, marital status, and self-reported skill confidence level.

When we similarly model the log hourly pay on the highest qualification attained by the job holder among diploma holders and ITE holders performing the same job type, we find that, for both Type B and Type D jobs, diploma holders earn a pay premium of 1.3 times as compared to ITE graduates performing the same job type (see Figure 9).

We note that it is possible that some of these variations in the wage returns may be explained by differences in the skills and abilities of job holders with different qualification attainment. In our models, even though we have attempted to account for some of the self-reported level of skills confidence, the finding shows that the pay premium experienced by degree holders over diploma holders and ITE graduates continues to persist over and beyond the job requirements.

Overall, the findings from our analyses in this section show a credential-driven wage structure in Singapore: firstly, jobs that require a degree to get command a premium over jobs that do not even when task requirements are low; and secondly, where the pay premium of degree holders over diploma holders and ITE graduates persists for most job types.

Conclusion and policy implications

Evidence for skills-based pathways in Singapore?

Overall, the findings show that academic qualifications continue to play a strong signalling role in Singapore's labour market, with weak evidence of equitable skills-based pathways in Singapore. Within current skills-based opportunities, progression opportunities are limited, and rewards are still structured by academic qualifications with clear advantage of degree holders over non-degree holders. (See Table 5 for a summary based on the four criteria as set up earlier in the chapter.)

The findings also suggest early evidence of growing within-graduate inequality. The emerging 'degree-plus' trend, where employers look for more than the degree qualification when they hire, suggests more competition for jobs at the top end of the labour market.

Table 5 Current Evidence for Skills-based Pathway in Singapore

Do	**Challenging** Jobs with high task requirements that do not require the degree qualification exist.
Get	**Inclusive** These jobs are however typically constructed to be diploma jobs, with lower levels of task complexity compared to degree jobs.
Progression	**Coherent** They have lower requirements on work experience, suggesting limited progression opportunities.
Reward	**Fair** Rewards are structured mainly by academic credentials, even after accounting for job task requirements.

The discussion thus far highlights the limit to how much skills currently offer an equitable alternative to educational credentials in Singapore's labour market. It highlights the tensions underlying the policy narrative that skills can provide for better labour market opportunities and outcomes. While our findings do not discount the need to equip the workforce with the right skills to be prepared for challenges in the future of work, it underscores important lessons for policy to better support this objective.

Policy implications: Supporting skills-based pathways in Singapore

To support the goals of SkillsFuture in creating viable skills-based pathways in Singapore, there is current impetus for policy firstly to increase the job task content among jobs that do not require the degree qualification; and secondly to strengthen skills recognition more deliberately across key stakeholders and facilitate a shift from credential-linked to skills-based rewards.

Findings on Deep Learning Dispositions: Profiles of Workforce Learners in Singapore

Introduction

This section presents findings from the learner perspective of SLS2, which investigates how workers engage in learning and skill development across different workplace contexts. Building on psychological and workplace learning theories, the analysis examines how motivation, skills mastery, and job learning environments influence the adoption of deep learning strategies. By identifying distinct learner profiles and their associated outcomes, this perspective highlights how individual readiness and workplace conditions interact to shape participation, transfer of learning, and career advancement.

Findings

Relationship Between Motivation, Skills Mastery, Learning Environment and Deep Learning

This analysis first examined the relationship between the three key components, and their influence on an individual's adoption of a deep approach to learning. The results from the SEM analysis demonstrated a strong and acceptable model fit, as indicated by the following fit indices shown in Table 6.

Table 6 Goodness of fit measures for SEM

Goodness of fit measures	Values	Recommended value
Chi square	1657.78 (p=0.00)[2]	p>0.05
RMSEA	0.047	<0.08
CFI	0.968	>0.90
TLI	0.962	>0.95
SRMR	0.032	<0.8

The findings revealed that all three components were significant predictors of deep approach to learning. Both MtL and Drive for SM showed strong and positive relationships with deep learning (Figure 10), reinforcing the view that workers who are intrinsically motivated and driven to achieve mastery are more likely to engage in deep learning strategies. MtL plays a large role in predicting

[2] Noting that with large sample sizes, chi-square tests often reject the null hypothesis even in well-fitting models).

deep learning (0.63), especially when motivation is internally driven. SM also has a significant effect (0.39) on deep learning. This means workers are learning or participating in training, not just to comply, but because they find value, meaning, or purpose in doing so. These findings are consistent with the key propositions of Self-Determination Theory (Ryan & Deci, 2000), which highlights the role of autonomous motivation in sustaining meaningful learning behaviours.

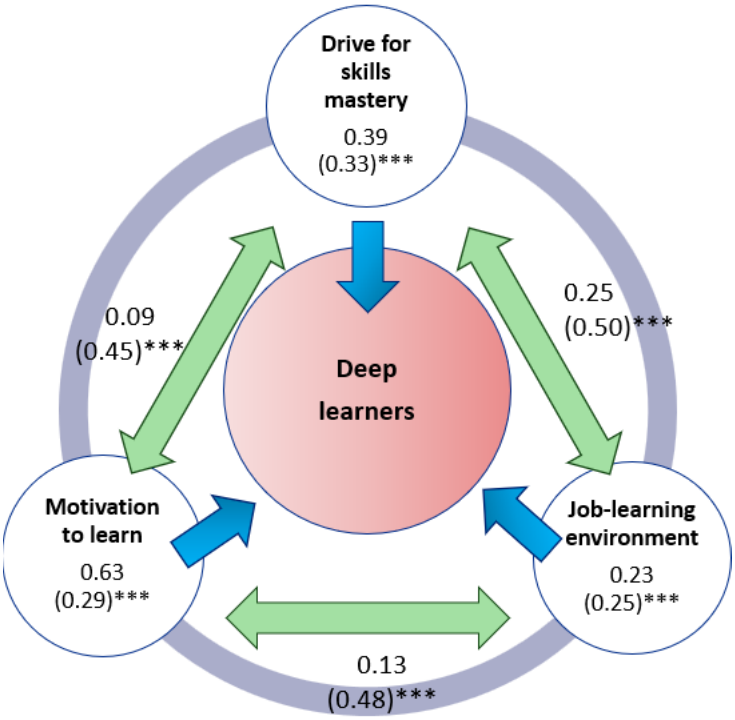

Figure 10 Relationship between Motivation, Skills Mastery, Learning Environment and Deep Learning

Note: Both the coefficients and standardised coefficients are shown. The numbers in brackets are the standardised coefficients which show how strong the connection is between two components:

- *0.10–0.20 = weak link*
- *0.20–0.50 = moderate link*
- *Above 0.50 = strong link*

Interestingly, while the JLE also significantly predicted deep learning, its direct effect was smaller (0.23) compared to the other two components. However, the JLE demonstrated strong indirect effects (Figure 10), as it positively influenced both MtL (0.48) and drive for SM (0.50). This suggests that the learning opportunities within the workplace may not always directly lead to deep learning, but they play a crucial role in cultivating the learning orientation that encourage it. These findings align with research on workplace learning, which emphasises the interaction between individual agency and environmental affordances in shaping learning outcomes (Billett, 2004; Deci & Ryan, 2000a; Kyndt, Dochy, & Nijs, 2009).

Together, this model tells us that if we want to promote deep learning in the workplace, we need to do more than offer training, we also need to shape environments that fuel intrinsic motivation and support skills development over time

It is crucial to recognise, nonetheless, a flaw in the present model in which the analysis focus just on learning happening within the workplace. Data limits prevented inclusion of other possibly important contexts as external training, personal learning networks. Future studies should try to include these more aspects for a more complete perspective.

Although the structural model clarifies how workers MtL, SM, and JLE link to deep learning, the next important step is to know whether distinct profile of learners can be recognised inside the workforce. More specifically, do deep learners fit a homogeneous group based on their MtL, SM, and JLE or do they belong to different clusters?

Profile of deep learners

Using cluster analysis, we have identified six learners' profiles of workers in Singapore workforce, each with a unique mix of MtL, SM, and JLE characteristics. These clusters provide insights into the learning and training behaviour in the workforce and can inform strategies for targeted support and intervention. The six learner profiles help shed light on the distribution of learning orientations throughout the Singaporean workforce (as shown in Table 7), revealing substantial differences in their readiness and capacity to benefit from development opportunities.

