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AI TRENDS FOR A PRODUCTIVE AND INCLUSIVE AI TRANSITION

Singapore before Generative AI

Augmentation, Degradation and the Shades in Between

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Pre-Generative AI trends (2017 – 2022)

Executive summary

The question is no longer how fast Singapore adopts technology. It is whether technology creates better work.

As Singapore enters the generative-AI era, the national challenge is to translate technological transformation into better jobs, stronger capabilities and more broadly shared wage gains. This study establishes a pre-generative-AI baseline using Singapore's only nationally representative job-task panel data from 1,732 jobholders observed in 2017 and 2022, including 1,066 who remained with the same employer. By tracking technological adoption, job tasks and wages over time, it reveals both worker outcomes and the organisational contexts associated with them.

1 Digital gains were concentrated at the top

Digital use was widespread by 2022: 86% used basic tools, 59% intermediate applications and 18% advanced programming or coding. Yet increasing digital complexity was concentrated among managers, professionals, and technicians and associate professionals. Managers experienced the broadest gains in complex tasks; professionals saw more selective gains; and technicians and associate professionals faced declining analytical requirements even as digital demands increased. Lower-skilled occupations saw no significant digital deepening.

Patterns of digital and tasks gains in occupations (2017-2022)

Occupation	Digital demands	Task gains
Managers	↑ **Increased digital complexity**	**Broad gains** in complex tasks
Professionals	↑ **Increased digital complexity**	**Partial gains** in complex tasks
Technicians & associate professionals	↑ **Increased digital complexity**	**Decline** in analytical tasks
Other occupations (e.g. clerical, service and sales, production and transport)	— No significant increase	**No or limited gains**

WHAT THIS MEANS

Digital adoption does not lead directly to job upgrading, and may even weaken jobs. Deliberate strategies to enrich work are needed.

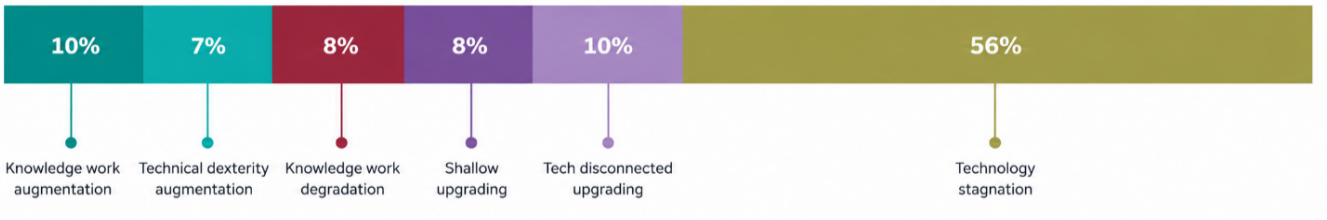
2 Technology opened two routes to augmentation—and one to degradation

Two augmentation pathways covered 17% of workers: knowledge-work augmentation (10%), associated with AI, machine learning and data analytics; and technical-dexterity augmentation (7%), associated more strongly with computerised and automated equipment. The latter produced the broadest growth across cognitive, social, judgement and physical task requirements.

But knowledge-work degradation affected another 8% of workers. Here, similar AI and data-intensive technologies accompanied rising digital complexity but which led to 'containerisation' of work as collaboration tasks declined while quality standards with technology stagnated. All pathways of augmentation and degradation are associated with high business innovation. This signals that sophisticated technology and business innovation can coexist with narrower work.

The wider challenge is the limited reach of augmentation. Nearly three-quarters of workers experienced shallow upgrading (8%), technology-disconnected upgrading (10%) or technology stagnation (56%). These pathways were associated with low-to-moderate business innovation.

Six technology-jobs pathways (2017-2022)



WHAT THIS MEANS

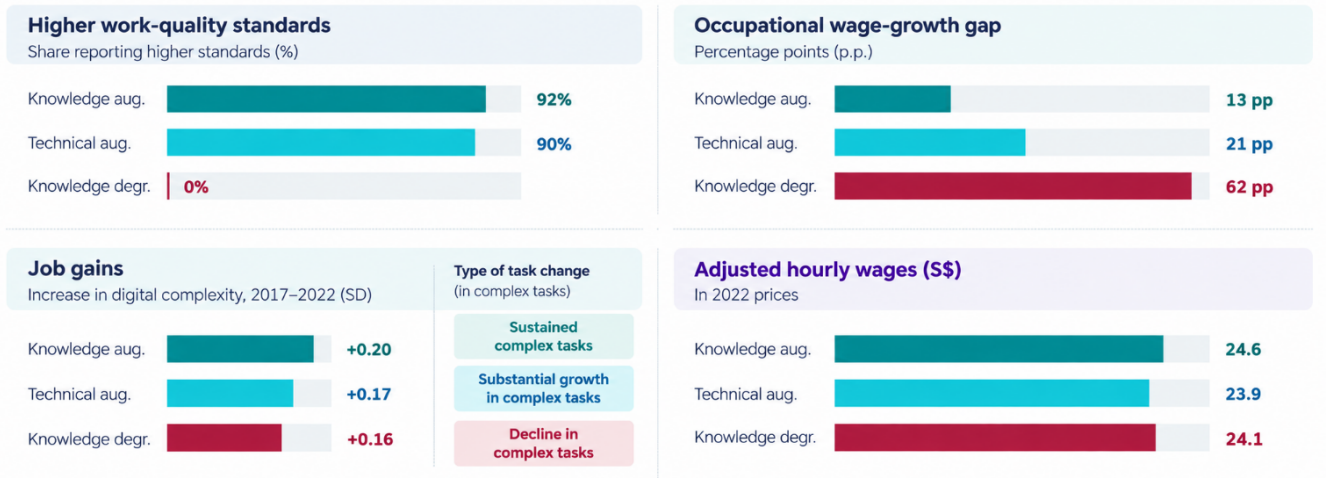
Singapore should pursue cognitive and physical AI for augmentation gains, while watching for cognitive degradation of work and non-elevation of technical work. Identifying business strategies that augment is central.

3 Augmentation offers a credible shared-gains proposition

In both augmentation pathways, more demanding work was accompanied by improved work-quality standards: 92% of knowledge-work and 90% of technical-dexterity workers reported higher standards following technological change. Wage gains were also more evenly distributed across occupations: the gap was 13 percentage points in knowledge-work augmentation and 21 points in technical-dexterity augmentation, compared with 62 points in knowledge-work degradation.

Adjusted hourly wage levels were broadly comparable across pathways, despite richer task requirements in the augmentation groups. This is consistent with more productive use of workforce capabilities without a large wage-cost premium, although the study does not directly measure firm productivity or profits. Conventional markers of good jobs were also unreliable: foreign large enterprises were relatively prominent in degradation. Local SMEs were prominent in technology stagnation, while there are no clear trends for large local enterprises.

Associations with augmentation and degradation in work (2017-2022)



WHAT THIS MEANS

Augmentation shows clear signs of delivering shared gains for firms and workers. The priority is to identify the business contexts that enable these gains.

THE POLICY FRONTIER: Augmentation by design

The central finding is that technology does not lead to job upgrading. Enterprise strategies, work organisation and the development of human capabilities shape whether technology enlarges, narrows or leaves jobs unchanged. Risks of knowledge-work degradation increase with AI adoption as larger, well-resourced and high innovation firms embrace AI. Yet, nearly three-quarters of workers were in pathways characterised by limited upgrading or no reported technology-driven change. Simply accelerating adoption will not be enough.

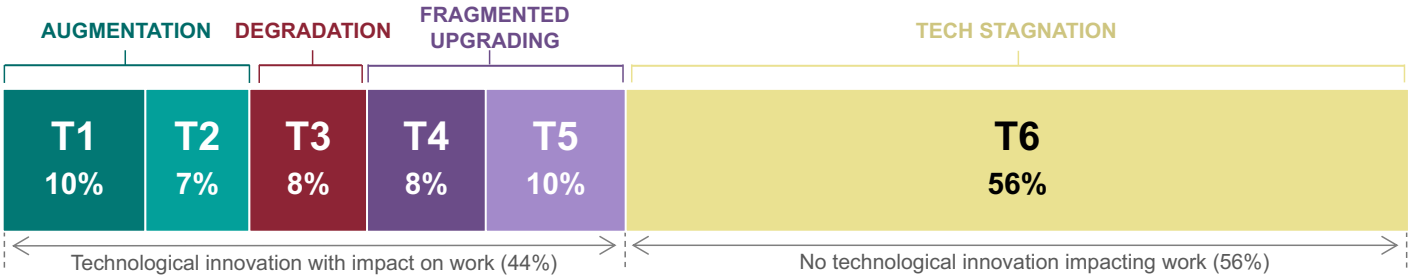
A national augmentation strategy should connect technology investment to specific types of business innovation that deliver quality enterprise outcomes and better jobs. Building up the business case for augmentation with AI is key.

STEER	DISCOVER	OBSERVE
Align funding support with credible business and workforce outcomes.	Identify, test and diffuse enterprise practices that create quality business outcomes and richer jobs.	Track actual job-task, wage and business outcomes longitudinally.

A third wave of the longitudinal study would make it possible to examine generative-AI-era changes and select enterprises for deeper investigation of the strategies behind augmentation.

Figure A. Six Clusters of Technological Change in Singapore

SIX CLUSTERS OF TECHNOLOGICAL CHANGE



	T1 **Knowledge-work augmentation**	T2 **Technical-dexterity augmentation**	T3 **Knowledge-work degradation**	T4 **Shallow upgrading**	T5 **Tech-disconnected upgrading**	T6 **Technology stagnation**
Self-reported tech impact on work	▲ Task complexity ▲ Task discretion ▲ Task variety ▼ Task repetition ▲ Quality standards	▲ Task complexity ▲ Task discretion ▲ Task variety ▲ Task repetition ▲ Quality standards	▲ Task complexity ▼ Task discretion ▲ Task variety — Task repetition — Quality standards	— Task complexity ▲ Task discretion — Task variety — Task repetition ▲ Quality standards	— Task complexity — Task discretion — Task variety — Task repetition — Quality standards	No technology impact
Actual job-task trajectory 2017–2022	**Knowledge-intensive task enrichment** Highest task requirements ▲ Digital complexity ▲ Continuous learning ▲ Decision-making (modest)	**Technical-intensive task enrichment** Strongest growth in task requirements ▲ Digital complexity (modest) ▲ Continuous learning ▲ Dexterity ▲ Strength ▲ Decision making ▲ Complex problem-solving (modest) ▲ Persuading & influencing (modest)	**Knowledge-intensive task degradation** Decline in social task requirements ▲ Digital complexity (modest) ▼ Collaboration	**Mixed patterns in task enrichment** Moderate task requirements ▲ Digital complexity (modest) ▲ Dexterity ▲ Continuous learning (modest) ▼ Decision-making (modest)	**Non-technology-led task enrichment** Moderate task requirements – Digital complexity ▲ Continuous learning ▲ Decision-making (modest) ▲ Persuading & influencing (modest) ▲ Dexterity (modest)	**Stagnating jobs** Lowest task requirements – Digital complexity ▲ Continuous learning (modest) ▲ Dexterity (modest)
Innovation context	**High** adoption of AI/ML and data analytics + **High** business innovation	**High** adoption of computerised/ automated equipment + **High** business innovation	**High** adoption of AI/ML and data analytics + **High** business innovation	**Moderate** adoption of computerised/ automated equipment + **Moderate** business innovation	**Moderate** adoption of computerised/ automated equipment + **Moderate** business innovation	No adoption of new technology + **Low** business innovation
Wage growth						
2017-2022	+16% growth	+21% growth	+11% growth	+29% growth	+13% growth	+13% growth
Occupational distribution	Uniform (13pp gap)	Uniform (21pp gap)	Highly dispersed (62pp gap)	Highly dispersed (71pp gap)	Moderately dispersed (39pp gap)	Uniform (20pp gap)
Worker profile	Degree holders; PMEs	TAPs	Degree holders; TAPs	Diploma holders	TAPs, clerical support workers	Below diploma; production & related workers
Firm profile	Foreign-owned SMEs	No clear trend	Foreign-owned large enterprises	No clear trend	No clear trend	Local SMEs

Source: SLS 2017–2022 longitudinal sample, same-employer workers (n = 1,066).

1. Before Generative AI: Establishing the Baseline

The next frontier in Singapore's artificial intelligence journey is ensuring that workers advance with it.

Artificial intelligence (AI) presents Singapore with an opportunity to sustain its economic relevance in an AI-driven world. The city-state has set its sights to cultivate a comparative advantage as an effective, responsible and fast adopter of AI in the speed and scale that it can turn advances at the technological frontier into trusted and commercially valuable AI applications across the economy (Ministry of Finance, 2026). This is a deliberate national strategy: to compete not principally on the ability to build frontier AI models, but on Singapore's ability to deploy AI effectively in industries where it has deep capabilities, attracting global firms to set up AI innovation hubs locally while nurturing the capabilities of local enterprises. Success could unlock new sources of value, raise productivity and strengthen firms' global competitiveness. Yet it also raises a question that has only recently moved to the centre of national debate: can advanced technologies continue to drive economic growth without leaving workers behind?

Before generative AI became widely accessible and entered public consciousness, Singapore's prevailing discourse reflected considerable optimism about technological change. Successive waves of digital innovation were widely regarded as engines of productivity, new industries and better jobs. It was accepted that particular jobs or occupations might disappear but with limited concerns that technology posed a broader threat to employment. The prevailing expectation was that technology would create more—and better—jobs than it displaced. Affected workers would be retrained and redeployed into new areas of higher-value growth. This reflected the conventional account of skill-biased technological change: technological progress raises demand for more highly skilled workers, generating productivity gains and better employment opportunities (Goldin & Katz, 2008; Brynjolfsson & McAfee, 2012).

The widespread visibility—and rapid workplace uptake—of generative AI unsettled this confidence. The release of ChatGPT in November 2022 allowed a mass audience to see AI draft reports, synthesise information, write software and undertake other tasks associated with professional expertise and human judgement. These capabilities have not remained a technological novelty. As generative AI began to enter everyday work, it also started to reshape corporate expectations about which tasks could be automated, what individual workers should produce and which capabilities organisations would continue to value. Indeed, unlike earlier forms of automation, generative AI appear capable of reaching deeply into the work of professionals and executives—those with the highest levels of skills, education and training that have typically been considered as relatively insulated from technological displacement (Brown & Sadik, 2025).

The possibility of jobless growth consequently entered Singapore's policy debate with unprecedented force. By July 2025, Prime Minister Lawrence Wong had called on Singapore to "think equally hard" about deploying AI in ways that create jobs, rather than assuming that the employment gains associated with earlier technological waves would automatically continue (Wong, 2025). In February 2026, this concern crystallised into an explicit national commitment, with Prime Minister Wong assuring Singaporeans that the country's AI push would not result in jobless growth and that economic expansion would translate into "good jobs and better wages" (Lee, 2026). Three months later, the Singapore Parliament unanimously supported a motion calling for AI-enabled growth to be anchored in fairness and opportunity, while acknowledging that technological change would inevitably replace some jobs (Koh, 2026). Singapore's updated National AI Strategy further cautioned the risk of K-shaped outcomes, where a small group of businesses, workers, and countries pull strongly ahead of others (Ministry of Digital Development and Information, 2026).