The labels assigned to each cluster reflect the main characteristics of learners, which is based on learners' levels of MtL, drive towards SM and their reported JLE. These labels succinctly capture the dominant learning orientation observed in each cluster.

Cluster 1 (C1): Alienated Learners (20.7% of workers)

With an average aged of 52 years, the Alienated workers mostly have little educational background; most have less than diploma-level certification (74%). Notably in the cleaner's sector, where over 85% of the group is employed, their occupational profile indicates a strong share in the Rank-and-File (R&F) employment. This cluster reveals a very high percentage of workers (88%) reporting amotivation, and small proportion reporting internal motivation (5.2%) and using deep learning (8%). Furthermore, just 13% of workers in this cluster reported inclination towards SM and only 0.9% reported their workplace provides learning opportunities. This combination implies that Alienated Learners encounter several structural and personal obstacles to participate in learning.

Cluster 2 (C2): Discouraged Learners (20.0% of workers)

The Discouraged Learners accounts for 20% of the workforce. The average age in this group is 45 years. While this group is slightly more educated than the Alienated Learners, with 31% holding a university degree and another 28% holding a diploma, they still report high levels of amotivation (89%), low internal motivation (3.1%) and low engagement in deep learning (10%). Only 22% of this profile report inclination towards SM, and the JLE is rated positively by just 11% of workers. Interestingly, despite these poor indicators, the occupational profile for this group mainly comprises of PMETs (>50%) and clerical roles. This profile suggests that even with relatively higher education and more structured jobs, barriers to learning can persist when workplace and motivational conditions are not favourable.

Cluster 3 (C3): Unmotivated Learners (14.8% of workers)

The Unmotivated Learners, which comprises 14.8% of the workforce. The average age is 42 years, with 41% of this cluster holding university degrees, and more than 71% of this cluster are employed in PMET roles. 37% report inclination toward SM. Interestingly, although a majority (57%) of workers in this cluster report having a supportive job-learning environment, the incidence of deep learning remains low at only 16%, and amotivation remains high at 90%. This finding highlights an important point: even with better educational qualifications and more supportive environments, deep learning will not materialise if motivation is lacking.

Table 7 Profile of deep learners

Clusters Attributes and Worker Profiles	C1 Alienated Learners	C2 Discouraged learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners
	n= 909, 20.7%	n= 881, 20.0%	n= 652, 14.8%	n= 696, 15.8%	n=724, 16.5%	n= 536,12.2%
Deep learning	Low (8%)	Low (10%)	Low (16%)	Moderate (29%)	Moderate (47%)	High (58%)
Amotivation	High (88%)	High (89%)	High (90%)	Low (7%)	Moderate (32%)	Low (6.2%)
External motivation	Moderate (37%)	Moderate (48%)	Moderate (55%)	Moderate (32%)	High (72%)	Low (19%)
Internal motivation	Low (5.2%)	Low (3.1%)	Low (7%)	Low (15%)	High (62%)	High (94%)
Drive for skills mastery	Low (13%)	Low (22%)	Moderate (37%)	Moderate (34%)	High (68%)	High (65%)
Job-learning environment	Poor (0.9%)	Poor (11%)	Good (57%)	Moderate (38%)	Good (74%)	Good (50%)
Average age	52	45	42	39	39	39
Occupation	R&Fs (>85%) (mostly cleaners)	PMETs (>50%) & clerical	PMETs (>71%)	PMETs (>76%)	PMETs (>74%)	PMEs (>76%)
Qualification	Below dip 74% Diploma 16% Degree 10%	Below dip 31% Diploma 28% Degree 31%	Below dip 33% Diploma 26% Degree 41%	Below dip 17% Diploma 25% Degree 58%	Below dip 21% Diploma 25% Degree 54%	Below dip 14% Diploma 29% Degree 57%

Note: The values represent their proportion among each cluster

Cluster 4 (C4): Indifferent Learners (15.8% of workers)

The fourth cluster, referred to as Indifferent Learners, represents 15.8% of the workforce. Workers in this group are relatively younger, with an average age of 39 years, and 58% hold university degrees. Over 76% of them are employed in PMET roles. Unlike the earlier clusters, amotivation is only reported by 7% of the cluster, suggesting a baseline willingness to engage with learning, though actual deep learning engagement remains at a moderate 29%.

A closer look at the motivational profile provides further insight. While external motivation is moderate, with 32% of the cluster, the share of workers reporting high intrinsic motivation is only 15%, which is considerably lower than in the Goal-Oriented and Autonomous Learner clusters (see below). This combination points to a group that is neither strongly self-driven nor sufficiently influenced by external incentives to pursue deeper learning. Similarly, 34% report inclination toward SM, which is moderate but not particularly high, given their occupational and educational profile. In terms of the learning environment, 38% report experiencing a supportive workplace, again suggesting that although some structural support is available, it is not necessarily translating into higher levels of deep learning engagement.

Taken together, the Indifferent Learners appear to occupy a transitional space, they are neither disengaged from workplace learning nor highly committed to pursue SM and deep learning. Their moderate external motivation combined with low intrinsic motivation might explain the lukewarm learning engagement, again, underscoring the importance of fostering both internal interest and supportive organisational structures if deeper workplace learning is to be encouraged.

Cluster 5 (C5): Goal-Oriented Learners (16.5% of workers)

The Goal-Oriented Learners make up 16.5% of the working population and shows a significant shift towards active learning orientation. The average age of this group is 39 years, and a majority, 54%, hold university degrees. Over 74% are employed in PMET roles, indicating these occupational roles are more likely to offer learning opportunities. A high proportion of workers in this cluster (68%) report high inclination towards SM, and 62% indicate strong internal motivation. Correspondingly, their deep learning engagement is notably higher, with 47% of workers reporting deep learning behaviours. The JLE is also favourable, with 74% reporting workplace support for learning. This cluster highlights the importance of alignment between motivation, workplace support, and individual effort in fostering deep learning.

Cluster 6 (C6): Autonomous Learners (12.2% of workers)

The final cluster, the Autonomous Learners, comprises 12.2% of all workers. Autonomous Learners are similar in age to Goal-Oriented Learners, averaging 39 years, and are also highly educated, with 57% attaining a degree qualification. A majority (over 76%) are employed in PMET roles, indicating that the nature of their jobs may be better aligned with their learning needs. What distinguishes this group is their strong intrinsic motivation, with 94% reporting high internal drive for learning, and 65% actively pursuing SM. Even though only 50% report a supportive learning environment at their workplace, this group still shows the highest engagement in deep learning, with 58% indicating deep learning behaviours. This profile reflects the kind of self-directed learners who can thrive regardless of the learning conditions around them, highlighting the critical role of workers' learning orientation in lifelong learning.

Job-Learning Environment: A Closer Look

Beyond individual learner orientations, the workplace learning environment plays a critical role in shaping how workers engage in knowledge and skill development. While the cluster profiles previously summarised the overall learning environment as "Poor", "Moderate", or "Good", a more detailed breakdown of specific learning opportunities reveals important nuances in the actual conditions experienced by each cluster.

Table 8 shows the proportion of workers in each cluster who report having access to various forms of learning at work.

Alienated Learners (Cluster 1)

Workers in this cluster report the lowest exposure to learning opportunities across all learning variables, with only a small minority participating in initial (5.3%) or continuous learning (3.4%). The same pattern holds for collaborative learning, such as helping others (2.5%) or informal learning (7.0%). This aligns with their reported "Poor" in JLE and reflects highly restricted developmental prospects, possibly reinforcing their sense of detachment and high amotivation.

Discouraged Learners (Cluster 2)

Discouraged Learners have slightly better access to learning opportunities than Cluster 1. Only 31.8% report opportunities for initial learning, and engagement in continuous (8.3%) or helping others learn (9.9%) is still marginal. This suggests that while their JLE offers slightly more room for learning than Alienated Learners, the opportunities are neither frequent nor substantial enough to make up for their high amotivation and lower internal motivation.

Unmotivated Learners (Cluster 3)

Workers in this cluster report the highest level of initial learning (42.8%) compared to all other clusters. This suggests that their job roles likely involve substantial knowledge or skills requirements at the start, perhaps due to complex tasks, role transitions, or onboarding processes. However, this initial learning demand does not appear to translate into sustained engagement, as although their participation in continuous learning (65.5%) is high, but it seems to be driven more by external requirements than intrinsic motivation.

Indeed, this group shows one of the highest levels of amotivation (90%) and low internal motivation (7%), indicating a lack of personal interest over their skills development. Their learning behaviour seems to be shaped largely by their job requirement rather than self-driven growth. While their jobs offer structured opportunities for learning, the low presence of internal motivation and SM suggests that much of this learning may be compliance-based rather than curiosity or ambition driven.

Table 8 Breakdown of job-learning environment

Job-learning environment	Alienated learners	Discouraged learners	Unmotivated learners	Indifferent learners	Goal-Oriented learners	Autonomous learners
Initial learning	5.3%	31.8%	42.8%	39.5%	35.9%	34.1%
Continuous learning	3.4%	8.3%	65.5%	39.4%	50.0%	44.4%
Helping others learn	2.5%	9.9%	35.6%	22.0%	55.5%	32.7%
Learning new things	2.2%	7.3%	34.7%	28.0%	51.4%	42.2%
Informal learning	7.0%	23.8%	45.9%	41.0%	60.8%	46.6%

Indifferent Learners (Cluster 4)

Indifferent Learners represent an interesting middle ground between compliance and engagement. Workers in this cluster show a moderate tendency for deep learning (29%), higher than the other low-motivation clusters (C1–C3), and report low amotivation (7%), which sets them apart from the more disengaged profiles. These results suggest that, while they are not highly driven by intrinsic motivation for learning, they also do not actively resist it. It may be possible that their learning engagement appears passive and situational, shaped by their JLE rather than personal ambition.

Their job-learning environment is rated as Moderate (38%), which indicates that learning opportunities exist, although their initial learning (39.5%) and informal learning participation (41.0%) are relatively substantial, their participation in helping others learn (22.0%) and learning new things (28.0%) is notably lower than that of Goal-Oriented or Autonomous learners.

This pattern suggests that, for Indifferent Learners, the workplace provides a stable but not particularly stimulating setting. The opportunities for learning are present, but perhaps not meaningful or challenging enough to foster sustained engagement or growth. In short, they possess the potential for deeper learning and growth, but the combination of moderate job learning demands and a JLE that lacks strong developmental signals may limit their active pursuit of further knowledge.

Goal-Oriented (Cluster 5) and Autonomous Learners (Cluster 6)

Both of these clusters stand out for their consistently high participation of learning at workplaces. Notably, Goal-Oriented Learners are the most likely to help others learn (55.5%) and engage in informal learning (60.8%). Autonomous Learners also report high learning opportunities, which appears to reinforce their high intrinsic motivation and strong sense of self-directed learning.

In summary, the cluster analysis reveals diverse learner profiles within the Singaporean workforce. While structural conditions such as JLE, educational qualifications and occupational roles do play a role in the level of engagement in deep learning, intrinsic motivation and the inclination toward SM emerge as decisive factors, particularly for Goal-Oriented and Autonomous Learners. The differences between these clusters underline the need for differentiated learning strategies and workplace interventions, as not all workers respond equally to the same conditions.

Three distinct learner profile

To facilitate clearer interpretation and more targeted discussion, the six learner clusters have been regrouped into three overarching categories. This consolidation not only simplifies the complexity of the cluster findings but also highlights meaningful patterns in the relationship between worker motivation and learning environment. The three new groups, *Defeated Learners*, *Nonchalant Learners*, and *Deep Learners*, reflect progressively increasing levels of learning engagement (see Table 9).

To deepen this understanding, the following section explores how these three learner groups relate to key job characteristics. While JLE is important, context of work that includes factors such as organisational trust, task variety, and knowledge demands, play a critical role in learning orientation. Examining these connections offers valuable insight into how JLE and workplace design can shape and sustain different learning behaviours through workers' MtL and SM.

Table 9 Key Characteristics of the Three Learner Groups

Learner Group	Description
Group 1: Defeated Learners (C1 & C2)	Learners who exhibit very low motivation, minimal drive for skills mastery, and poor engagement in deep learning. They typically perceive their learning environment as unsupportive, which reinforces their disengagement from deep learning.
Group 2: Nonchalant Learners (C3 & C4)	Learners with moderate motivation and some efforts toward skills mastery, but C4 reported higher deep learning engagement and lower amotivation. Although their learning environments are more supportive than Group 1, they do not fully translate this into strong learning orientation.
Group 3: Deep Learners (C5 & C6)	Learners who are highly motivated, actively pursue skills mastery, and consistently engage in deep learning. They tend to perceive their learning environments as supportive, enabling self-directed and sustained learning efforts.

Work Outcomes and Their Organisational Determinants

Table 10 below shoes that Deep Learners (C5 & C6) consistently demonstrate better work outcomes across all indicators. These include significantly higher levels of training transfer (>60%), discretionary effort (>69%) and organisational commitment (>55%). These learners also report stronger career efficacy (>53%) and satisfaction with their occupational choices (>28%). Notably, their perceived internal and external job prospects are also markedly better than other clusters, suggesting a greater sense of mobility and confidence in career progression.

These positive outcomes appear to be supported by good job design. Deep Learners are situated in roles with the highest levels of communication (53-54%), vertical and horizontal trust (>47%), and decision-making (>40%) (see Table 11). Their work content is also cognitively demanding and diverse, with high scores in task complexity, task variety, cognitive tasks, and specialist knowledge. Such roles align closely with their strong intrinsic motivation and drive for SM, reinforcing the importance of designing work that provides opportunity for learning, autonomy, and cognitive engagement.

In contrast, Defeated Learners (C1 and C2) report the weakest outcomes across all indicators. These workers exhibit low levels of discretionary effort (24–47%), poor training transfer (24–35%), minimal organisational commitment (11–24%), and very limited career efficacy (10–15%). Their internal and external job prospects are also the lowest across all clusters, with perceived internal prospect as low as 3% for C1. These clusters are also characterised by low job satisfaction (≤41%) and a high sense of job insecurity (up to 18%). These outcomes are compounded by poorly designed environments. Their jobs are typically repetitive and low in complexity, with minimal decision-making autonomy and limited communication and trust within the organisation. Such structural conditions stifle motivation and reinforce disengagement.

Table 10 Work outcomes across the 6 learner clusters

	C1 Alienated learners	C2 Discouraged learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners
Transfer of training	24	35	52	49	66	61
Discretionary effort	24	47	65	58	72	69
Organisational commitment	11	24	27	39	55	57
Internal prospects	3	10	16	19	32	31
External prospects	4	16	23	28	47	40
Job satisfaction	35	41	47	53	62	65
Occupational choice satisfaction	14	14	17	22	28	35
Risk of losing job	18	11	8	7	10	10
Career efficacy	10	15	22	32	53	60

Interestingly, Nonchalant Learners (C3 and C4) occupy a middle ground. While they report relatively strong levels of discretionary effort (65% and 58%) and job satisfaction (47% and 53%), they show weaker alignment in terms of transfer of training (52% and 49%), organisational commitment (27%

and 39%), and career efficacy (22% and 32%). Their jobs tend to be cognitively rich but lack sufficient decision-making authority, (<30%) which may explain the moderate learning orientation. These findings suggest that while job content alone may support discretionary effort and job satisfaction, it is insufficient to shift learning orientation, in terms of strengthening MtL and drive for SM, without also fulfilling the needs for autonomy and relatedness. Moreover, job satisfaction should be interpreted cautiously, as prior research shows that it does not necessarily reflect objective working conditions, particularly in constrained job contexts (Muñoz de Bustillo, Fernández-Macías, Enrique, Antón, & Esteve, 2011). In the absence of decision making and strong relational support, workers may not internalise learning as personally meaningful, thus limiting their engagement with deeper, self-directed learning.

Table 11 Organisational and job factors by the 6 learners clusters

	C1 Alienated learners	C2 Discouraged learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners
Organisational factors						
Communication	7	34	49	47	53	54
Vertical trust	7	15	20	29	47	49
Horizontal trust	8	18	25	37	53	56
Decision making	5	17	27	28	41	45
Job factors						
Tasks complexity	9	28	47	44	54	53
Repetitive tasks	84	66	64	58	63	58
Variety of tasks	27	51	71	65	77	72
Work intensity	29	54	67	63	74	70
Social tasks	8	27	44	49	63	63
Cognitive tasks	6	16	30	29	48	47
Product knowledge	37	65	78	71	82	80
Organisation knowledge	36	68	77	80	88	84
Specialist knowledge	41	73	85	82	89	86

Taken together, the findings reinforce the notion that deep learning and its associated outcomes are not merely a function of training but are rooted in the interaction between MtL and JLE. This highlights the importance of job design as a policy lever. Environments that foster autonomy, trust, and task variety can unlock greater learning orientation. Equally, the findings underscore the need to support nonchalant learners with strategies that strengthen purpose alignment and to uplift defeated learners through psychological safety, coaching, and foundational skill scaffolding.