Together, these developments mark a shift from confidence that technological progress will continue to generate good jobs to an explicit recognition that its employment outcomes must be actively shaped. The question is no longer simply how quickly Singapore should adopt technology, but how technological change should be steered to sustain employment and improve work. Avoiding jobless growth is now an essential national commitment. Fulfilling it, however, requires looking not only at number of jobs created or displaced, but also what technology does within jobs in terms of job quality—whether it extends workers' knowledge and judgement, produces only shallow improvements, leaves work substantively unchanged, or reduces the capabilities workers are expected to exercise (European Training Foundation, 2026).

Is it the technology?

Tempting as it may be to attribute these risks to the inherent capabilities of generative AI, technological determinism—the idea that technology produces inevitable social and economic outcomes—has little empirical support historically (Acemoglu & Johnson, 2023; Brown et al., 2022). Technologies do not determine how work evolves independently of the institutions and organisations through which they are deployed. Technological effects are indeed shaped by firms' strategic objectives, the design of jobs, industrial relations and the choices made about which human capabilities to extend, retain or replace.

Evidence from Singapore in 2017 and 2022 predating the visibility of generative AI had already demonstrated this complexity. Studying technology adoption patterns of 3,800 establishments in Singapore in 2017 drawn from the Business Performance and Skills Survey, Souto-Otero et al. (2023) found that technology did not shield high-skilled workers. High-skilled workplaces offered no protection against job displacement: firms' competitive strategies and managerial perceptions were more influential in protecting employment.

Using the same 2017 enterprise dataset, Sadik et al. (2025) further traced the outcomes of technological change to the interaction between firms' business and talent strategies. High-skilled firms pursuing greater proximity to customers and markets were more likely to use technology to augment workers—including those on the frontline—while retaining employment and investing in skills. By contrast, high-skilled firms pursuing efficiency-led innovation were more likely to reduce headcount while upgrading the jobs that remained. Low-skilled firms that tended to compete based on prices or shallow customisation avoided technological adoption; when they did adopt, they were more likely to shed jobs without upgrading those that remained as part of a strategy of cost optimisation. Again, these findings demonstrate that firms' technology strategies were shaped by the integration of business and talent strategies.

By 2022, nationally representative data on Singapore's jobholders already pointed to a corresponding pattern of high-skill-degradation drawing on an analysis of 4,218 working-age Singapore citizens and permanent residents in the cross-sectional sample of the Skills and Learning Survey 2 (Brown & Sadik, 2025). There was no statistically significant difference for observations of job loss across all occupational groups, corroborating the earlier evidence from enterprise data that even complex jobs were not insulated from the substitution effects of technological change. When assessed in terms of job quality, compared with managerial roles, professional jobs showed signs of degradation. They had remained comparable in task complexity but had fallen behind in task discretion—indicating less control over how work was performed. Professional roles were also the most exposed to digital offshoring, given their suitability for remote delivery and reliance on cross-border collaboration. Meanwhile, job quality in non-professional roles remained largely stagnant, with no significant gains in either task complexity or discretion—despite the greater scope for technology to improve jobs starting from a lower base.

Together, these studies shift attention from the technology itself to firms' deployment strategies: what they seek to achieve, how they redesign work, and which human capabilities they cultivate, substitute or leave untouched—including through decisions not to adopt technology at all. International evidence reinforces the central insight: there is every chance that AI, including generative AI, will benefit the broader workforce. Autor (2024) argues that AI could rebuild middle-class jobs by enabling more workers to perform tasks previously reserved for experts. Tay et al. (2025) similarly suggest that vocational workers could realise some of the greatest gains from an abundance

of cognitive tools—an opportunity often overlooked by enterprises. Acemoglu et al. (2026) identify "pro-worker AI" as linked to technological strategies that create new tasks. Understanding the conditions that enable augmentation, as well as those that lead to degradation, is therefore essential to steering inclusive technological change.

Establishing Singapore's pre-generative AI starting point: a rare dataset

This study provides rare—and the strongest evidence to date in Singapore—of how digital technologies reshape work. Cross-sectional studies referred to earlier provided valuable evidence of the associations between technology adoption, firm strategies and job outcomes. However, they could not establish whether those outcomes followed technological change. Overcoming these limitations requires evidence that combines three elements seldom found in a single dataset: temporal ordering by tracking the same workers over time before and after technology use, nationally representative coverage of the workforce for the generalisability to the wider population, and task-level measurement of jobs. The latter matters because technology reshapes jobs task by task, rather than affecting occupations uniformly (Acemoglu et al., 2026; European Training Foundation, 2026). Workers in the same occupation may experience technological change very differently, depending on firm-level strategies.

The longitudinal component of the Skills and Learning Survey (SLS) brings these elements together through its technology module. Covering 1,732 working residents in 2017 and 2022, SLS is the only known national-level dataset in Singapore to connect technology use with the job requirements approach—an established method for measuring job quality through the tasks workers actually perform (Felstead et al., 2007). Indeed, job-task analysis is an established, internationally recognised approach for assessing whether jobs are being enhanced over time (OECD, 2013, 2016). It is especially important for studying technological change because technologies reshape jobs task by task—automating or standardising some tasks, while complementing workers or creating new tasks that require different skills (Acemoglu & Restrepo, 2019). By showing whether technology expands or narrows workers' task portfolios and the complexity, judgement and discretion embedded in their roles, job-task analysis reveals whether adoption is developing and productively using human capital, rather than merely increasing digital intensity.

Following the same workers over time provides a more robust assessment of technological impact on work than a cross-sectional snapshot: it establishes whether technology use preceded changes in job design and enables workers' overall assessments of its impact to be triangulated against actual changes in their tasks, skills and discretion.

Yet if enterprise strategies ultimately shape workers' outcomes, jobholder data may appear limited to showing the effects of technological change, without providing a direct lens into what drives those effects.

But what if this dataset is viewed differently—not merely as records of workers' experiences, but as a means of surfacing the organisational imprint from enterprise strategies? Holm and Lorenz (2016) established an important methodological precedent by applying Ward's hierarchical clustering to infer distinct forms of work organization from jobholder data. The SLS creates an opportunity to extend this approach by following a subset of the longitudinal dataset–1,066 jobholders employed with the same employer from 2017 to 2022–examining whether divergent work environments led to divergent changes in tasks, discretion, wages and other outcomes following technological change. This exploratory approach could generate more actionable policy intelligence on enterprise strategies. Although enterprise surveys measure firm strategies more directly, they often lack the granularity to show actual impact on the range of jobs within the firm, requiring triangulation with administrative data on employees that are hard to obtain. Longitudinal same-employer jobholder data may allow for the specification of the business contexts associated with actual worker outcomes, providing matched insights that capture the state of enterprise-workforce transformation.

Working level definitions

Following Adler (2004, pp. 4–5), the enhancement of labour across occupations comprises two components: "mastery of the complexity of tasks" and "mastery of the relations" required to coordinate activity across them. These attributes can be examined through two lenses: workers' proficiency in performing their tasks, and skills utilisation—the extent to which jobs require and enable those skills to be exercised (Buchanan et al., 2010; Green, 2013; Sung & Ashton, 2014; Warhurst et al., 2017). This study focuses on the latter because firms' decisions about technology precede and reshape job-task requirements, which in turn determine the skills workers need to develop and those that may fall out of use.

Building on this distinction, the report conceptualises the augmentation of work as changes in job design through which technology increases task complexity and/or strengthens workers' control over the relations required to coordinate activity across tasks. Conversely, the degradation of work refers to technological changes that reduce task complexity and/or diminish workers' control over these relations.

These dimensions proved important in significantly earlier periods of technological change (Braverman, 1974; Fox, 1974; Noble, 1986; Hanley, 2014), more recent periods of digitalization (Brown et al., 2011; Head, 2014) and remain durable in the AI age because AI can reshape task complexity and workers' coordination control. It can perform increasingly complex cognitive tasks while also altering the social interaction and coordination through which work is accomplished. Task complexity and social task requirements therefore continue to provide a robust basis for assessing whether AI preserves, extends or erodes workers' skills. This job-task approach is as much about business performance and the economy as it is about workers and social outcomes: it reveals the extent to which firms are deploying human capital productively, while enabling workers to share in the benefits of technological change.

Emerging AI research already points to risks to workers' job-tasks with technological change. For complex work, extensive delegation to AI may produce cognitive offloading, as workers cease to exercise important cognitive and creative capabilities, with wider consequences for organisational capabilities (Caosun & Aral, 2026; Goel et al., 2026; Maya, 2026). For social tasks, the digital 'containerisation' of jobs (Deming, 2026) enabled by remote working and potentially extended by agentic AI—may separate individual production from the interaction, observation and informal learning through which workers develop expertise. Garicano et al. (2026) similarly argue that "messy jobs" are more resilient to AI because judgement, coordination, accountability and human relationships bind their constituent tasks together, making them difficult to separate or automate and helping to preserve demand for high-value human labour.

A related strand of research seeks to identify the distinctive human capabilities that remain complementary to AI. The EPOCH framework, for example, emphasises empathy, presence, opinion and judgement, creativity, and hope (Loaiza & Rigobon, 2025). Important as these capabilities are, they are not necessarily distinct from those embedded in complex and social task requirements. Empathy and presence may be expressed through interpersonal tasks, while creativity and judgement may be exercised through complex problem-solving and decision-making. This study therefore treats them as detailed dimensions of established task requirements, that include analytical work, decision-making, discretion over how work is performed, responsibility for judging its quality, and interpersonal tasks involving collaboration and influence.

Constructing the analysis using technology module in SLS longitudinal data

Describing the dataset

The analysis draws on a unique longitudinal sample of 2,004 Singapore residents aged 25-65 who participated in both the 2017 and 2022 editions of the SLS. To examine on the impact of technological change at work in Chapter 2, the analysis is restricted to the 1,732 respondents who were job holders. For the subsequent analyses in Chapter 3, which examine how firm-level context mediates these changes, the sample is further restricted to the 1,066 job holders who remained with the same employer between 2017 and 2022. This allows changes in job

requirements and outcomes to be examined within a consistent employer context, without being conflated with changes arising from employer mobility.

Technological content of jobs and self-reported impact on work

In the 2017 edition of the Skills and Learning survey, respondents were asked about their use of basic digital skills, including the internet, spreadsheet software and online discussion platforms, as well as advanced digital skills such as programming and coding. These questions were repeated in 2022, with data analytics and specialised software added to capture a broader range of advanced digital skills.

Responses on technology's impact on work were introduced only in the 2022 edition of the Skills and Learning Survey. As basic digital skills were already used by 84% of employed respondents in 2017, responses were sought only for more sophisticated technologies in 2022 namely 1) computerised or automated equipment; 2) artificial intelligence and machine learning (AI/ML), and 3) data analytics. Respondents were asked whether their workplace had introduced these technologies during the preceding three years and whether these had significantly changed their jobs. Those reporting significant change were then asked about its effects along two dimensions: 1) employment, measured by gains or losses in similar roles within the firm; and 2) job quality, measured through changes in task complexity, discretion, variety and repetition, as well as work-quality standards. These self-reported assessments provide an important starting point because jobholders are best placed to judge whether technology has materially affected their work and responsibilities.

Longitudinal analysis of job-task requirements

Evidence of augmentation or other effects of technological change should ultimately be reflected in job-task requirements, consistent with the skills-utilisation framework. Temporal ordering helps establish whether workers' assessments of technological impact in 2022 correspond with changes in job content between 2017 and 2022. The tasks selected for analysis are aligned with broad categories of human capabilities considered important in the AI age discussed earlier is provided in **Table 1.1**.

Table 1.1 Types of Job-Task Requirements in the Singapore Skills and Learning Survey

Categories	Job-task requirements	
Cognitive	Analytical thinking	Complex problem-solving
Social	Collaboration	Persuading and influencing
Judgment	Discretion	Decision-making
Physical	Dexterity	Strength
Others	Continuous learning	Task repetition

Broader firm level context, and individual characteristics

The analysis further situates each pattern within the broader conditions that may shape it. At the firm level, this includes innovation practices, firm size, ownership and industry, helping to identify where augmentation, degradation or limited transformation are concentrated. Individual characteristics—including occupation, educational qualifications and age—are also analysed to show which workers are most likely to experience each pattern. Together, these dimensions reveal how technological change varies across firms and workers, and who benefits from it.

Wage gains

Finally, wage gains provide an important lens for assessing whether technological change delivers material benefits to workers, whether those gains commensurate with changes in task requirements, and the resultant wage dispersion across occupations.

Two sets of analyses are presented in this report. Chapter 2 uses descriptive distributional analysis to provide an economy-wide assessment of digital-skills penetration and shifts in use between 2017 and 2022, including variations by technology type, occupation and reported impact on work. Building on the proposition that jobholder data can surface the organisational imprint of enterprise technology strategies, Chapter 3 applies Ward's hierarchical agglomerative cluster analysis to identify empirically distinct patterns in how digital technologies reshape work. These patterns are then examined against changes in job-task requirements, firm- and individual-level characteristics, and wage gains.

Summary

Singapore's challenge is no longer simply to accelerate technology adoption, but to ensure that it creates better work and advances workers alongside firms. Although public concern now extends to high-skilled workers, empirical studies show that these pressures predate generative AI. Granular evidence is needed to guide national augmentation strategies. Drawing on a robust longitudinal dataset that follows the same jobholders from 2017 to 2022, this study maps distinct patterns of technological change and links them to shifts in job requirements and wages, as well as firm and worker characteristics. It establishes Singapore's pre-generative-AI augmentation baseline—revealing how widely augmentation had taken hold, the alternative pathways technological change produced, new risks that may emerge and the range of levers through which technological change could be steered nationally for productive and inclusive economic growth.

Findings

2. Digital Skills Across the Economy: Widespread Foundations With Signs of Occupational Fault Lines

Between 2017 – 2021, Singapore's workforce sustained widespread digital foundations, but digital deepening remained uneven, revealing signs of occupational fault lines.

Chapter 2 establishes Singapore's pre-generative-AI digital landscape by tracing the reach and depth of workers' digital capabilities across technology types, and the impact on jobs, occupations and wages.

A stable digital base and an intermediate frontier

Between 2017 and 2022, participation at both ends of Singapore's digital-skills spectrum—from basic digital use to advanced programming and coding improved modestly (**Table 2.1**).

Table 2.1 Digital Tool Use at Work

	2017 → 2022 Share of workers	**Change** (percentage points)
Basic use	**84% → 86%**	**+2 pp ▲**
Use the internet	78% → 82%	+4 pp ▲
Use email	80% → 81%	+1 pp
Use spreadsheet software	73% → 75%	+2 pp ▲
Use a word processor	72% → 74%	+2 pp ▲
Participate in real-time discussions online	54% → 73%	+19 pp ▲
Conduct online transactions	38% → 45%	+7 pp ▲
Intermediate use	*2022 only:* **59%**	-
Use data analytics to support processes	*2022:* 51%	-
Use specialised software to deliver professional tasks	*2022:* 40%	-
Advanced use	**14% → 18%**	**+4 pp ▲**
Programme or write code	14% → 18%	+4 pp ▲

▲ indicates a statistically significant change at the 90% confidence level (paired t-test).

Basic digital participation, including the use of the internet and email, was already widespread in 2017 and increased marginally from 84 to 86 % of workers by 2022. Patterns of use nevertheless continued to evolve within this established foundation. Most notably, the use of online tools for real-time discussions rose by 19 percentage points, from 54 per cent in 2017 to 73% in 2022, likely reflecting the normalisation of virtual meetings and hybrid work during the Covid-19 pandemic.