Training Participation Across Learner Profiles

Building on the earlier analysis of work outcomes and their organisational determinants, this section examines the relationship between learner profiles and their training participation, and use of SkillsFuture Credit (SFC). While access to training is a necessary condition for workforce development, this analysis highlights that Mt, SM and JLE significantly influence whether such access translates into meaningful skill transfer and application.

Equal Access, Unequal Gains: The Role of Motivation and Mastery

Although job-related training participation is relatively comparable across Nonchalant and Deep Learners group (~53–63%), only the Deep Learners report high levels of training transfer (≥60%) that are significantly higher than Nonchalant and Defeated Learners (Table 12). This finding reinforces the finding that training participation alone is insufficient for impact. Instead, MtL and drive for SM are critical drivers of effective learning, echoing research that links intrinsic motivation with stronger workplace learning outcomes (Gagné & Deci, 2005; Noe, Clarke, & Klein, 2014).

Table 12 also shows that for non-job-related training, Autonomous Learners (C6) are significantly more participative (>45%) than other clusters (<40%), suggesting that they are proactively investing in future-proofing their skills beyond immediate job demands. This pattern signals a broader learning mindset and learning agility, which are increasingly vital in a dynamic labour market.

Influence of Learning Environment on Participation

Discouraged Learners (C2) and Unmotivated Learners (C3) illustrate the effect of JLE on training participation. Although both clusters share relatively low internal motivation (<7%) (Table 7), C3 learners report higher job-related training participation (53% vs. 33%) and training transfer (52% vs. 35%) than C2 learners (Table 12). A key differentiator lies in their perceived JLE. C3 learners report markedly more supportive learning conditions at work, with 57% rating their learning environment positively, compared to just 11% of C2 learners, providing a compelling case for how workplace learning environments can shape training behaviours

In contrast, Alienated Learners (C1), the most disengaged cluster, report both poor learning environments (7%) and the lowest job-related training participation (11%) and transfer rates (24%), reinforcing the view that the combination of low motivation and unsupportive environments severely hinders learning. On the other end of the spectrum, Deep Learners (C5 and C6), who exhibit high MtL, drive for SM and operate in supportive learning environment, consistently outperform other clusters across all training outcomes, including non-job-related training.

In short, these findings suggest that even modest improvements in workplace learning support can drive better outcomes among moderately disengaged learners.

SkillsFuture Credit Utilisation Across Learners Profiles

Patterns of SFC usage reveal stark differences across learner profiles, highlighting how both MtL, drive for SM and JLE shape not only access but also the effectiveness of lifelong learning investments. Table 12 shows that among the most engaged clusters, the Deep Learners demonstrate the highest SFC utilisation rates (C6: 20%, C5: 22%) and report strong alignment of SFC-funded training with their career development (C6: 59%, C5: 58%). These learners are both intrinsically motivated and supported by positive workplace environments, enabling them to make strategic and purposeful use of available resources to advance their skills and career progression.

In contrast, Defeated Learners (C1 and C2) show markedly lower SFC utilisation. Only 12–13% of these learners reported using their SFC, and just 24–31% reported the training relevant to their career needs. These low figures show that SFC access alone is insufficient to activate learning for these learners, and more effect is needed to stimulate use and ensure training relevance.

Nonchalant learners (C3 and C4) present a mixed picture as their SFC usage is slightly higher (14–16%), but perceived career relevance remains relatively low to moderate (C3: 38%, C4: 46%). This suggests that while these learners may be utilising the SFC, the outcomes may not always translate into meaningful career development. Without targeted guidance and support, the effectiveness of SFC in driving purposeful learning, whether for career progression or personal development, may be diminished, especially for learners with lower clarity on how learning connects to their broader aspirations.

Taken together, to maximise the impact of SFC-supported learning, equitable access must be complemented by efforts that strengthen learning orientation. Policy measures should move beyond passive credit provision and incorporate targeted interventions such as career guidance, training transfer supports, and motivational nudges. These are especially critical for less engaged segments, where building agency and linking learning to both career development and personal aspirations is essential to realising the full potential of SFC as a lifelong learning instrument.

Table 12 Training participation across profiles of learners

	C1 Alienated learners	C2 Discouraged learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners
Job-related training	11	33	53	57	63	62
Transfer of training	24	35	52	49	66	61
Non-job-related training	19	31	35	40	39	46
Use of SFC	13	12	14	16	22	20
SFC use relevant to career#	24	31	38	46	58	59

Engagement in Non-Job-Related Training

The patterns observed in non-job-related training reinforce the importance of intrinsic motivation in shaping learning behaviours. Autonomous Learners (C6) report significantly higher participation in non-job-related training at 46% than other clusters. This reflects a strong future-oriented mindset and a proactive approach to learning that extends beyond immediate job requirements. Goal-

Oriented Learners (C5) follow at a significantly lower rate of 39%, indicating purposeful engagement that is still anchored in personal growth and long-term goals.

On the other hand, Defeated Learners (C1 and C2) show much lower levels of engagement. Only 19% of C1 learners and 31% of C2 learners participate in non-job-related training. These low figures suggest a lack of learning agency and limited interest in pursuing skills that are not directly required by their jobs.

Nonchalant Learners (C3 and C4) fall somewhere in between. While 35% of C3 learners and 40% of C4 learners take part in non-job-related training, the underlying motivation appears weaker. Non-job -related training is driven by intrinsic motivation rather than external motivation or a clear desire for skills mastery or career development.

Overall, non-job-related training serves as a valuable signal of learner autonomy, individual agency, and long-term adaptability. Higher participation in non-job-related training among the more intrinsically motivated clusters illustrates the critical role of motivation and mastery orientation in sustaining lifelong learning. At the same time, lower participation among less motivated learners underscores the need for targeted interventions that build learning ownership, enhance motivation, and support more intentional engagement in both career-relevant and self-directed learning pathways.

Personal and Social Development Across Learner Clusters

This section explores broader life outcomes across learner profiles, including personal growth, community engagement, and social enrichment activities. The analysis investigates how differences in learners' learning orientation and JLE shape development beyond formal training participation. These insights help uncover how workplace and personal factors jointly contribute to lifelong learning engagement and well-being.

Life Satisfaction Is Not a Sufficient Indicator of Broader Development

Across all learner clusters, there are no significant differences in reported life satisfaction. However, this apparent parity conceals meaningful disparities in engagement with personal growth and community-oriented activities. Table 13 shows that Nonchalant Learners (C3 and C4), for instance, report moderate life satisfaction (C3: 45%, C4: 46%) and personal growth (C3: 48%, C4: 55%), yet display low participation in volunteerism (C3: 28%, C4: 31%) and community activities (C3: 11%, C4: 14%). This suggests that satisfaction alone does not translate into proactive development or social participation.

In contrast, Deep Learners (C5 and C6) consistently demonstrate the highest levels of personal and social development. Autonomous Learners (C6) lead with 68% reporting personal growth, followed closely by Goal-Oriented Learners (C5) at 62%. Their engagement in community activities (C6: 22%, C5: 18%) and volunteering (C6: 44%, C5: 40%) is significantly higher than other clusters. Additionally, Deep Learners show greater interest in learning new cultures, with 70% of C6 and 62%

of C5 participating in such activities. These patterns affirm that learning orientation support continuous self-directed development across both personal and professional domains.

At the other end of the spectrum, Defeated Learners (C1 and C2) report the lowest levels of personal growth and social engagement. Table 13 shows that only 21% of C1 and 32% of C2 indicate personal growth, while community involvement is significantly lower (C1: 6%, C2: 10%). Their limited participation in activities such as volunteering and cultural learning further signals disengagement from broader development opportunities, potentially due to both low motivation and drive towards SM.

Personal and social development outcomes are not evenly distributed across the workforce. While life satisfaction may appear similar, deeper indicators such as personal growth and community engagement highlight the role of intrinsic motivation and inclination towards SM. Policies and programmes aiming to foster holistic lifelong learning must consider not just participation, but also the depth of learner engagement and the conditions that enable broader developmental outcomes.

Table 13 Personal and Social Development Across Learner Clusters

	C1 Alienated learners	C2 Discouraged learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners
Life satisfaction	37	40	45	46	57	59
Learn new culture	21	30	37	46	62	70
Community activities	6	10	11	14	18	22
Volunteer	11	23	28	31	40	44
Personal growth	21	32	48	55	62	68

Linking Job Types and Learner Clusters

While the job and learner analyses were presented separately for clarity, they describe two interconnected dimensions of the skills ecosystem. Table 14 below brings both perspectives together by showing how the six learner clusters are distributed across the four job types. This provides an empirical view of how job conditions and learning dispositions coexist within the workforce.

Table 14 Distribution of job type by learner clusters (%)

	C1 Alienated learners	C2 Discourage d learners	C3 Unmotivated learners	C4 Indifferent learners	C5 Goal-Oriented learners	C6 Autonomous learners	Total
A	2.1	12.9	18.6	23.3	24.2	19.0	100
B	5.9	14.3	22.8	16.3	26.1	14.6	100
C	11.3	28.4	15.6	21.7	11.6	11.6	100
D	42.0	28.2	9.4	8.6	6.0	5.8	100
Total	18.8	20.3	15.7	16.2	16.6	12.5	100

The distribution of clusters across the four job types reveals a clear pattern of stratification. High-task roles (Types A and B) contain the largest concentrations of goal-oriented and autonomous deep learners (43.2% & 40.6%), suggesting that richer task environments, those with complexity, autonomy, and opportunities for judgement, are more conducive to developing and sustaining deep learning dispositions. In contrast, low-task jobs, particularly Type D, are dominated by Alienated and Discouraged clusters (70.2%), indicating that workers in routine or constrained roles have fewer opportunities to use or deepen their skills, which may dampen learning motivation over time. Type C roles, while requiring a degree, show a notably high proportion of Discouraged learners (28.4%), implying that credential-heavy but task-light jobs may not provide the stimulus necessary for meaningful learning engagement. Overall, the pattern highlights how job design shapes the kinds of learners that emerge within different parts of the labour market, reinforcing the interdependence between job structures and individual learning orientations.

Conclusion

This analysis provides a detailed and evidence-based understanding of how different types of workers in Singapore engage with learning. By integrating job-level opportunity structures with learner-level dispositions, the analysis demonstrates how job design and learning orientations jointly shape deep learning behaviours across the workforce. Drawing on validated frameworks such as Self-Determination Theory and Illeris's learning dimensions, the analysis identifies how motivation to learn, drive for skills mastery, and the job-learning environment interact to shape deep learning behaviours across the workforce.

We have used structural equation modelling to uncover the complex relationship between the different components follow by which, cluster analysis, that reveals six distinct learner profiles. These profiles reflect meaningful differences in workers' learning orientation, workplace learning environment and learning behaviours. Importantly, the findings show that deep learning and training transfer are not solely determined by participation in training. Rather, they depend significantly on internal motivation, mastery orientation, and supportive work conditions.

Key findings highlight the central role of intrinsic motivation and the drive for skills mastery in sustaining meaningful learning outcomes. The study reveals that learners with higher internal motivation and drive towards skills mastery are more likely to engage deeply, apply their skills effectively, and pursue lifelong learning. In contrast, those with low motivation often struggle to benefit from training, even when opportunities are available. The analysis also shows wide variation in the use and perceived career relevance of SkillsFuture Credit (SFC), with more engaged learners using it purposefully while others remain disconnected from its potential value. Additionally, the design of plays a significant role in enabling or constraining learning behaviours. Together, these insights point to the need for a more differentiated and learner-responsive approach to lifelong learning policy.

Ultimately, the findings underscore the need to move beyond broad-based access policies toward targeted, learner-centred strategies. For lifelong learning policies to be impactful, they must recognise the diversity of learner learning orientation and environments. This includes embedding segmentation in programme design, supporting learning-oriented job environments, and aligning learning opportunities with both career and personal development goals.

In the face of technological disruption and evolving workforce demands, building a truly inclusive learning ecosystem requires not just more training but the right conditions for deep, meaningful, and sustained learning to occur.

Summary and Interpretation of Findings

This chapter interprets the SLS2 findings through economic, sociological, and psychological lenses and integrates the two core constructs at the heart of this study: **Skills Pathway Opportunities** (job structures) and **Deep Learning Dispositions** (workers' motivation and skills mastery, shaped by job-learning environments). The discussion examines how these elements interact to influence skills development, utilisation, and mobility in Singapore's workforce.

The SLS2 evidence reinforces the idea that skills are developed and utilised within an ecosystem shaped by both opportunity structures in jobs and workers' learning orientations. Learning does not occur in isolation. Workers bring motivation and a desire for mastery to their roles, but their ability to deepen and apply skills depends heavily on the job-learning environment—including autonomy, feedback, challenge, and opportunities for application. The findings provide empirical support for the integrated theoretical framework underpinning the study. From an economic perspective, the results highlight the continued role of qualifications in signalling competence, while also revealing limits to credential-based explanations of progression. From a sociological perspective, the findings underscore the importance of job design and organisational context in shaping skills utilisation and learning opportunities. From a psychological perspective, the results demonstrate how deep learning dispositions interact with job environments to influence learning engagement and capability development. Together, the findings extend existing theory by showing how these perspectives operate jointly within Singapore's skills ecosystem.

Skills development is therefore best understood as the product of an interaction between:

- Job structures: the task complexity, autonomy, and skill-use expectations embedded in work; and
- Learning dispositions: motivation and skills mastery orientation, shaped by the supportiveness of the job-learning environment.

This ecosystem framing emphasises that both sides must align for skills to translate into capability, performance, and progression.

Economic Perspective: Uneven Skills-Use Opportunities Across Job Roles

From an economic perspective, SLS2 highlights substantial variation in the extent to which different job roles enable workers to use and extend their skills. Jobs with higher task complexity and autonomy offer richer opportunities for deepening skills and engaging in higher-order work.
While the data does not suggest widespread underutilisation of capability, it does point to uneven opportunity structures. Many mid-level and routine roles offer limited avenues for skill application, and this constrains the degree to which motivated workers can grow. In contrast, high-opportunity jobs amplify capability and unlock deeper learning.

These patterns underscore the importance of job design and task structure in shaping long-term productivity and human capital development.

Sociological Perspectives: The Continued Role of Qualifications

SLS2 findings also highlight the persistence of qualifications as important labour market signals. Higher-opportunity jobs are more likely to specify degree requirements, and wage models indicate enduring educational premiums.

At the same time, skills-based pathways are emerging, particularly in technical, specialised, and practice-oriented domains. However, these pathways remain narrower compared to qualification-led routes.

The findings suggest that Singapore functions within a balanced system, where qualifications continue to play a meaningful role, and skills recognition is gaining importance. There is no strong evidence of credential inflation, but ongoing monitoring is needed to ensure that expanded higher education opportunities do not inadvertently constrain skills-based mobility.

Psychological Perspective: Learning Dispositions Influenced by Job-Learning Environments

The SLS2 analyses show that workers’ motivation and skills mastery orientation, the two core components of Deep Learning Dispositions, are strongly associated with skills transfer, performance, and career confidence.

Crucially, these dispositions are shaped by the job-learning environment. Workers exhibit stronger dispositions when they experience:

- autonomy and meaningful challenge,
- opportunities to apply learning,
- constructive feedback and mentoring, and
- supportive workplace cultures that encourage growth.

Motivation and skills mastery do not function independently of job context. Instead, the job-learning environment acts as a key enabler (or inhibitor) that strengthens workers’ capacity to learn deeply and apply skills effectively.

Alternative Theoretical Perspectives

While the findings are broadly consistent with human capital perspectives (Becker, 1964), they also offer an implicit critique of the stronger assumptions associated with Becker’s formulation of human capital theory, which posits a relatively direct link between skill acquisition and labour market returns. The results show that learning dispositions and skills alone are insufficient to generate returns unless they are embedded within jobs that allow for recognition, discretion and skill utilisation. In this sense, the study aligns with growing international critiques of skills policies that emphasise supply-side investment without sufficient attention to demand-side and institutional mediators of skill value (OECD, 2019; Brown, Lauder, & Ashton, 2011).