At the advanced end of the spectrum, the proportion of workers using programming and coding similarly increased modestly, from 14% in 2017 to 18% in 2022. Programming therefore remained an occupationally specialised capability rather than becoming a general requirement across the workforce. Its limited diffusion does not necessarily constrain wider digitalisation: improvements in software-development productivity and the growth of low-code and no-code platforms increasingly allow workers without advanced programming expertise to build or configure digital applications (Kergroach & Héritier, 2025).

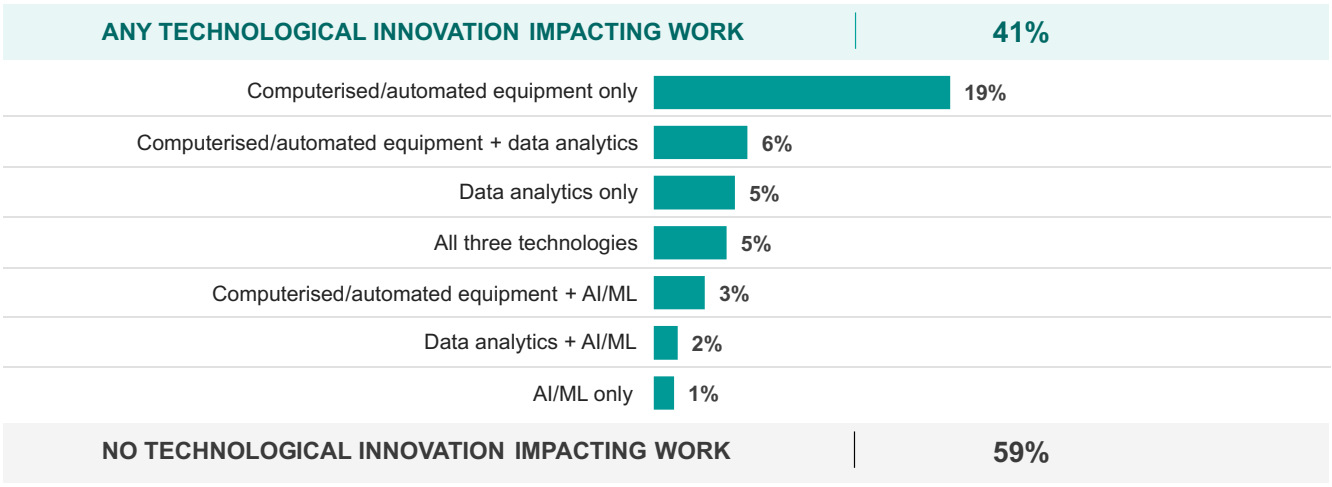
Between these two poles lay a substantial intermediate layer of digital application. Measured only in 2022, 58% of workers reported using specialised software, data analytics or both. These applications were neither as widespread as basic digital tools nor as occupationally concentrated as programming and coding, making this intermediate frontier particularly important. Its reach across nearly three-fifths of the workforce indicated that Singapore had established a substantial foundation for deeper digitalisation.

Mapping technological exposure to impact on work

The findings in the preceding section show that Singapore entered the pre-generative-AI period with widespread basic digital participation and a substantial intermediate layer of digital application. However, the distribution of digital skills does not reveal whether technology materially changed workers' jobs—or whether those changes improved the quality of work. To examine this, the 2022 survey separately asked workers whether computerised or automated equipment, artificial intelligence and machine learning, or data analytics had been introduced in their workplaces and had significantly changed their work, and the impact of these technologies on their work. These three forms of technologies were selected because they involve more sophisticated forms of automation, computation or data-driven analysis than routine digital tools such as email and internet applications.

A total of 41% of workers reported that at least one of the above-mentioned forms of technologies had significantly changed their work during the preceding three years (**Figure 2.2**). Computerised or automated equipment was the most common source of change, affecting 33% of workers; for 19%, it was the only advanced technology reported. Data analytics significantly changed the work of 18% of the workforce, while exposure to AI and machine learning was only emerging, at 6% of the workforce.

Figure 2.2 Technological Innovation at Work
Distribution of job holders by combinations of technological innovation (%)



Workers who reported that these technologies had significantly changed their work were then asked about two sets of outcomes: changes in the quality of their jobs, and gains or losses in the number of similar roles within their firms.

The reported job-quality outcomes were mixed (**Table 2.3**). Slightly more than half (54–57%) experienced increases in task complexity, task variety and work-quality standards, suggesting that technology had enriched some dimensions of work. However, most experienced neither greater task discretion nor reduced repetition. In fact, repetition increased for 21% of affected workers but decreased for only 18%, challenging the expectation that technological adoption tended to eliminate repetitive work.

Table 2.3 Impact of Technology Innovation on Work

	Distribution of jobs (%)		
	Increased	Remained the same	Decreased
Job quality of own's work			
Task complexity	54%	43%	4%
Task discretion	37%	60%	3%
Task variety	57%	40%	3%
Task repetition	21%	61%	18%
Quality standards	54%	43%	3%
Employment in similar role			
Job quantity	27%	60%	14%

Base: Respondents who reported technological innovation at work.

Employment effects within firms were relatively modest. 60% reported no change in the number of similar roles at their employer, compared with 27% who reported an increase and 14% who reported a decrease. Even so, these figures capture only changes reported by workers who remained with the same employer. They do not account for workers who had left or for employment effects arising through reduced hiring.

Taken together, the aggregate findings indicate neither consistent augmentation nor predominant degradation. Improvements in complexity, variety and work-quality standards coexisted with limited gains in discretion and, for some workers, greater repetition. These aggregate results may also conceal different combinations of change: the workers gaining complexity may not be the same workers gaining discretion or experiencing less repetition. The next section therefore examines changes in job-task requirements across occupational groups for a more granular understanding of the impact of digital technologies on jobs.

Digital deepening was concentrated at the top—but with uneven gains

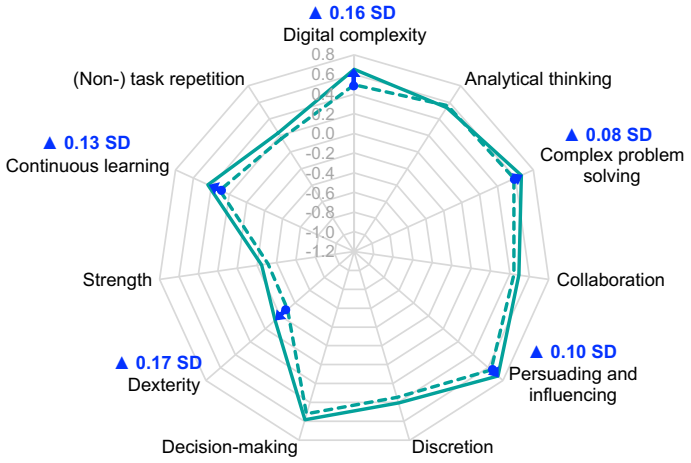
Moving beyond workers' self-reported experiences, the analysis traces more structural shifts in jobs by examining how digital complexity evolved alongside other task requirements between 2017 and 2022. In this analysis, digital complexity captures the depth and sophistication of digital tasks required in a job, rather than simply whether the workers use digital tools. It combines the range and frequency of digital activities across the nine measures spanning basic, intermediate, to advanced applications, into a single measure of the digital demands of the job. This allows the changes in the digital complexity of jobs to be compared consistently over time.

Of the analytical approaches tested, occupation provided the clearest lens for identifying systematic differences across the workforce. Specifically, increases in digital complexity were distinctly top-loaded (**Figure 2.4**). Statistically significant increases were confined to managers, professionals, and technicians and associate professionals (TAPs). Clerical, service and sales, and other occupational groups recorded no significant digital deepening. This raises questions about expectations that technology will absorb routine tasks and enable workers in routine-intensive occupations to undertake more complex work.

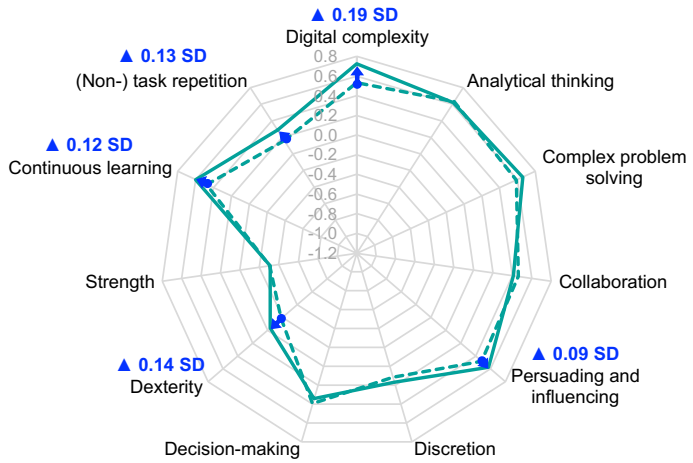
Figure 2.4 Changes in Job-Task Requirements by Broad Occupation (2017-2022)

2017 2022 ▲ / ▼ indicates a statistically significant change at the 90% confidence level (paired *t*-test).

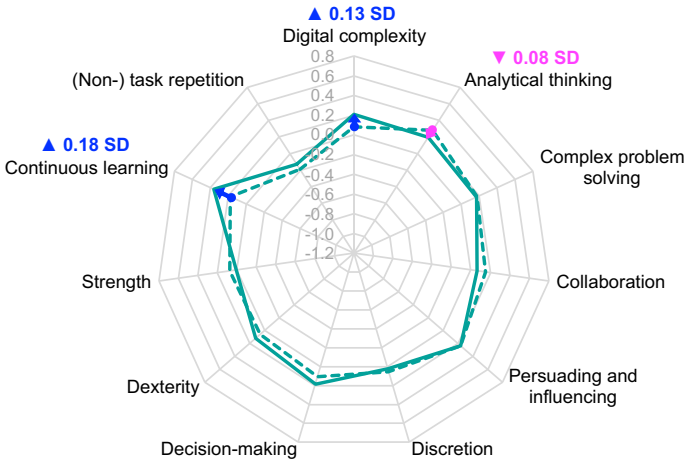
Managers



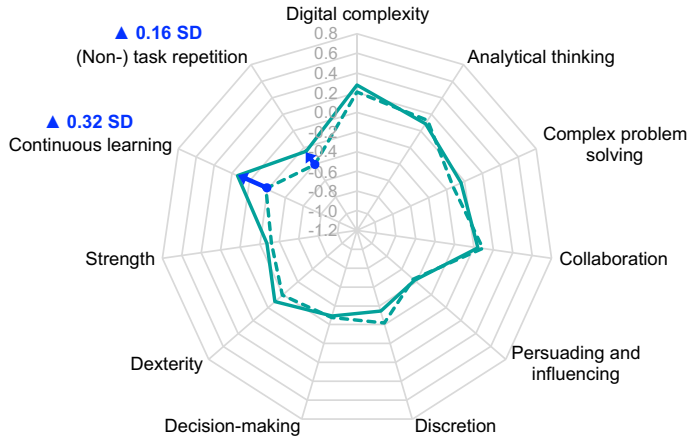
Professionals



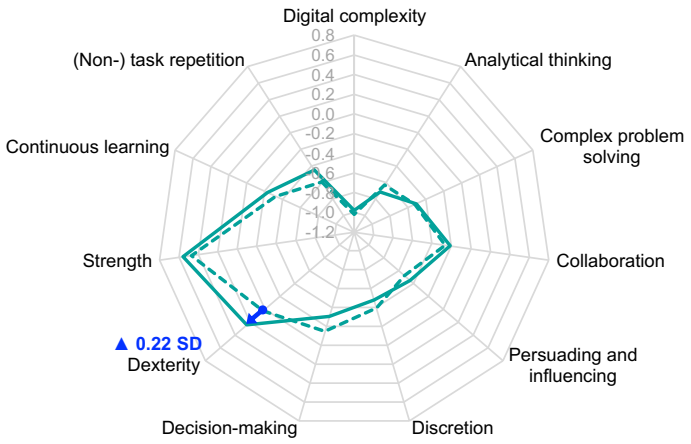
Technicians and associate professionals



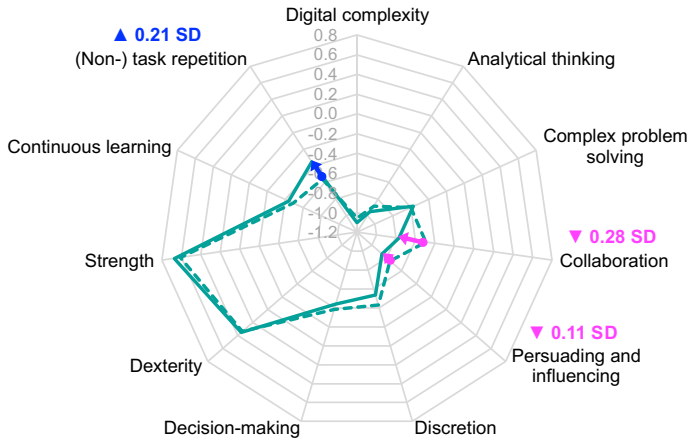
Clerical support workers



Sales and service workers



Production and related workers



Yet digital deepening did not produce uniform upgrading even within PMET occupations. Managers registered the broadest gains: from an already high base, greater digital complexity coincided with increases in complex problem-solving, persuading and influencing, and physical dexterity. Professionals recorded gains in persuading and influencing and physical dexterity, but no significant growth in complex problem-solving. TAPs followed a more concerning trajectory. Despite rising digital complexity and greater requirements for continuous learning, their analytical requirements declined, with no corresponding gains in complex problem-solving or decision-making.

These task requirements were already lower among TAPs than among managers and professionals, making the absence of growth concerning.

The concentration of digital deepening among higher-skilled occupations is not unique to Singapore. Finnish evidence similarly found stronger complementarity between digital technologies and workers' skills among PMETs than across the rest of the workforce (Alasoini & Tuomivaara, 2023). What is more notable in Singapore is the divergence within the PMET hierarchy. The TAP trajectory complicates a straightforward skill-biased account in which technological change increases demand for higher-value skills. For this group, greater digital complexity was associated with increased demands for continuous learning but lower analytical requirements—suggesting that learning to use more sophisticated technologies does not necessarily translate into more cognitively demanding work.

These longitudinal findings sharpen earlier cross-sectional evidence from the Singapore Skills and Learning Study (Brown & Sadik, 2025). That analysis identified an occupational divide: when technology significantly changed jobs, managers and professionals reported similar gains in task complexity, but only managers experienced corresponding gains in discretion; non-professional workers gained in neither dimension. However, cross-sectional data could not show how job-task requirements evolved over time, while the broad grouping of non-professional workers obscured the distinct trajectory of TAPs. The longitudinal data therefore has a key strength: to be able to spot job upgrading and degradation. It does not establish that digitalisation caused these changes, but provides a stronger basis for identifying differentiated occupational trajectories.

Taken together, the findings point to signs of hierarchically stratified technological change. Digital deepening was concentrated higher in the occupational hierarchy, but the task gains associated with it diminished—and, in some dimensions, reversed—further down the PMET hierarchy.

Wage gains from digital skills

A final aspect to examine is whether digital deepening translated into wage gains for workers. The evidence suggests that this relationship was weak. Digitalisation accounted for only a small share of differences in wage growth between 2017 and 2022 (**Table 2.5**). Digital task requirements explained 2.4% of the variation in wage growth, while exposure to advanced technological innovations that affected work explained a further 0.04%. Together, these technology-related factors accounted for just over 2%.