An alternative and complementary framing of the findings can be offered through the Ability–Motivation–Opportunity (AMO) framework (Appelbaum, Bailey, Berg, & Kalleberg, 2000). The study's core constructs map closely onto this approach: skills mastery orientation reflects ability, motivation to learn captures motivational resources, and the job learning environment represents opportunity. From this perspective, the findings reinforce the AMO proposition that performance and development outcomes emerge not from any single dimension, but from their interaction. In particular, the results suggest that opportunity which is operationalised here through job design and learning environments, plays a critical enabling role, helping to explain why similar levels of motivation and skill can yield divergent outcomes across jobs.

The strong association between job learning environments and deep learning outcomes also raises the possibility that organisational form may act as an intervening variable. Research on learning organisations highlights how systems-level features, such as shared vision, continuous improvement norms, and distributed decision-making, shape learning opportunities beyond individual job roles (Senge, 1990). Conversely, studies of Taylorism and control-oriented work organisations emphasise how narrow task design and limited discretion constrain learning and skill utilisation (European Foundation for the Improvement of Living and Working Conditions, 2009). While the present study focuses on job-level conditions, the findings are consistent with these organisational theories and suggest that future research could examine whether organisational type moderates the relationship between job design and deep learning.

Integrating the Two Lenses: Alignment Between Job Opportunities and Learning Dispositions

When we bring the job and learner perspectives together, a clear insight emerges skills development is most effective when job structures and learning dispositions are aligned.

- Motivated workers with strong mastery orientation grow fastest in roles that provide challenge, autonomy, and opportunities for application.
- Workers in routine roles, regardless of motivation, face structural limits on capability growth.
- Supportive job-learning environments strengthen learning orientations, encouraging deeper engagement with skills.

This alignment is central to understanding how capability develops and how skills can be mobilised within Singapore's workforce.

Taken together, SLS2 findings point to opportunities for strengthening Singapore's skills ecosystem:

- Job structures vary widely in their ability to support deeper learning and skill utilisation.

- Qualifications remain important signals, but skills-based recognition pathways are growing in relevance.
- Motivation and skills mastery matter for skill transfer and performance, yet they are profoundly shaped by job-learning environments.
- Alignment between opportunity structures and learning dispositions is essential for developing and retaining capability.

These insights form the foundation for the strategic levers outlined in the Implications chapter: balancing skills and qualifications, enhancing job design and skill utilisation, and building workforce deep learning capacity.

Implications

Singapore's skills ecosystem is shaped by an interplay of actors and institutions, in which workers' learning dispositions, the opportunity structures and learning environments embedded in jobs play a central role. The SLS2 findings show that both matter: workers bring different levels of motivation and mastery orientation, while jobs vary in the extent to which they support skill application, autonomy, and deeper skills development. Strengthening this alignment across the system is essential for supporting productivity, capability growth, and equitable opportunity in the labour market.

While several of the patterns observed in this study are consistent with earlier research on job quality, learning, and skills utilisation, the findings add to a growing weight of evidence by showing how these relationships operate jointly within Singapore's skills ecosystem.

The implications below are organised around three strategic levers for strengthening Singapore's skills ecosystem, with targeted actions for policymakers, employers, training providers, and learners.

Strengthen Skills Recognition while Maintaining a Balanced Role for Qualifications

The findings highlight that while learning dispositions and workplace capability matter, formal qualifications continue to play a strong signaling role, even where job task requirements and skills utilisation differ little. Rather than advocating a shift away from qualifications, the evidence points to a need for a balanced approach where both demonstrated skills and relevant credentials contribute to hiring and progression decisions.

The analysis shows that skills and qualifications are frequently conflated in practice. This study's contribution lies in demonstrating how this conflation interacts with job design and learning dispositions to shape progression outcomes, rather than treating credential effects in isolation. As a result, workers who develop skills through work-based learning or non-linear pathways may experience constrained progression despite possessing relevant capabilities. Over-reliance on credentials can therefore narrow skills-based pathways and contribute to inefficient skills utilisation.

Implications across the ecosystem

Responsibility for strengthening skills recognition is shared across key stakeholders.

Policy-makers shape signaling norms and incentive structures by refining qualification and skills frameworks and encouraging recognition of demonstrated skills alongside formal credentials. Singapore has foundational mechanisms for recognising work-demonstrated skills, such as Recognition of Prior Learning (RPL), competency-based assessments in Career Conversion Programmes, and the Skills Passport, though uptake varies across sectors. Monitoring qualification trends among younger cohorts to ensure expanded educational attainment does not unintentionally narrow skills-based pathways.

Employers determine how skills are recognised and rewarded in practice, including hiring, progression, and pay decisions, and how skills utilisation is valued relative to credentials. Employers can implement structured ways to assess and recognise employees' work-performed skills by leveraging existing tools such as Workplace Skills Recognition (WPSR), Skills Framework–aligned competency matrices, and task-based assessments. These approaches complement qualification requirements and support competency-based progression.

Training providers can support this shift by articulating learning outcomes in employer-relevant terms, supporting workplace-based assessment, and aligning programmes with job roles and progression pathways. It is important to ensure that there is closer alignment between training outcomes and workplace skill requirements.

Learners play an active role by demonstrating skills in the workplace, engaging in opportunities for skills validation, and making informed choices about how training and credentials support their career development. Learners can leverage existing tools such as the Skills Passport to document applied skills and work achievements, build simple work portfolios that capture project-based contributions, and request supervisor attestations to complement formal credentials with evidence of capability.

A more balanced approach to skills recognition is expected to:

- reduce reliance on credential escalation as the primary route to progression;
- improve alignment between skills developed through work and skills recognised by employers; and
- support more inclusive and flexible skills-based pathways across the workforce.

Improve Job Design and Skills Utilisation Opportunities

The SLS2 data shows that opportunities for deep learning and skill utilisation vary widely across roles. Jobs offering higher task complexity, autonomy, and problem-solving demands enable workers to translate learning dispositions into performance and capability. Redesigned jobs would provide workers with greater task discretion, autonomy, and opportunities for problem-solving, alongside structured opportunities for informal learning, collaboration, and feedback. Jobs would be designed to enable skills utilisation and development over time rather than narrowly defined task execution.

The findings show that while job content alone may support discretionary effort and reported job satisfaction, it is insufficient to shift learning orientation or strengthen deep learning dispositions without autonomy, decision-making authority, and relational support. Poorly designed jobs therefore constrain skills utilisation and weaken the impact of training investments. While the cross-sectional design does not allow causal direction to be fully established, the convergence of these findings with prior research strengthens confidence in the policy relevance of job design as a key lever.

Implications across the ecosystem

Responsibility for learning-oriented job redesign is distributed across the skills ecosystem.

Policy-makers play an enabling role by shaping incentives, guidelines, and capability frameworks that encourage learning-oriented job design and signal the importance of skills utilisation, not just training participation. It is important to support organisations in reviewing workflows and task structures to identify where opportunities for skill utilisation can be enhanced. Encourage job redesign that raises cognitive challenge in suitable roles, particularly in mid-level occupations. While programmes such as the Productivity Solutions Grant for Job Redesign (PSG-JR) provide an important foundation, their adoption remains uneven. The potential for deeper skill-utilisation redesign is emerging, but not yet widespread across firms or sectors.

Employers are the primary agents of job redesign, responsible for reshaping task allocation, expanding autonomy and decision-making authority, and embedding learning opportunities within roles. Employers can create pathways for employees to apply and grow their skills through stretch assignments, expanded responsibilities, and greater decision-making autonomy. Many organisations already provide such opportunities through job redesign efforts, CCP on-the-job training structures, and internal development programmes. Building on these existing practices can further strengthen employees' opportunities for skill application and capability growth.

Training providers support redesign by aligning learning provision with evolving job roles and collaborating with employers to embed training into work processes rather than delivering it as a stand-alone intervention. Workplace-relevant and application-oriented learning is already embedded in many WSQ and sectoral programmes. Strengthening project-based assessments, workplace simulations, and transfer-focused follow-up can deepen impact.