Non-digital factors were more consequential within the model. Non-digital job-task requirements explained 2.7% of the variation, followed by individual characteristics, including age and education, at 2.6% and occupation at 1.8%. This meant that wage gains were more closely associated with non-digital content of the jobs and workers' broader characteristics than with digitalisation itself.

Most importantly, 89.0% of the variation in wage growth remained unexplained by the model. Wage trajectories were therefore shaped predominantly by factors not captured in the analysis, potentially including firm-level wage-setting practices, labour-market conditions, wage policies and other changes in the wider economy. Digital deepening, on its own, was neither a strong predictor nor a guarantee of material gains for workers between 2017 and 2022.

Table 2.5 Contributions of Selected Factors to Wage Growth (2017–2022)
Fields' decomposition of the variation in the change in log hourly wages between 2017 and 2022 (%)

Selected factors	**11.0%**
Digital task requirements	2.4%
Non-digital task requirements	2.7%
Technological innovation *(computerised and automated equipment, AI and machine learning, data analytics)*	0.04%
Other business innovation	0.5%
Industry sector	1.0%
Firm characteristics	0.8%
Occupation	1.0%
Individual characteristics	2.6%
Residual (unexplained variation)	**89.0%**

Summary

Chapter 2 establishes a mixed picture of Singapore's pre-generative-AI digital landscape. Basic digital participation was widespread, specialised software and data analytics formed a substantial intermediate layer, and programming remained occupationally concentrated. At present, it is unclear how the proliferation of generative AI since 2022 will alter this distribution. Combining easy to use tools with more sophisticated forms of applications, generative AI may support basic, intermediate and advanced forms of digital work. Future evidence will need to establish whether it diffuses mainly as a widely accessible tool, enables deeper applications across the workforce, or does both. Tracking not only its adoption but also its effects on work will be essential to steering technological change towards stronger workforce outcomes.

Among workers directly affected by advanced technologies, increases in task complexity, variety and quality standards coexisted with limited gains in discretion and, for some, greater repetition. Comparing changes in job-task requirements between 2017 and 2022, significant occupational differences were observed. Digital deepening was concentrated among PMETs, with managers experiencing the broadest gains, professionals more limited upgrading and TAPs declining analytical requirements. Lower occupational groups saw little digital deepening. Technology-related factors also explained little variation in wage growth. Together, these findings suggest neither uniform augmentation nor widespread degradation, warranting closer analysis of how technology reshaped work.

3. Advanced Technology at Work: Pathways and Possibilities for Augmentation

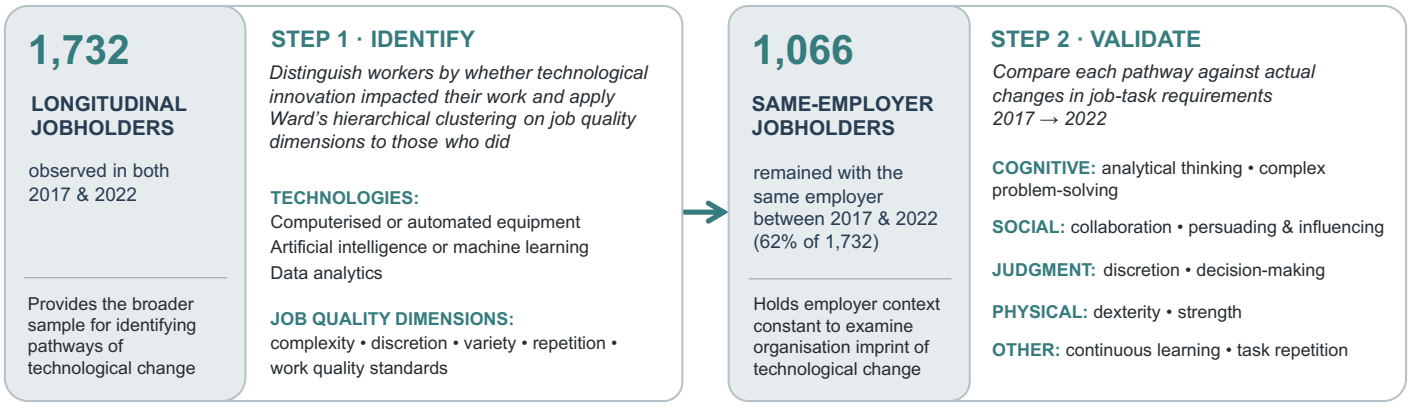
Two augmentation pathways show that hierarchically stratified technological change is not inevitable in Singapore, but a clear degradation pathway is also evident

Chapter 2 leaves an unresolved picture. Digital skills were broadly embedded across the economy at basic, intermediate and advanced levels. Yet occupational patterns suggested that digital skills were not translating evenly into better work across the occupational hierarchy. Workers' direct assessments of advanced technology's impact on their work produced no conclusive overall finding at the aggregate level. This ambiguity is not unexpected. Dominant theories of technological change have established that technology does not exert a single, uniform effect; its outcomes are shaped by institutional and enterprise strategies (Acemoglu & Johnson, 2023; Brown et al., 2022). Empirical evidence also demonstrated that a variety of strategies exist in Singapore (Brown & Sadik, 2025; Souto-Otero et al., 2023; Sadik et al., 2025). Distinct augmentation pathways may therefore be present but remain hidden within the aggregate findings in Chapter 2. This chapter explores how different pathways of technological change can be observed from the longitudinal data.

The analysis began with the 1,732 jobholders in the longitudinal sample, distinguishing workers according to whether they reported technological innovation significantly changing their work. Among those who did, Ward's agglomerative hierarchical clustering—drawing on the approach developed by Lorenz and Valeyre (2005) and subsequently applied by Holm and Lorenz (2015)—was used to identify patterns in how workers experienced technological change. The clustering was based on technology's reported effects on five aspects of job quality in 2022: task complexity, discretion, variety, repetition and work-quality standards. Five distinct clusters emerged.[1] Workers who reported no technological innovation significantly changing their work were retained as a sixth pathway alongside these five clusters. Together, these provide an empirical basis for distinguishing augmentation, degradation and other pathways of technological change.

The six pathways were then examined longitudinally among the 1,066 workers who remained with the same employer between 2017 and 2022, representing 62% of the 1,732 jobholders. Their reported experiences of technological change were examined alongside actual changes in job-task requirements between 2017 and 2022. Restricting this analysis to same-employer workers holds the employer context constant and avoids conflating changes in work with those arising from employer mobility. More importantly, because firms make choices about how technology is implemented alongside wider business strategy and work design, these patterns provide a window into the organisational imprint shaping technological change (**Figure 3.1**).

Figure 3.1 Methodological approach: identifying and examining technological change pathways



Key results of the cluster analysis

Figure 3.2 summaries the distinguishing characteristics of six distinct clusters through which workers in Singapore experienced technological change between 2017 and 2022. Approximately one in six workers followed augmentation pathways (17%), comprising **knowledge-work augmentation** (**T1: 10%**) and **technical-dexterity augmentation** (**T2: 7%**). A further 8% experienced **degradation** (**T3**). Another 8% experienced **shallow upgrading** (**T4**), while 10% experienced **tech-disconnected upgrading** (**T5**)**,** where technological innovation was reported but produced limited observable change in work. The largest group—56%—experienced **technology stagnation** (**T6**), reporting no technological innovation that significantly changed their work.

Three findings stand out.

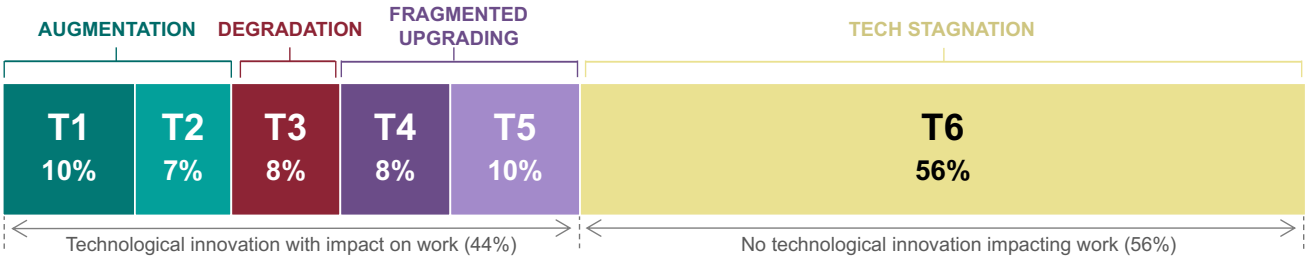
First, augmentation is not a singular phenomenon. The analysis identifies two different routes to better work. Knowledge-work augmentation (**T1**) combined AI, machine learning and data analytics to sustain high-skill work. Technical-dexterity augmentation (**T2**) was much more strongly associated with computerised and automated equipment and produced the largest overall gains in job-task requirements. **T2** is particularly important because it challenges conventional assumptions that augmentation necessarily reduces physical demands or repetitive work. Repetition increased, yet so did discretion and complexity, alongside requirements for physical strength and dexterity, decision-making and problem-solving. Technology can therefore augment advanced practical work by extending the combination of technical, cognitive and physical capabilities workers are required to exercise. Both augmentation pathways were also associated with relatively broadly distributed wage gains across occupations, demonstrating how well-deployed technology can improve work while supporting inclusive growth. These gains also caution against allowing AI investments to crowd out automation, robotics and other technologies capable of uplifting practical and technical work.

Second, the degradation cluster (**T3**) highlights the risks of AI and data-intensive technologies. Despite resembling **T1** in its innovation profile, **T3**'s pathway produced sharply different outcomes: technology increased task complexity without improving task quality, while collaboration and broader task requirements declined—suggesting a possible 'containerisation' of work that may lead to further automation (Deming, 2026). The greatest concern, however, is that wage gains were more unevenly distributed across occupations than in any other pathway. Its concentration among large foreign-owned firms is particularly significant. The conventional concern about a K-shaped economy is that technologically advanced firms pull ahead while others remain behind; these findings reveal a further risk—that even firms pulling ahead may not bring their workers and wider society with them. Without complementary people and work-design strategies, technological advancement may concentrate gains rather than build capabilities and support inclusive growth.

Third, the next frontier for Singapore's technological transformation may lie among the **56%** of workers experiencing technology stagnation (**T6**), while a further **18%** are already experiencing technological change but only limited gains through shallow (**T4**) or tech-disconnected upgrading (**T5**). Moving firms from non-adoption to adoption is therefore insufficient: without a different approach; the 56% could merely join the 18% already experiencing limited gains. An important observation from the analysis is that these pathways recorded only low-to-moderate levels of business innovation, suggesting that weak business innovation may underlie both limited adoption and limited impact. A major opportunity is to learn from the augmentation playbooks of **T1** and **T2**, where technology was integral to broader business innovation, while avoiding degradation (**T3**), where strong business innovation and technology adoption failed to produce meaningful gains for work.

The next sections that follow unpack these differences by examining in detail the technologies involved, the wider organisational context surrounding them, how job-task requirements evolved, and whether technological change was accompanied by learning, employment and wage gains.

Figure 3.2 Six Clusters of Technological Change in Singapore



	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Self-reported tech impact on work	▲ Task complexity ▲ Task discretion ▲ Task variety ▼ Task repetition ▲ Quality standards	▲ Task complexity ▲ Task discretion ▲ Task variety ▲ Task repetition ▲ Quality standards	▲ Task complexity ▼ Task discretion ▲ Task variety – Task repetition – Quality standards	– Task complexity ▲ Task discretion – Task variety – Task repetition ▲ Quality standards	– Task complexity – Task discretion – Task variety – Task repetition – Quality standards	No technology impact
Actual job-task trajectory 2017–2022	**Knowledge-intensive task enrichment** Highest task requirements ▲ Digital complexity ▲ Continuous learning ▲ Decision-making (modest)	**Technical-intensive task enrichment** Strongest growth in task requirements ▲ Digital complexity (modest) ▲ Continuous learning ▲ Dexterity ▲ Strength ▲ Decision making ▲ Complex problem-solving (modest) ▲ Persuading & influencing (modest)	**Knowledge-intensive task degradation** Decline in social task requirements ▲ Digital complexity (modest) ▼ Collaboration	**Mixed patterns in task enrichment** Moderate task requirements ▲ Digital complexity (modest) ▲ Dexterity ▲ Continuous learning (modest) ▼ Decision-making (modest)	**Non-technology-led task enrichment** Moderate task requirements – Digital complexity ▲ Continuous learning ▲ Decision-making (modest) ▲ Persuading & influencing (modest) ▲ Dexterity (modest)	**Stagnating jobs** Lowest task requirements – Digital complexity ▲ Continuous learning (modest) ▲ Dexterity (modest)
Innovation context	**High** adoption of AI/ML and data analytics + **High** business innovation	**High** adoption of computerised/ automated equipment + **High** business innovation	**High** adoption of AI/ML and data analytics + **High** business innovation	**Moderate** adoption of computerised/ automated equipment + **Moderate** business innovation	**Moderate** adoption of computerised/ automated equipment + **Moderate** business innovation	No adoption of new technology + **Low** business innovation
Wage growth						
2017-2022	+16% growth	+21% growth	+11% growth	+29% growth	+13% growth	+13% growth
Occupational distribution	Uniform (13pp gap)	Uniform (21pp gap)	Highly dispersed (62pp gap)	Highly dispersed (71pp gap)	Moderately dispersed (39pp gap)	Uniform (20pp gap)
Worker profile	Degree holders; PMEs	TAPs	Degree holders; TAPs	Diploma holders	TAPs, clerical support workers	Below diploma; production & related workers
Firm profile	Foreign-owned SMEs	No clear trend	Foreign-owned large enterprises	No clear trend	No clear trend	Local SMEs

Source: SLS 2017–2022 longitudinal sample, same-employer workers (n = 1,066).

Deep dives

Different technologies underpin different clusters, but technology alone does not determine the outcome

The six clusters were associated with distinct technological profiles, but no single technology was uniquely associated with either augmentation or degradation (**Table 3.3**).

Table 3.3 Technological Innovation Profile Across Clusters

Share of job holders impacted by each technology (%)

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Technological innovation						
Computerised/ automated equipment	77%	92%	73%	83%	85%	–
AI/ML	43%	23%	26%	27%	21%	–
Data analytics	64%	28%	49%	37%	33%	–

Note: Within each row, darker shading indicates a higher share. Shades are not compared across rows.

The two augmentation clusters illustrated this most clearly. **T1** combined the highest adoption of AI/ML (43%) and data analytics (64%), but had comparatively more average adoption of computerised or automated equipment (77%). By contrast, **T2** was characterised by the highest adoption of computerised and automated equipment (92%), while AI/ML (23%) and data analytics (28%) were considerably less prevalent. Augmentation therefore emerged through different technological configurations—one centred more strongly on digital and analytical technologies, and another on technology embedded within technical and practical work.

More importantly, similar technologies were associated with very different experiences of work. Similar to **T1, T3** recorded high adoption of data analytics (49%). Yet its job outcomes diverged sharply from **T1**.

Table 3.4 makes this contrast visible. In **T1**, technological change increased task complexity, discretion, variety and work-quality standards while reducing repetition. In **T3**, greater task complexity was accompanied by declining discretion and no corresponding improvement in work-quality standards. This contrast is particularly relevant to data-intensive technological change. Data analytics can expand workers' ability to interpret information and exercise judgement, but it can also facilitate standardisation, measurement and managerial control (Baiocco et al, 2022) – making it compatible with both augmentation and degradation. The technology itself therefore cannot completely explain the outcome.

T2 provides a second important contrast. Like **T1**, workers reported improvements in complexity, discretion, variety and work-quality standards. Unlike **T1**, however, repetition increased rather than declined. This complicates conventional accounts of routine-biased technological change: repetitive work can coexist even where technology simultaneously increases the complexity, judgement and capabilities required to perform that work.

The remaining pathways occupied the middle ground. **T4** experienced greater task discretion and improved work-quality standards, but little change in task complexity or variety, suggesting that technology improved aspects of work without substantially expanding its scope. **T5** experienced little meaningful change across the five dimensions of job quality despite technological innovation affecting their work.

Table 3.4 Impact of Technology Innovation on Work Across Clusters

Distribution of responses within each cluster (%) – responses for each task impact sum to 100%

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Job quality of own's work						
Task complexity						
Increased	93%	81%	84%	7%	3%	-
Remained the same	7%	19%	16%	83%	92%	-
Decreased	0%	0%	0%	10%	6%	-
Task discretion						
Increased	53%	63%	21%	61%	1%	-
Remained the same	45%	37%	67%	39%	95%	-
Decreased	2%	0%	11%	0%	4%	-
Task variety						
Increased	100%	76%	76%	39%	0%	-
Remained the same	0%	24%	24%	61%	90%	-
Decreased	0%	0%	0%	0%	10%	-
Task repetition						
Increased	0%	97%	30%	0%	0%	-
Remained the same	60%	3%	64%	81%	78%	-
Decreased	40%	0%	6%	19%	22%	-
Quality standards						
Increased	92%	90%	0%	83%	8%	-
Remained the same	8%	10%	94%	17%	85%	-
Decreased	0%	0%	6%	0%	7%	-
Employment in similar role						
Job quantity						
Increased	26%	41%	18%	26%	19%	-
Remained the same	58%	43%	63%	58%	74%	-
Decreased	16%	16%	19%	17%	8%	-

Base: Respondents who reported technological innovation at work.

Taken together, these patterns establish a theme that runs through the remainder of the chapter: technological innovation is an input into transformation, but not a measure of its outcomes.

Finally, employment quantity, although not used to derive the clusters, provides a complementary perspective. Differences across clusters were generally modest, but **T2** was more likely than other clusters to report increases in the number of employees performing similar roles. Technical-dexterity augmentation therefore combined improvements in work with signs of employment expansion rather than displacement.

Longitudinal changes in job-task requirements corroborate the cluster differences

The cluster solution is based on workers' assessments of how technology affected their jobs. **Figure 3.5** provides an independent longitudinal check by examining how their underlying job-task requirements actually changed between 2017 and 2022. The resulting patterns provide strong corroboration for the distinctions between pathways.

T1 began from an already high job-task baseline and broadly sustained this position through 2022. Its most pronounced development was in continuous learning, alongside increasing digital complexity and a more modest increase in decision-making. Rather than replacing expertise, technological change appears to have increased the need for workers to continually update and extend their capabilities.

T2 recorded the most extensive task development of all six pathways. Starting below **T1** in 2017, it experienced strong growth in continuous learning, physical strength and dexterity and decision-making, alongside more modest increases in complex problem-solving, persuading and influencing, and digital complexity. By 2022, it had developed one of the strongest overall task profiles. This is important because the gains were multidimensional. Technical augmentation did not simply make jobs more digital. It combined expanding technical and physical demands with greater cognitive, social and judgement requirements. The result is a form of capability deepening that cuts across conventional distinctions between practical and knowledge work.

T3 presents a markedly different trajectory. Digital complexity increased, but this was not accompanied by comparable expansion across the broader task profile. Collaboration declined. Combined with workers' reports of reduced discretion, this suggests that more digitally demanding work can nevertheless become narrower in scope and potentially more controlled. Technology increased the digital content of these jobs without producing the broader capability development evident in the augmentation pathways.

T4 showed more selective development. Growth was concentrated in physical dexterity, with more modest increases in digital complexity and continuous learning, while decision-making declined. This is consistent with shallow upgrading: particular requirements strengthened, but the overall scope of workers' contribution did not expand to the same extent as in **T1** or **T2**.

T5 showed developments disconnected from technology. Continuous learning increased strongly, but this was accompanied only by modest increases in decision-making, persuading and influencing, and physical dexterity. The combination suggests that workers were learning without a commensurate transformation of their jobs.

Finally, **T6** retained a comparatively low and stable task profile. In the absence of reported technological innovation, only modest improvements occurred in continuous learning, physical dexterity and task repetition.

The longitudinal evidence therefore sharpens the distinctions visible in workers' reported experiences. Augmentation is characterised not simply by the presence of technology, but by the broadening or deepening of the capabilities required in work. Conversely, digital deepening can occur without broader task enrichment.

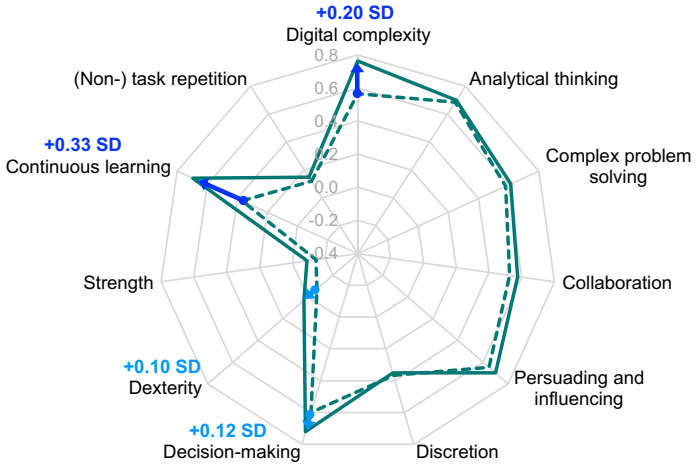
Figure 3.5 Longitudinal Changes in Job-Task Requirements Across Clusters (2017-2022)

2017 2022

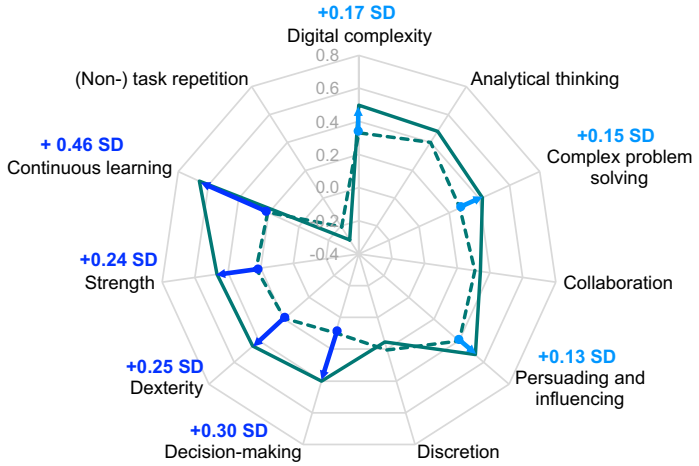
Arrows – change between 2017 and 2022 in standard deviations (SD)

▲: Increase ≥ +0.20 SD; ▲: Increase +0.10 to +0.20 SD (modest); ▼: Decrease -0.10 to -0.20 SD (modest); ▼: Decrease ≤ -0.20 SD;

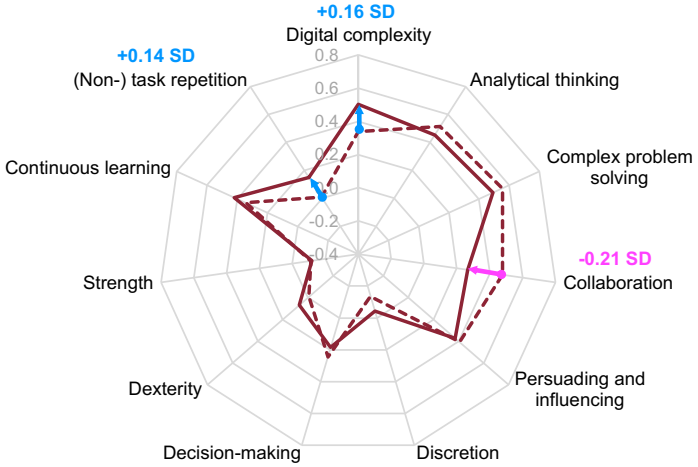
T1 Knowledge-work augmentation



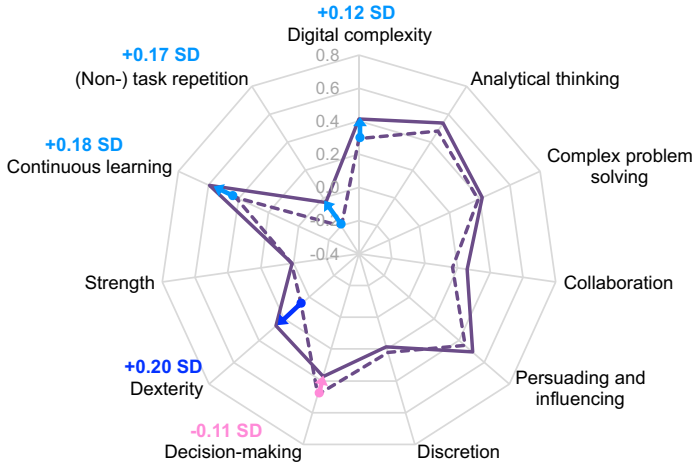
T2 Technical-dexterity augmentation



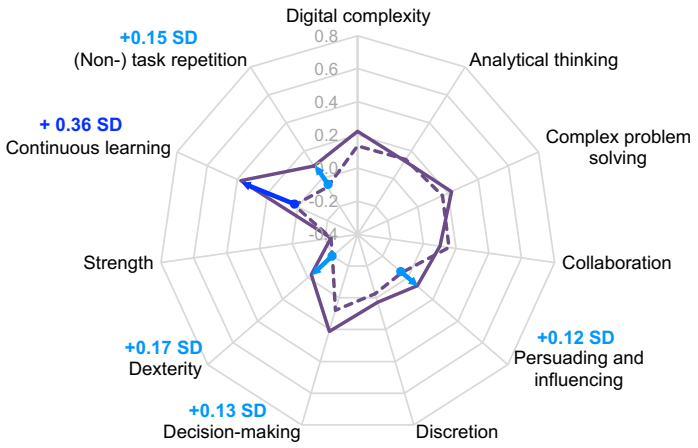
T3 Knowledge-work degradation



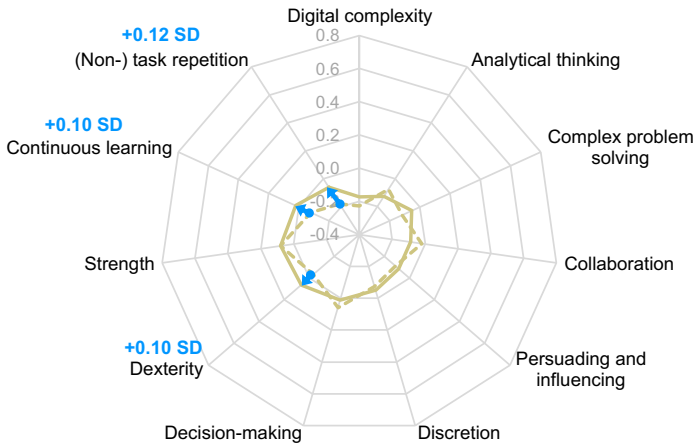
T4 Shallow upgrading



T5 Tech-disconnected upgrading



T6 Technology stagnation



Business innovation complements technological adoption but does not guarantee augmentation

If technological outcomes depend partly on how organisations implement technology, the next question is whether the six clusters were embedded in different patterns of wider business change. **Table 3.6** suggests that they were.

Table 3.6 Business Innovation Profile Across Clusters

Share of job holders reporting each item (%)

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Technological innovation						
Computerised/ automated equipment	77%	92%	73%	83%	85%	–
AI/ML	43%	23%	26%	27%	21%	–
Data analytics	64%	28%	49%	37%	33%	–
Business innovation						
Working methods & practices	70%	70%	63%	57%	53%	35%
Product or services	31%	41%	29%	21%	20%	11%
Amount of contact with clients/customers	37%	48%	34%	37%	27%	23%
Outsourcing or relocation	21%	13%	19%	10%	8%	5%
Working arrangements						
Remote working	72%	52%	65%	53%	57%	41%
Global team working	41%	22%	27%	16%	24%	19%

Note: Within each row, darker shading indicates a higher share. Shades are not compared across rows.

The two augmentation clusters combined technological adoption with substantial business innovation. Both **T1** and **T2** reported high levels of changes to working methods and practices (70%). **T2** also stood out for recording the highest incidence of changes to products or services (41%) and the amount of contact with clients or customers (48%), while **T1** had a more globally-connected model of work, including comparatively higher levels of outsourcing or relocation (21%) and global team working (41%), indicating a more globally connected model of work. Technology in these pathways therefore appears to have been embedded within wider changes to how organisations produced, delivered and coordinated their activities rather than introduced in isolation.

Yet business innovation alone did not guarantee augmentation. **T3** also recorded relatively high levels of organisational change, including changes to working methods and practices (63%), products or services (29%), and outsourcing or relocation (19%). The critical difference is that this innovation was not accompanied by the improvements in work-quality standards or broader task development observed in **T1** and **T2**.

This distinction matters. Business innovation can be directed towards different objectives. It may enable higher-value products, services and ways of working that expand workers' contribution; but it may also support efficiency, standardisation or tighter control without similarly extending workers' capabilities. The contrast between **T1** and **T3** therefore suggests that what organisations innovate towards matters alongside how much they innovate.

Patterns of remote and global working provide a further indication. **T1** combined the highest prevalence of remote working (72%) with extensive global team working (41%). **T3** also had high levels of remote working (65%) but lower global team working (27%). Similar changes in where work is performed can therefore coexist with different levels of social coordination and collaborative work.

T4 and **T5** occupied more intermediate positions, while **T6** consistently recorded the lowest levels of business innovation. The overall pattern therefore suggests a continuum extending beyond technology adoption itself: limited business innovation accompanies technological stagnation and shallow transformation, while extensive innovation creates the potential—but not the guarantee—for augmentation.

Gain-risk profiles: organisational and workforce differences across clusters

The clusters occurred across the economy, but their concentration among particular firms and workers provides useful indications of where augmentation opportunities and degradation risks may lie (**Table 3.7**).

T1 was strongly associated with knowledge-intensive work. Managers and professionals each accounted for 36% of the cluster, 65% were degree holders, and workers aged 30–39 were relatively prominent. Foreign-owned small enterprises and the public sector were also comparatively well represented.

T2 had a different workforce profile. Technicians and associate professionals (TAPs) (29%) were particularly prominent, and the pathway was more strongly represented in the public sector (32%). Its occupational composition reinforces the earlier task evidence: augmentation can extend beyond conventional professional knowledge work into technically demanding occupations.

T3 presents perhaps the most important risk signal. Like **T1** it contained a relatively highly educated workforce (degree holders at 54%) and large proportion of workers aged 30–39 (34%). However, it was disproportionately concentrated in foreign-owned large enterprises (20%), the highest share across all six clusters. This cautions against assuming that conventional markers of high-quality employment—scale, foreign ownership, technological sophistication and highly educated workers—necessarily protect against degradation. Organisations with substantial technological and managerial resources may also possess greater capacity to standardise workflows, centralise decision-making or use data to intensify managerial control. The combination observed in **T3**—declining discretion, limited broader task development and relatively uneven wage gains—is consistent with this risk.