Learners can leverage existing opportunities such as project participation, cross-functional collaborations, workplace improvement initiatives, and tools like the Skills Passport to document and extend their skills application.

Learning-oriented job redesign is expected to:

- improve skills utilisation and training transfer;
- strengthen intrinsic motivation and skills mastery orientation; and,
- increase returns on training investments, and support more sustainable and inclusive skills-based progression pathways.

Build Workforce Deep Learning Capacity

Deep learning dispositions, motivation, mastery orientation, persistence, and confidence, are shaped by job contexts, feedback environments, and organisational culture. Strengthening these dispositions by making learning as an integral part of work rather than an episodic activity is an important lever for capability development.

The findings demonstrate that access to training alone does not guarantee learning impact. Deep learning dispositions interact with job environments to shape how learning is internalised and applied.

Without supportive environments, even motivated workers may struggle to sustain engagement and transfer learning to practice.

Implications across the ecosystem

Responsibility for building deep learning capacity is shared across stakeholders:

Policy-makers can support deep learning through funding models, guidance, and capability frameworks that emphasise learning quality, adaptability, and long-term employability rather than participation metrics alone. Invest in adult educator capability-building programmes that equip AEs with pedagogies fostering deep learning (e.g., metacognitive strategies, reflective practice). Track deep learning indicators in future SLS waves to monitor changes in the workforce.

Employers influence deep learning capacity through job design, management practices, and workplace culture, including support for reflection, experimentation, and learning from experience. Build learning-supportive environments through structured feedback, mentoring, guided learning, and psychologically safe spaces for experimentation and stretch tasks. Employers can tap on existing initiatives such as Work-Study Programmes (WSP), Company-Led Training (CLT), and workplace learning support offered by IAL to strengthen these practices. These programmes provide structured frameworks for supervisor feedback, mentoring, and the safe application of new skills. While such elements are present in existing schemes, the depth and consistency of learning-supportive practices still vary across firms.

Training providers play a critical role by designing learning experiences that emphasise reflection, application, and problem-solving, and by supporting trainers to adopt pedagogies that promote deep learning. Use pedagogical approaches that cultivate deep learning habits, such as reflective activities, application across contexts, and strengthening learners' self-belief in their ability to learn and apply skills. Many TPs and AEs already incorporate elements of these practices through WSQ's application-oriented assessment requirements and IAL-trained pedagogical approaches, though the depth and consistency of implementation vary across providers.

Learners remain central actors by cultivating motivation to learn, engaging in self-directed learning, and actively applying learning to new and challenging work contexts. Learners need to understand their learning profiles and adopt strategies that build deep learning habits. Learners can access tools on MySkillsFuture, seek guidance from WSG and e2i career coaches, participate in reflective learning activities offered by many training providers, and draw on workplace feedback and mentoring to better understand their strengths and learning needs.

Strengthening deep learning capacity is expected to:

- improve learning transfer and skills retention,
- enhance adaptability and resilience in the face of technological change; and,

- support lifelong learning habits, and contribute to a more responsive and future-ready workforce.

The findings and implications in this report are based on data collected in 2021 as part of the Skills and Learning Survey (SLS2). While this introduces a time lag between data collection and reporting, the analysis focuses on structural relationships between job design, skills utilisation, and learning dispositions that tend to evolve incrementally rather than rapidly. These features of work remain central to workforce development and lifelong learning. If anything, ongoing technological change and the increasing adoption of AI are likely to have heightened the importance of learning-intensive job design and deep learning capacity. The findings therefore provide a robust and policy-relevant evidence base for informing current and future workforce initiatives.

Strengthening Singapore’s skills ecosystem requires coordinated progress on multiple fronts: recognising skills alongside qualifications, redesigning jobs to enable deeper skill utilisation, and building workforce learning capacity. Addressing these levers in isolation is unlikely to yield sustained impact; their alignment determines whether skills are effectively developed, recognised, and mobilised in a changing economy.

Conclusion

This study provides an integrated view of how skills are developed, applied, and rewarded in Singapore's labour market by examining both the structure of jobs and the learning orientations of workers. The findings show that high-task, skills-intensive jobs offer richer environments for autonomy, learning, and capability development, yet returns to these skills continue to be shaped by qualification requirements that remain important labour market signals. Skills-based pathway jobs (Type B jobs) demonstrate productive potential but yield comparatively weaker wage and progression outcomes, reflecting the continued influence of established credential norms.

At the same time, deep learning dispositions, centred on motivation and skills mastery and shaped by the job-learning environment, are more prominent in high-task roles and strongly influenced by workplace conditions. This underscores the central role of job design and learning-supportive environments in enabling workers to deepen and apply their skills.

Taken together, the findings highlight the importance of strengthening alignment across Singapore's skills ecosystem. Workers' dispositions support long-term adaptability, skill transfer, and collaboration, while job structures determine the extent to which these dispositions can be expressed and developed. A resilient, productive, and inclusive workforce therefore requires coordinated action across job design, learning environments, and organisational practices, ensuring that workers can develop meaningful skills, and that these skills can be effectively recognised and mobilised in the labour market.

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Appendix A: Survey Items used in Analysis

‘Do’ requirement: whether the job has high task requirements			
		In your job, how important is …?	
Cognitive	Reading	Reading written information such as forms, notices or signs	- Essential - Very important - Fairly important - Not very important - Not at all important/ does not apply
	Reading	Reading short documents such as short reports, letters or memos	
	Reading	Reading long documents such as long reports, manuals, articles or books	
	Writing	Writing material such as forms, notices or signs	
	Writing	Writing short documents (for example, short reports, letters or memos)	
	Writing	Writing long documents with correct spelling and grammar (for example, long reports, manuals, articles or books)	
	Numeracy	Adding, subtracting, multiplying or dividing numbers	
	Numeracy	Calculations using decimals, percentages or fractions	
	Numeracy	Calculations using more advanced mathematical or statistical procedures	
	Analysing	Analysing complex work-related problems in depth	
	Planning own work	Planning your own activities	
	Paying attention to details	Paying attention to details	
Social	Dealing with people	Dealing with people	
	persuading or influencing others	Persuading or influencing others	
	giving speeches and presentations	Giving speeches or presentations	
Task complexity			
	Complex problem solving	In your job, how often are you confronted with new or complex problems that take at least 30 minutes to find a good solution? Only consider the time needed to THINK of a solution, not the time needed to carry it out.	- More than five times a week - Two to five times a week - Once a week - Less than once a week

			- Neve
		In your job, how often do you usually…	
	digital complexity	use email?	- Everday - At least once a week but not everyday - Less than once a week but at least once a month - Less than once a month - Never
	digital complexity	use the internet in order to better understand issues related to your work?	
	digital complexity	conduct transactions on the internet, for example buying or selling products or services, or banking?	
	digital complexity	use spreadsheet software, for example Excel?	
	digital complexity	use a word processor, for example Word?	
	digital complexity	use a programming language to program or write computer code?	
	digital complexity	participate in real-time discussions on the internet, for example online conferences, or chat groups?	
	digital complexity	use data analytics to support operational and decision-making processes?	
	digital complexity	use specialised software to deliver professional tasks, for example computer-aided design, sound and images, or quality control?	
	continuous learning	How much continuous learning is normally expected in your job every year?	- Very little or negligble - A few days - More than a few days but less than 2 weeks - More than 2 weeks but less than 1 month - More than 1 month but less than 2 months - More than 2 months but less than 3 months - More than 3 months

	task variety	To what extent does your job require the performance of a wide range of tasks	- A great deal - Quite a lot - To some extent - A little - Not at all
	managerial and supervisory duties	Do you supervise other employees? Do you have other managerial duties?	- Yes - No
		How much influence do you <u>personally</u> have on…?	
Task discretion		… deciding how hard you work?	- A great deal - A fair amount - Not much - Not at all
		… deciding what tasks you are to do?	
		… deciding how you are to do the task?	
		… deciding the quality standards to which you work?	
Get' requirement: whether the job requires a degree to get			
Qualification		If they were applying today, what qualifications, if any, would someone need to **<u>GET</u>** the type of job you have now?	- No formal qualification/ Pre-primary/ Lower primary - Primary (PSLE or equivalent) - Lower secondary (without a GCE 'O'/ 'N' Level pass or their equivalent) - Secondary ('O'/ 'N' Level or equivalent) - Post-secondary (non-tertiary): General ('A' level or equivalent) - Post-secondary (non-tertiary): Vocational (ITE) - Polytechnic diploma - Professional qualification and other diploma

			- Bachelor's or equivalent - Postgraduate diploma/ Certificate (excluding Master's and Doctorate) - Master's or equivalent - Doctorate or equivalent
Self-determinant Theory			
		To what extent do you agree or disagree with the following statements?	-
SDT	Amotivation	I don't see why I should have to learn	- Strongly disagree - Disagree - Agree - Strongly agree
	Amotivation	I don't see the point in learning	
	Amotivation	I think learning is a waste of time	
	External regulation	I learn because other people say I should	
	External regulation	I learn because others will not be pleased with me if I don't	
	External regulation	I feel under pressure from my friends/family/work colleagues to learn	
	Somewhat external regulation	I feel guilty when I don't learn	
	Somewhat external regulation	I feel ashamed when I miss a learning session	
	Somewhat external regulation	I feel like a failure when I haven't learned in a while	
	Somewhat internal regulation	I value the benefit of learning	
	Somewhat internal regulation	It's important to me to learn regularly	
	Somewhat internal regulation	I think it is important to make the effort to learn regularly	
	Somewhat internal regulation	I learn because it is consistent with my life goals	
	Somewhat internal regulation	I consider learning to be part of my identity	

	Somewhat internal regulation	I consider learning a fundamental part of who I am	
	Intrinsic motivation	I enjoy my learning sessions	
	Intrinsic motivation	I find learning a pleasurable activity	
	Intrinsic motivation	I get pleasure and satisfaction from participating in learning	
Skills Master			
SM		How true is each of the following statements for you?	-
		I aspire to be so good at what I do so that my expert advice will be sought continually	- Never true of me - Occasionally true of me - Often true of me - Always true of me
		I am most fulfilled in my work when I am able to use my skills and talents.	
Job learning environment			
JLE	Learning new things	How often does your job require you to keep learning new things?	- Always - Often - Sometimes - Rarely - Never
	Help others learn	*How much do you agree or disagree with the following statement?* My job requires that I help my colleagues to learn new things	- Strongly disagree - Disagree - Agree - Strongly agree
		In <u>the last 12 months</u>, how often have you done any of these types of training or learning related to your <u>**current**</u> job?	
	Informal learning	Learn new work-related things from co-workers or supervisors	- Everday - At least once a week but not everyday - Less than once a week but at least once a month
	Informal learning	Learning-by-doing from the tasks you perform	

			- Less than once a month - Never
	Continuous learning	(See above)	
	Initial learning	How long did it take for you, after you first started doing this type of job, to learn to do it well?	- Less than 1 week - Less than 1 month - 1 month and over, up to 3 months - 3 months and over, up to 6 months - 6 months and over, up to 1 year - 1 year and over, up to 2 years - 2 years and over
	Task discretion	(see above)	
Deep learning			
Deep learning		How true is each of the following statements for you?	
		I am good at thinking of unusual ways to do things	- Never true of me - Occasionally true of me - Often true of me - Always true of me
		I am better than most people are at trying to find out things I need to know	
		If there is something I want to learn, I can figure out a way to learn it	
		If I discover a need for information that I don't have, I know where to go to get it	
- Additional outcome measures used in cluster profiling			
Work outcomes	Training transfer	Would you say that the training or learning has improved your skills …	- Yes - No
	Discretionary effort	How much effort do you put into your job beyond what is required? Is it...	- A lot - Some

			- Only a little - None
	Organisational commitment	I am willing to work harder than I have to in order to help this organisation succeed.	- Strongly disagree - Disagree - Agree - Strongly agree
		I feel very little loyalty to this organisation.	
		I find that my values and the organisation's values are very similar.	
		This organisation really inspires the very best in me in the way of job performance.	
		I am proud to be working for this organisation.	
		To what extent do you agree or disagree with the following statements? Over time, my job provides opportunities for…	
	Internal prospect	Increases in pay	- Strongly disagree - Disagree - Agree - Strongly agree
		Increases in managerial responsibility	
		Increases in job scope	
		Thinking of your current job, to what extent do you agree to the following…	
	External prospect	Your job provides work experiences that make you more marketable	- Strongly disagree - Disagree - Agree - Strongly agree
		Your job provides educational experiences that make you more marketable	
		Your resume improved as a result of having this job	
	Job satisfaction	All in all, how satisfied are you with your job?	- Completely satisfied - Very satisfied - Fairly satisfied - Neither satisfied nor dissatisfied - Fairly dissatisfied - Very Dissatisfied - Completely dissatisfied

	Job security	How likely is it that you will lose this job in the next 12 months?	- Very likely - Likely - Unlikely - Very unlikely - Not likely at all
		To what extent do you agree with the following statements?	
	Career efficacy	When I make plans for my career, I am confident I can make them work.	- Strongly disagree - Disagree - Agree - Strongly agree
		If I can't do a job the first time, I keep trying until I can	
		When I have something unpleasant to do that will help my career, I stick with it until I am finished	
		When I decide to do something about my career, I go right to work on it	
		When trying to learn something new on my job, I soon give up if I am not initially successful	
		I avoid trying to learn new things that look too difficult to me	
		I rely on myself to accomplish my career goals	
		I do not seem capable of dealing with most problems that come up in my career	
		At your workplace, does management hold meetings in which you can express your views about what is happening in the organisation? If yes, At these meetings can you express your views about…	
Organisational factors	Communication	The financial position of the organisation	- Yes - No
	Communication	The investment plans of the organisation	
	Communication	Planned changes in working practices	
	Communication	Planned changes in products or services	
	Communication	Health and safety issues	
	Communication	Training plans	
	Communication	Planned changes for performance improvement	
	Communication	Introducing automation	

		Thinking about your feelings towards the organisation you work for, to what extent do you agree or disagree with the following statements.	
	Vertical trust	Employees involved in the implementation of the project are informed about the stages of the project.	- Strongly disagree - Disagree - Agree - Strongly agree
		My employer/manager is interested in my needs and problems, if they occur.	
		Overall, my employer/manager keeps their promises.	
		I believe that the motives and intentions of my employer/manager are good.	
	Horizontal trust	I can get advice from my colleagues about troubles or concerns I have with my work.	
		I am confident that my colleagues wish me well.	
		I am certain that I would get help from my colleagues.	
		I am confident about the honesty of my colleagues	
	Decision making	*How true would you say each of the following statements is about your job?* My job allows me to take part in making decisions that affect my work.	- Very true - True - Somewhat true - Not at all true
		In your job, how important is …?	
	Product knowledge	Knowledge of particular products or services	- Essential - Very important - Fairly important - Not very important - Not at all important/ does not apply
	Organisation knowledge	Specialist knowledge or understanding	
	Specialist knowledge	Knowledge of how your organisation works	
Training	Job-related/ non-job-related training	About how much of this time was spent on activities that were job-related?	- All of the time - More than half o the time - Up to half of the time - Up to quarter of the time

			- None of the time
	Use of SkillsFuture Credit	Has any of your training or learning that happened in the last 12 months been funded or partially funded by SkillsFuture Credit?	- Yes - No
	SFC use relevant to career	To what extent is the training subsidized by SkillsFuture Credit relevant to your career development?	- A great deal - Quite a lot - To some extent - A little - Not at all
Life outcomes	Life satisfaction	Overall, how satisfied are you with life as a whole these days?	- Completely satisfied - Very satisfied - Fairly satisfied - Neither satisfied nor dissatisfied - Fairly dissatisfied - Very Dissatisfied - Completely dissatisfied
	Learn new culture	*To what extent do you agree or disagree with the following statement?* You spend time learning about other cultures	- Strongly disagree - Disagree - Agree - Strongly agree
	Learn new culture	To what extent would you be willing to learn a new language or improve your command of another language?	- A great deal - Quite a lot - To some extent - A little - Not at all
		How often did you engage in the following activities in <u>the past 12 months</u>?	
	Community activities	Took part in activities organised by your community (e.g. community centers, religious organisation etc.).	- Everday - At least once a week but not everyday
	Volunteer	Did voluntary work, including unpaid work for a charity, political party, trade union or other non-profit organisation	

	Personal growth	Engaged in recreational activities such as craft, music, art, etc.	- Less than once a week but at least once a month - Less than once a month - Never