T4 showed fewer distinctive organisational or workforce concentrations, suggesting that shallow upgrading can occur across a relatively broad range of settings.

T5 was more concentrated among TAPs (25%) and clerical support workers (19%). This middle-skilled concentration makes the pathway particularly relevant for intervention: these are workplaces in which technological investment is already occurring, but has yet to translate into substantial job development.

Table 3.7 Gain-Risk Profiles Across Clusters

Distribution of job holders within each cluster (%) – categories within each characteristic block sum to 100%

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Industry sector	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Manufacturing	15%	16%	21%	12%	23%	14%
Construction	3%	4%	1%	6%	3%	4%
Wholesale & retail trade	15%	8%	7%	3%	10%	14%
Transportation & storage	5%	10%	11%	12%	11%	9%
Accom & food service	3%	3%	3%	4%	3%	6%
Information	7%	3%	3%	2%	4%	6%
Financial & insurance	12%	1%	10%	14%	11%	8%
Real estate	3%	6%	0%	7%	5%	2%
Professional, scientific & technical	2%	6%	11%	7%	8%	7%
Admin & support services	4%	4%	6%	2%	4%	5%
Public admin & defence	12%	9%	10%	13%	6%	3%
Education	11%	10%	8%	8%	6%	9%
Health & social services	7%	15%	3%	6%	6%	7%
Other services	1%	5%	2%	3%	1%	5%
Others	1%	0%	2%	0%	1%	2%
Firm characteristics	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Local SME	25%	34%	23%	36%	43%	48%
Local large enterprise	10%	13%	13%	11%	11%	12%
Foreign SME	19%	10%	16%	15%	16%	13%
Foreign large enterprise	11%	5%	20%	7%	15%	8%
Public sector	31%	32%	25%	27%	11%	14%
Non-profit sector	3%	6%	2%	4%	3%	4%
Occupation	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Managers	36%	28%	28%	26%	18%	23%
Professionals	36%	19%	22%	27%	22%	16%
Technicians & associate professionals	15%	29%	25%	18%	25%	14%
Clerical support workers	7%	15%	10%	11%	19%	15%
Sales & service workers	5%	3%	6%	5%	6%	11%
Production & related workers	2%	6%	9%	13%	10%	21%
Educational attainment	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Degree	65%	38%	54%	43%	43%	35%
Diploma	23%	24%	26%	27%	23%	20%
Below diploma	12%	38%	20%	30%	34%	46%
Age band	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
25-29 years old	2%	0%	3%	3%	1%	2%
30-39 years old	31%	24%	34%	28%	21%	21%
40-49 years old	28%	27%	28%	28%	27%	24%
50-59 years old	29%	33%	26%	27%	32%	29%
60-70 years old	10%	16%	9%	14%	19%	24%

Note: Within each row, darker shading indicates a higher share. Shades are not compared across rows.

T6 presents a different challenge. Local SMEs (48%), production and related workers (21%), and below-diploma workers (46%) were comparatively prominent. Given that **T6** encompasses 56% of workers, technological stagnation is not a peripheral phenomenon. It represents a substantial part of the economy where both technology adoption and wider organisational innovation remained limited. The policy challenge is therefore two-sided: prevent technologically advanced workplaces from moving towards degradation while enabling firms and workers currently experiencing limited transformation to move towards augmentation.

Learning and capability development accompany technological augmentation

If technological augmentation produces richer and more complex work, workers should also need opportunities to develop the capabilities required to perform it. **Table 3.8** broadly supports this expectation.

Table 3.8 Non-Formal Structured Training and Informal Learning Across Clusters
Adjusted share of job holders participating in each form of learning (%)

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Structured training						
Job-related training	82%	69%	79%	74%	67%	58%
Employer-required training	85%	70%	70%	72%	69%	54%
Employer-financed training	72%	57%	57%	60%	63%	50%
Informal learning						
Learning from co-workers	86%	82%	75%	76%	71%	64%
Learning-by-doing	98%	94%	89%	87%	83%	84%

Note: Adjusted shares are predicted probabilities from logistic regression models, controlling for industry sector, firm characteristics, occupation, educational attainment, gender and ethnicity. Within each row, darker shading indicates a higher share. Shades are not compared across rows.

Workers in **T6** consistently recorded the lowest participation in workplace training and informal learning. By contrast, workers experiencing technological innovation generally reported greater engagement in workplace learning—even where the resulting changes in their jobs remained limited.

T1 provides the clearest example of a structured capability-development model. It recorded the highest participation across almost every learning measure, including employer-required training (85%), employer-financed training (72%), learning from co-workers (86%) and learning-by-doing (98%). This complements its already high task requirements and substantial growth in continuous learning.

T2 followed a different model. Participation in structured training was closer to the average (70% employer-required and 57% employer-financed), but informal workplace learning was particularly strong. High levels of learning from co-workers (82%) and learning-by-doing (94%) are consistent with workers adapting to new equipment, changing processes and increasingly demanding technical tasks through practice rather than primarily through formal courses.

The contrast between **T1** and **T3** cluster is again revealing. Despite both being associated with substantial technological and business innovation and relatively highly educated workforces, T3 recorded lower participation across both structured (employer-required training: 70%; employer-financed training: 57%) and informal forms of workplace learning (learning from co-workers: 75%; learning-by-doing: 89%). This mirrors its narrower task-development trajectory.

T5 offers an additional insight. Workers continued to participate in training and workplace learning despite limited change in their broader task requirements. Continuous learning therefore does not necessarily indicate augmentation by itself. Learning can help workers adapt to technology within existing job boundaries without expanding those boundaries.

The overall finding is consequently more specific than technology requiring more training. Augmentation appears to involve alignment between technology, richer job requirements and opportunities to develop and exercise the capabilities those jobs require.

Skills (mis-)match provides mixed signals across clusters

Perceived skills mismatch provides a more ambiguous signal (**Table 3.9**).

Table 3.9 Perceived Skills Mismatch Across Clusters

Adjusted distribution of job holders within each cluster (%) – skills mismatch categories sum to 100%

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Skills mismatch						
Over-skilled	23%	26%	19%	23%	13%	19%
Matched	65%	65%	72%	65%	79%	71%
Under-skilled	12%	9%	8%	12%	8%	10%

Note: Adjusted percentages are predicted probabilities from a multinomial logit model, controlling for industry sector, firm characteristics, occupation, educational attainment, gender and ethnicity. Within each row, darker shading indicates a higher share. Shades are not compared across row.

T1 and **T2**—and to a lesser extent **T4**—recorded relatively lower levels of skills match (65%) and higher levels of over-skilling (23–26%). At first sight, this may appear inconsistent with augmentation. However, over-skilling can reflect different dynamics. It may represent temporary capability headroom, as workers develop skills ahead of what their current jobs require, or more persistent under-utilisation where jobs do not make full use of workers' capabilities (McGuinness et al., 2018). The wider evidence for **T1** and **T2** is more consistent with the former interpretation. These were not stagnant jobs: job-task requirements were being enriched, technological adoption was accompanied by relatively extensive business innovation, and workplace learning was strong. Workers' capabilities may therefore have been developing alongside—and in some cases ahead of—the changing requirements of their jobs. Some over-skilling in these pathways may consequently represent productive capability headroom for further upgrading, rather than unused human capital.

T5 provides a useful counterpoint. It recorded the highest skills match (79%), despite comparatively limited growth in job-task requirements. A high level of skills match, in other words, does not necessarily indicate more dynamic capability utilisation.

Under-skilling remained relatively uncommon and showed little differentiation across clusters (8-12%). Technological innovation therefore did not appear to generate widespread inability among workers to meet the demands of their current jobs.

Skills match alone consequently provides an incomplete measure of successful transformation. A workforce can be closely matched to relatively static jobs, while workers in expanding jobs may possess capabilities that temporarily—or persistently—run ahead of what their roles require. This distinction is important for policy: capability headroom becomes an advantage only when job redesign continues to create opportunities for workers to use and develop those capabilities.

Employment and career outcomes show weaker differentiation across clusters

The strong differences in technology, job design and learning become less pronounced when the analysis moves to broader individual employment and career outcomes (**Table 3.10**).

Table 3.10 Employment and Career Outcomes Across Clusters

Adjusted outcome scores (0-100%) – higher scores indicate better outcomes

	T1 Knowledge-work augmentation	T2 Technical-dexterity augmentation	T3 Knowledge-work degradation	T4 Shallow upgrading	T5 Tech-disconnected upgrading	T6 Technology stagnation
Employment prospects						
Internal job prospects	62%	63%	59%	62%	59%	58%
External job prospects	70%	68%	70%	69%	67%	65%
Job satisfaction and discretionary effort						
Job satisfaction	78%	75%	73%	77%	78%	75%
Discretionary effort	82%	86%	83%	82%	80%	79%
Learning and capability						
Deep learning	71%	70%	68%	68%	64%	65%
Skills mastery	76%	75%	72%	73%	68%	71%
Career self-efficacy	68%	65%	66%	67%	64%	65%

Note: Adjusted scores are predicted values from OLS regressions controlling for the corresponding outcome in 2017, industry sector, firm characteristics, occupation, educational attainment, gender and ethnicity. Within each row, darker shading indicates a higher share. Shades are not compared across rows.

Employment prospects and job satisfaction varied relatively little across clusters. Career self-efficacy was similarly stable, suggesting that workers across quite different technological environments retained broadly comparable confidence in their ability to navigate their careers.

Discretionary effort provided the clearest exception. **T2** recorded the highest level of discretionary effort (86%). This is noteworthy because the same pathway experienced the largest expansion in job-task requirements and highest levels of over-skilling.

The relatively modest differences elsewhere are themselves informative. Organisational transformation and individual outcomes are related, but they are not synonymous. Enterprise-level technology and talent strategies shape the conditions in which workers perform and develop, but do not mechanically translate into individual outcomes. Workers may continue to learn, contribute and perform well even where organisational outcomes remain limited. However, these individual inputs may not compound into sustained improvements in job design, productivity or rewards unless technology adoption is coordinated with work organisation and capability development. Equally, where organisational change is more extensive, its benefits may take longer to become visible at the individual level.

Technological augmentation is associated with more evenly distributed wage gains, without incurring higher wages yet delivering better outcomes

Wages provide a final lens on the gains associated with different technological pathways (**Figure 3.11**).

First, augmentation was not associated with substantially higher wage levels. By 2022, adjusted hourly wages were relatively similar across the clusters, despite marked differences in technology adoption and job design. **T1** knowledge-work augmentation increased from S$22.2 to S$24.6 per hour, while **T2** technical-dexterity augmentation rose from a lower starting point of S$18.3 to S$23.9. Their 2022 wage levels were therefore broadly comparable with those of the other clusters. This is notable from an employer perspective. The richer task requirements associated with augmentation did not appear to come with substantially higher labour costs. Read alongside the earlier evidence of expanded worker capabilities and improved work-quality standards in **T1** and **T2**, this raises the possibility that augmentation enables firms to generate greater value from their workforce—through more complex or higher-quality contributions—without a correspondingly large wage-cost premium, suggesting a higher level of productive use of the workforce.

Second, **T2** stands out for its wage growth. Workers in technical-dexterity augmentation began with the lowest adjusted hourly wage among the technology-exposed clusters in 2017, but recorded the strongest overall adjusted wage growth, at 21%. By 2022, their wage level had largely converged with those of the other clusters. This is consistent with the substantial expansion in job-task requirements observed earlier. Wage growth therefore accompanied a broader increase in the demands and contribution of these jobs.

Third, the augmentation clusters were distinguished by how broadly wage gains were shared. **T1** and **T2** recorded comparatively narrow occupational spreads in wage growth—13 and 21 percentage points respectively. In **T1**, adjusted wage growth ranged from 10% among rank-and-file workers to 22% among managers and professionals. In **T2**, all four occupational groups also recorded positive gains, ranging from 12% to 33%.

T3 presents the clearest contrast. Its overall wage growth of 11% masks sharply divergent occupational trajectories: managers gained 48%, while TAPs experienced a 14% decline, producing a 62-percentage-point gap. In this cluster, technological and business innovation coincided with a much more uneven distribution of wage gains. This echoes the earlier evidence of declining discretion and limited broader capability development in **T3**.

T4 also recorded highly dispersed wage growth, with a 71-percentage-point gap across occupations. Its exceptionally strong TAP wage growth should, however, be interpreted cautiously given the cluster's concentration in commission-based occupations such as real estate and insurance sales. **T5** showed more moderate dispersion, while **T6** recorded a relatively narrow spread despite its low-technology and comparatively stable task profile. A narrow wage-growth distribution is therefore not, by itself, evidence of augmentation. What distinguishes **T1** and **T2** is the combination of relatively inclusive wage growth with the preservation or expansion of substantive job-task requirements.

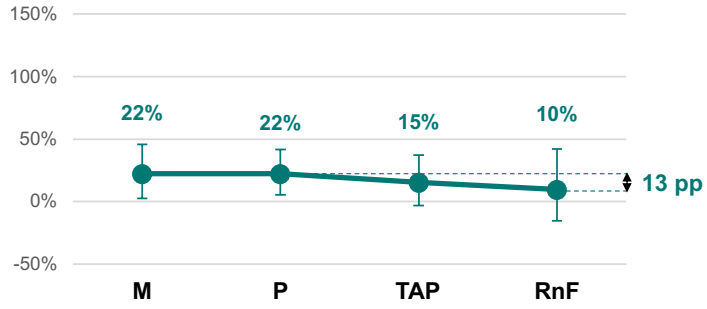
Figure 3.11 Wage Patterns Across Clusters (2017-2022)

T1 Knowledge-work augmentation

Adjusted hourly wage (nominal S$) (2017 → 2022)
22.2 → 24.6

Adjusted wage growth (controlled for 2017 levels)
+16%

Adjusted wage growth (2017-2022), by occupation

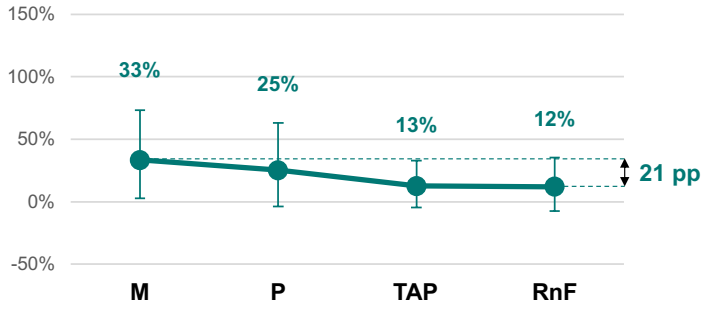


T2 Technical-dexterity augmentation

Adjusted hourly wage (nominal S$) (2017 → 2022)
18.3 → 23.9

Adjusted wage growth (controlled for 2017 levels)
+21%

Adjusted wage growth (2017-2022), by occupation

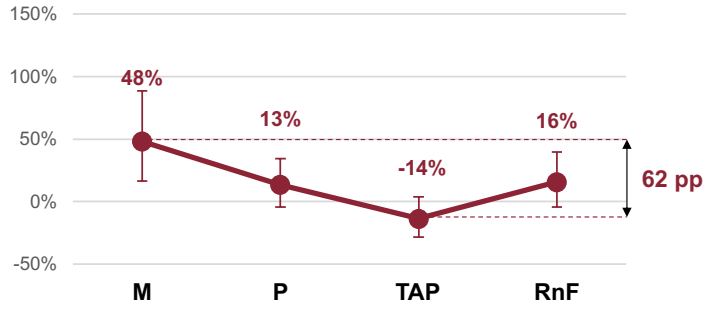


T3 Knowledge-work degradation

Adjusted hourly wage (nominal S$) (2017 → 2022)
22.1 → 24.1

Adjusted wage growth (controlled for 2017 levels)
+11%

Adjusted wage growth (2017-2022), by occupation

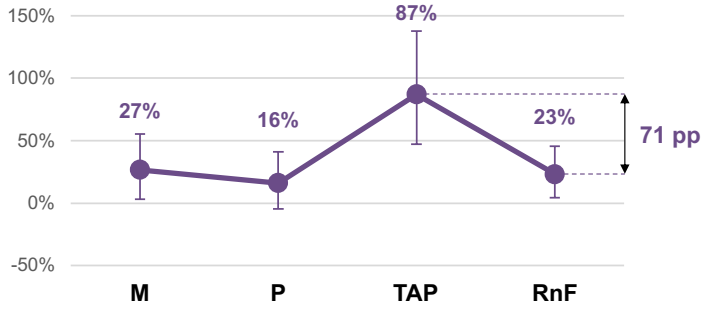


T4 Shallow upgrading

Adjusted hourly wage (nominal S$) (2017 → 2022)
23.6 → 29.2

Adjusted wage growth (controlled for 2017 levels)
+29%

Adjusted wage growth (2017-2022), by occupation

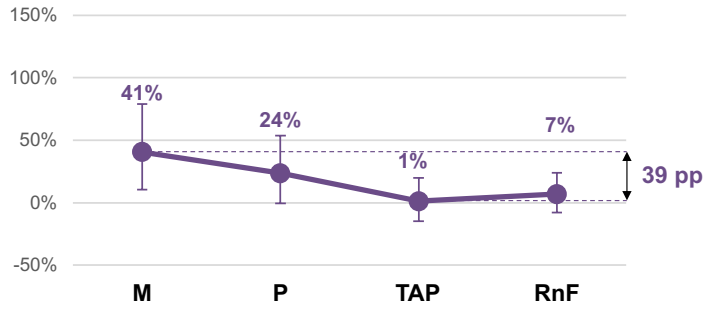


T5 Tech-disconnected upgrading

Adjusted hourly wage (nominal S$) (2017 → 2022)
22.9 → 25.1

Adjusted wage growth (controlled for 2017 levels)
+13%

Adjusted wage growth (2017-2022), by occupation

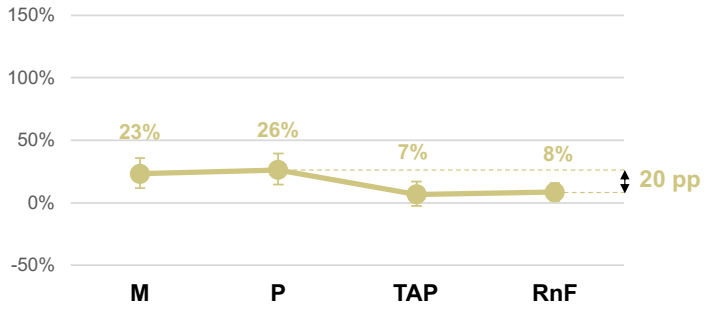


T6 Technology stagnation

Adjusted hourly wage (nominal S$) (2017 → 2022)
20.2 → 23.1

Adjusted wage growth (controlled for 2017 levels)
+13%

Adjusted wage growth (2017-2022), by occupation



Note: Adjusted hourly wages are model-predicted wage levels for 2017 and 2022. Adjusted wage growth is estimated separately using OLS regression of the change in log hourly wages between 2017 and 2022. Occupation-specific wage growth estimates are derived from the interaction between job cluster and occupation; error bar show 95% confidence intervals. Confidence intervals are relatively wide for T1-T5 due to their smaller sample sizes and should therefore be interpreted with caution, although the overall pattern provides an indication of differences across occupations. Models control for 2017 wage levels, industry sector, firm characteristics, educational attainment, age, gender and ethnicity. Log wage changes are converted to percentage changes.

The relatively inclusive wage trajectories with stronger productive outcomes observed in the augmentation pathways are consistent with a wealth-of-talent perspective (Sadik et al., 2025), in which technology creates shared gains between employers and workers due to business strategies of value-creation. The contrast is clearest between the knowledge-work pathways: **T1** combined capability development with broadly shared wage gains, whereas **T3** combined a narrowing of task requirements with substantially greater inequality in wage growth. Because **T3** workers did not report quality gains with technological use, it might provide an indication of value-capture technologies through cost-efficiency gains (Brown & Sadik, 2025).

The occupation-specific estimates should nevertheless be interpreted cautiously, as the smaller samples in **T1**–**T5** result in relatively wide confidence intervals. More important than the precise estimates is the pattern when considered alongside the wider evidence in this chapter: augmentation combined richer capability utilisation with relatively inclusive wage growth, without being associated with substantially higher wage levels.

Summary

The chapter began with an unresolved question from Chapter 2: if technology was increasingly embedded across Singapore's economy, did it translate into better work, and under what conditions? The longitudinal cluster analysis shows that there was no single trajectory of technological change. The same broad process of technological innovation was associated with augmentation, degradation, shallow upgrading, disconnected upgrading and stagnation. The strongest evidence points to augmentation as an organisational model rather than a technological outcome. Technology is most strongly associated with augmentation when technological adoption forms part of a wider organisational model that expands the capabilities workers are required and enabled to exercise, supports their development through workplace learning, and shares the resulting gains more broadly.

The policy question consequently shifts from “How quickly is technology being adopted?” to “What kind of transformation is technology producing?”. For Singapore, the next frontier is not technology diffusion alone, but the quality of organisational transformation around it: expanding the pathways through which technological investment creates richer work, stronger capabilities and more inclusive rewards, while identifying and mitigating the pathways through which the same technological frontier can narrow work and concentrate its gains.

Notes

1 The number of clusters was assessed using the Calinski–Harabasz (CH) pseudo-*F* criterion alongside the substantive distinctiveness and interpretability of alternative solutions. While the two-cluster solution produced the highest overall CH value, the five-cluster solution represented a local maximum and provided substantially greater differentiation of workers’ experiences without excessive fragmentation. Five clusters were therefore retained as the most parsimonious solution for distinguishing different pathways of technological change.

Looking ahead

4. Steering for Augmentation with AI

Singapore entered the generative-AI era with a warning of top-loaded gains—but also two proven pathways towards augmentation.

Singapore's pre-generative AI experience shows that technological progress did not automatically produce better work. Gains in digital complexity in work diminished down the occupational hierarchy, with evidence that technological change produced both augmentation and degradation. Drawing on these findings, this chapter outlines four areas for critical attention in the generative-AI era and three areas for national action.

Four critical lessons from pre-generative AI trends

01 **Generative AI may widen exposure to knowledge-work degradation.**

Generative AI reaches directly into knowledge-intensive tasks such as analysis, drafting and decision support. It may therefore expose a larger share of the economy to the divergent pathways already observed before its proliferation: knowledge-work augmentation (**T1**) and knowledge-work degradation (**T3**).

The two cluster types add a new dimension to concerns about K-shaped divergence. Firms at the technological frontier may not only pull away from the rest; they may also transform in fundamentally different directions. Both **T1** and **T3** combined high levels of technological and business innovation—including the use of AI, machine learning and data analytics—yet produced sharply different patterns of job-task growth and wage gains **(Figure 4.1 and 4.2)**. The over-representation of foreign SMEs in **T1** and large foreign corporations in **T3** provides an additional lens. Both would conventionally occupy the leading arm of Singapore's K-shaped economy, yet they appear to embody markedly different forms of transformation. This suggests that economic divergence is not simply between technological leaders and laggards, but also among leading firms—depending on whether innovation augments work or degrades it.

An important perspective to take is that **T1** was associated with improved quality, whereas comparable gains were absent in **T3**. Further enhancements to the survey instrument are required but the divergence in terms of quality outcomes may mirror the distinction between labour-enhancing value creation and labour-degrading value capture strategies warned by Brown and Sadik (2025). In the latter, cost-efficiency gains are prioritised over quality gains. The frontier to watch is professional work, given the likelihood of generative AI to impact on cognitive tasks.

The wage outcomes demonstrate what is truly at stake. **T1** recorded the most even occupational distribution of wage gains, with a wage gradient of 0.11; **T3** recorded the most uneven, at 0.54. Knowledge-work transformation could therefore produce some of the most inclusive—or most unequal—forms of technological change. Changes in job-task design, including task complexity, judgement, discretion and social coordination, therefore need to be monitored closely as indications of the direction of change. Doing so creates opportunities to intervene before degradation and its distributional consequences become entrenched—an approach also reflected in German policymakers' close attention to job design when steering AI's labour-market effects (Brown & Sadik, 2025).

> **How best can Singapore systematically identify and track patterns of generative-AI use that enhance labour or risks degrading work?**

Figure 4.1. How similar knowledge-work occupations evolved in contrasting ways in T1 and T3 firms

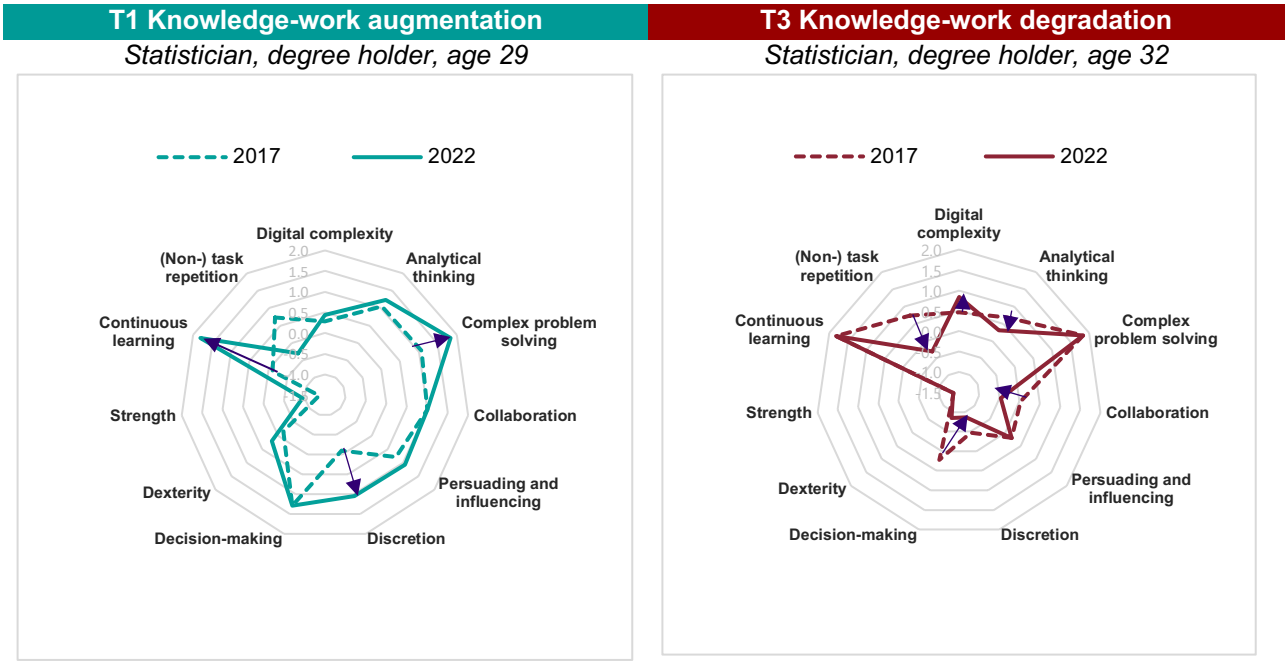
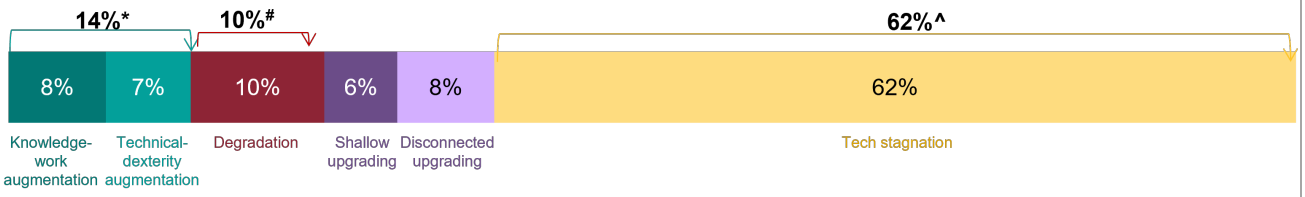


Figure 4.2 Signals for accountancy sector

Accountancy sector illustrates opportunities for augmentation with AI, but also risks of job degradation.

It also has a substantial share of workers not seeing technology changes at work.

Accountancy jobs should be nudged towards augmentation, especially for their TAP and clerical roles.



*National average – 17%; #National average – 8%; ^National average – 56%

Degree	42%
Diploma	35%
Below-diploma	23%

Managers	37%
Professionals	6%
TAPs	16%
Clerks	42%

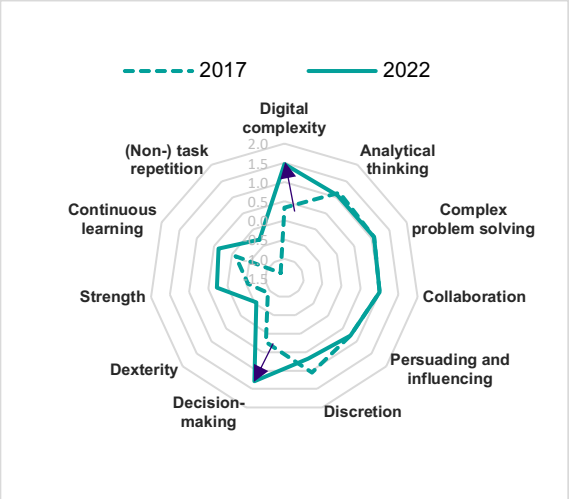
Local SME	52%
Local large	16%
Foreign SME	13%
Foreign large	6%
Public sector	12%
Non-profit	1%

Note: Estimates are based on a small sectoral subsample and should be interpreted as indicative rather than representative of definitive sector-wide patterns.

OCCUPATION IN FOCUS: ACCOUNTING ASSOCIATE PROFESSIONAL

T1 – Knowledge-work augmentation

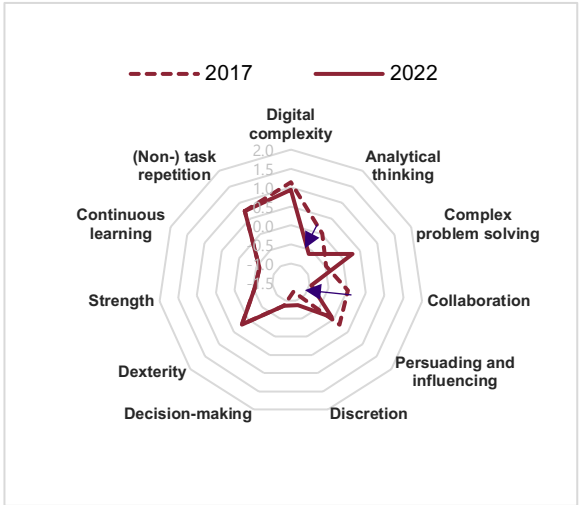
Degree holder, age 40



Job-holder experienced increases in digital complexity and decision-making tasks with technology use.

T3 – Knowledge-work degradation

Diploma holder, age 45



Job-holder experienced decreases in analytical thinking and collaboration tasks, and minimal change in digital complexity even with technology use.

02 Technical-dexterity augmentation is a vital pathway—and can proliferated with physical or embodied AI.

Technical-dexterity augmentation, demonstrated by the **T2** cluster, is a distinct and equally important model of technological change. In **T2**, technology extended physical demand of the jobs, alongside higher levels of repetition with technological change. This signals growth of expertise in technical dexterity accompanied by increased diagnostic ability and complex problem-solving. This pathway holds the potential to enrich the contribution of technicians, operators and other intermediate workers. It therefore complements knowledge-work augmentation rather than representing a less advanced form of transformation.

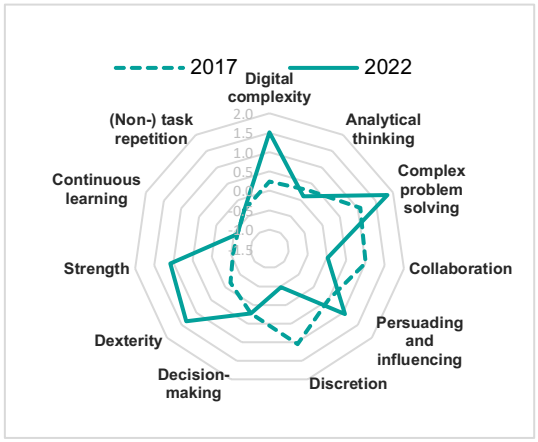
Maintaining this pathway requires Singapore to invests in physical or embodied AI, alongside cognitive AI. Technical augmentation often arises from integrated combinations of automated equipment, robotics, sensors, digital systems and AI. A poor focus on physical or embodied AI could inadvertently crowd out opportunities to achieve substantial expansion of jobs for a broad segment of the workforce. With cognitive AI easy to scale and more likely to be adopted by markets, it is imperative that public funding invests substantially in the use of physical or embodied AI to elevate jobs.

Indeed, **T2** is vital because it elevates the technical occupations that every advanced economy needs, and improves economic resilience. **T2** recorded the strongest overall gains in job-task requirements across the six pathways alongside a relatively even occupational distribution of wage gains (0.18). It signals that substantial technological change can enrich rather than diminish technical work. The choice of technologies in **T4**, **T5** and **T6**, with a comparatively higher proportion of computerised and automated equipment use further suggest that these clusters may benefit more from physical or embodied AI. Indeed. Tay et al. (2025) highlight its potential to extend cognitive tasks in vocational occupations such as landscape and manufacturing technicians. Possibilities may include industrial AI-enabled eyewear built on augmented reality (AR), computer vision, and voice controls. Used in this way, AI could connect practical expertise with analysis, diagnosis and decision-making—raising the scope and standing of technical work.

Figure 4.3. How engineering occupations evolved in contrasting ways in T2, T4 and T6 firms

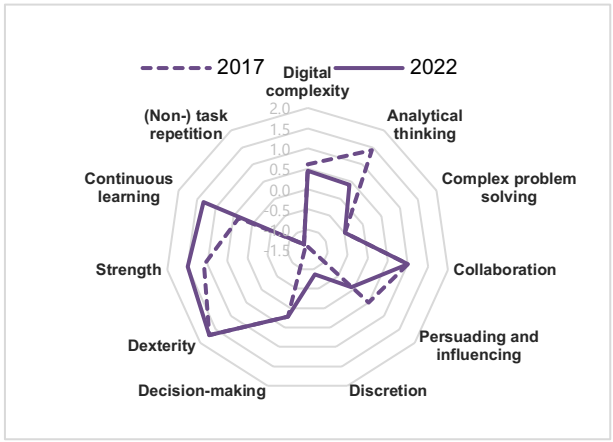
T2 Technical-dexterity augmentation

Civil engineer, diploma holder, age 53



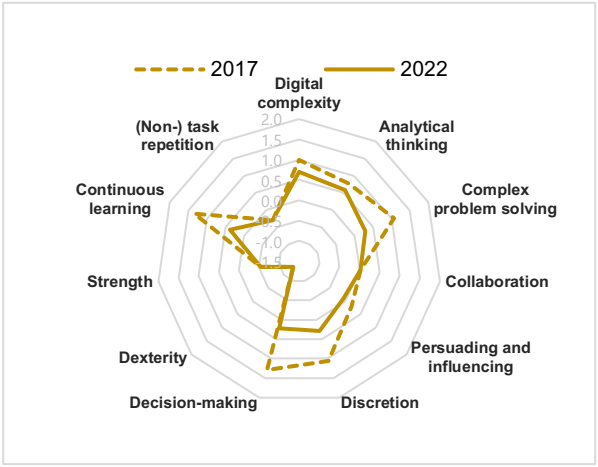
T4 Shallow upgrading

Production engineer, degree holder, age 42



T6 Technology stagnation

Civil engineer, degree holder, age 43



How can Singapore develop and diffuse technical-augmentation pathways across relevant firms and occupations?

03 Integrate business strategy with technology and job design to steer firms towards augmentation.

Business strategy appears to be a decisive differentiator, although finer-grained analysis is required. Value-creating business innovation may be hypothesised to help explain knowledge-work agumentation in **T1** that improves quality of work. Cost-efficiency business innovation may be hypothesised to explain knowledge-work degradation in **T3** that was in which technology use did not accompany work-quality gains.

Business strategy may also have constrained **T4**, **T5** and **T6**, whose low-to-moderate levels of business and technological innovation contrasted with the high levels observed in **T2** technical-dexterity augmentation, even as all tend to use the same underlying technological strategy. **T4** firms, for example, reported quality outcomes but not greater task complexity, suggesting a relatively shallow incorporation of technology arising possibly from less developed business strategies.

Technology support and job-design programmes must therefore actively engage with the business strategies of firms. Job redesign is unlikely to deliver augmentation when the underlying strategy centres primarily on cost-efficiency gains only or shallow, non-complex differentiation. Support should instead connect business innovation, technology adoption and job design around a common value-creation proposition—and evaluate improvements in business performance and work together. Finland offers a useful precedent in this regard. Its workplace-development programmes bring workplace innovation within a broader innovation-policy framework, linking business productivity and competitiveness with employee participation and improvements in quality of work. The approach recognises that sustainable transformation requires simultaneous changes in business, technology, management and work organisation—not just technology or job redesign in isolation (Alasoini, 2011; 2015).

> **How can Singapore integrate business innovation, technology support and job design so that public policy steer firms towards value-creating strategies that generate augmented outcomes?**

04 **Nurture a coalition of firms committed to delivering augmentation facilitated by common standards.**

The over-representation of large foreign corporations in **T3** knowledge-work degradation suggests that conventional markers of good jobs—such as firm size and foreign ownership—may not reliably produce augmented outcomes. Yet clear local alternatives were not prominent: local SMEs were under-represented in **T1** and **T2** and concentrated in **T6**, while large local enterprises did not feature strongly in any cluster.

Rather than favouring particular firm profiles, one way to steer practices amid disruptive change is to establish common business-compatible, job-enhancing standards that make the desired outcomes explicit. Evidence from firms demonstrating clear augmentation patterns, such as those in **T1** and **T2**, can help define these standards, establish the business case for augmentation and identify practical ways to align technology strategy with better work and stronger firm performance. Private-sector firms of different sizes, origins and industries could then be invited and incentivised to work towards these outcomes, with support allocated according to credible commitments and demonstrated progress. Internationally, observers have noted that market incentives favour value-capture strategies linked to cost reduction and efficiency gains (Acemoglu & Restrepo, 2022; Brown & Sadik, 2025). Public policy should direct additional support towards value-creating strategies that the market may underprovide, encouraging the pursuit of quality improvements alongside richer work.

Evidently, the public sector should lead by example. It was already strong in **T1** and **T2,** even as its presence in **T3** and **T4** points to opportunities to apply and spread stronger practices more consistently across agencies.

> **How can Singapore establish common augmentation standards and use them to incentivise a broader coalition of firms to jointly deliver augmentation goals?**

Three areas for national action towards augmentation: steer, discover, observe

Three areas of national action are proposed to form a coherent system for advancing augmentation: *steer, discover and observe. Steer* aligns public support with business and workforce outcomes; *discover* surfaces and diffuses effective augmentation practices from the ground-up across Singapore's corporate landscape; and *observe* tracks outcomes of technological transformation. Together, they create a continuous process for setting direction, harnessing evidence-backed actual corporate practice and adjusting policy as technologies and their effects evolve.

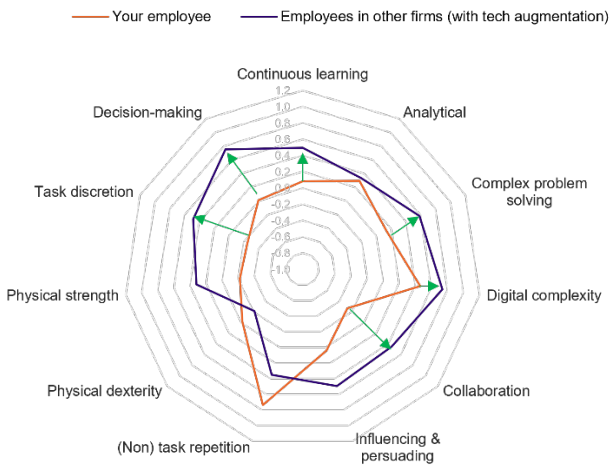
01 Steer: Make augmentation-conditioned support a national policy principle

Public support through public funding of programmes should be conditional on the quality of transformation firms propose—not merely the technology adopted or the number of workers trained. Technology grants, business-transformation support, job-redesign programmes and Job Transformation Maps should assess whether investments will:

- create higher-value products, services or markets;
- expand human judgement, discretion and substantive contribution;
- build workers' capabilities and progression;
- distribute productivity, wage and career gains more broadly; and
- manage displacement, work intensification and other transition costs credibly.

This connects technology assistance directly to business innovation and labour outcomes. Evaluation metrics will be critical and should be business-compatible while promoting the fuller utilisation and development of workforce capabilities. These expectations should not be treated as an additional burden on firms: public intervention is warranted precisely because markets tend to underinvest in value-creating, workforce-enhancing strategies. Emerging corporate concerns about cognitive offloading and organisational deskilling make it increasingly important to build such considerations into transformation support from the outset (Caosun & Aral, 2026; Goel et al., 2026). Indeed, human-centric outcomes serve not only workers' interests but also those of organisations seeking to maximise the full potential of their human capital. To further support employers, evidence-based nudges such as demonstrating to employers the task design and productive capacity of workers seen in augmentation firms, may catalyse stronger ways to design jobs that amplify their human potential (**Figure 4.1**). Consider a national campaign for advocating employers to augment work with AI drawing on evidence-based approaches.

Figure 4.4 Nudging employers towards new labour-enhancing task creation with AI technologies



Occupation
Commercial & Sales Marketing Executive

Use AI to create higher-value customer work
As you introduce new technology, redesign work around tasks that demand stronger judgement, responsibility and discretion.

Develop deeper customer intelligence
Use AI to identify emerging needs and recurring customer challenges—not simply to produce routine reports. Empower employees to validate insights and recommend decisive business action.

Turn insight into stronger propositions
Enable teams to design and test service improvements, personalised offers and retention initiatives. Use AI to support ideation, analysis and data gathering—while people shape the commercial response.

Other employers are already using AI to expand the role of their commercial and sales marketing executives and strengthen their sales pipeline. How about you?

Source: Institute for Adult Learning

02 Discover: Build a national engine to discover and diffuse augmentation

Multiple studies, including this one, show that concrete examples of augmentation already exist across Singapore (Souto-Otero et al., 2022; Sadik et al., 2025). There is every reason to expect further examples to continue emerging across Singapore's corporate landscape as AI adoption intensifies. These practices, backed by evidence of the outcomes they produced, should be harnessed as a collective source of corporate know-how—generated by firms, consolidated into practical transformation models and returned to firms in forms they can readily apply. A systematic evidence-based discovery process could surface these practices, including new augmentation pathways emerging with generative AI, and reveal:

- the business opportunities and innovation strategies pursued;
- the combinations of technologies deployed;
- the redesign of workflows and decision rights;
- the actual transformation of jobs, tasks and roles;
- the development and use of workers' capabilities;
- the business outcomes achieved; and
- how productivity, wage and career gains were distributed.

The role of public policy is to facilitate this systematic process of discovery, synthesis and diffusion. The practices identified could be translated into practical transformation models for firms and incorporated into Job Transformation Maps. In this way, evidence from Singapore's corporate landscape could provide a common reference for stakeholders, inform broad augmentation standards and demonstrate persuasively how augmentation can be achieved in practice.

03 Observe: Establish an observatory of outcomes for augmentation.

Singapore already tracks technology adoption, programme enrolment, training, investment and technology use. These indicators measure participation but cannot determine whether technological transformation is producing better firms and better work.

Greater emphasis should therefore be placed on tracking the outcomes of technological transformation with job-task analysis. The longitudinal method developed in this study offers one promising approach: it follows workers over time while retaining the organisational imprint of the enterprises in which they work. This dual lens connects changes in workers' job-tasks, capabilities and prospects to the business and technology strategies shaping them. A third iteration of the longitudinal survey with more detailed technology-linked questions could enable a higher quality understanding of technological impact on work, alongside being an evidence-based source for developing rich evidence-based case studies. Together, the data could provide a more complete view of:

- business productivity, value added, innovation and quality;
- job creation, job loss, reduced hiring and occupational mobility;
- changes in jobs, tasks and roles;
- task complexity, creativity, judgement and decision authority;
- wages, progression and the distribution of gains;
- cognitive offloading and capability atrophy;
- work intensification, surveillance and algorithmic management; and
- social disconnection, fragmentation and precarity.

Such an observatory would connect the worker outcomes Singapore seeks with the enterprise strategies, labour-market shifts and institutional conditions driving them—providing a stronger basis for identifying emerging patterns and adjusting policy before adverse outcomes become entrenched.

Summary

Singapore entered the generative-AI era with both a warning and a foundation for action: technological gains were already concentrated higher in the occupational hierarchy, yet proven pathways towards knowledge-work and technical-dexterity augmentation also existed. Generative AI could widen the reach of knowledge-work degradation but also the possibilities for knowledge-work augmentation. Meanwhile, an excessive focus on AI should be avoided as it risks overlooking the broader technological combinations needed to augment technically-dexterity work. Steering towards better outcomes therefore requires integrating business strategy, technology and job design around value creation, while mobilising firms across different sizes, origins and industries through common augmentation standards. Three national actions can turn this ambition into practice: *steer* by conditioning public support on the quality of firms' proposed transformations; *discover* by systematically surfacing and diffusing augmentation practices from Singapore's corporate landscape; and *observe* by tracking business and workforce outcomes over time, rather than adoption and programme participation alone.

5. Conclusion: The Way Forward

Technology does not determine the future of work—strategy does. Singapore's pre-generative AI baseline shows why the next phase of technological transformation must be steered towards augmentation—not assumed to produce it.

Between 2017 and 2022, digital technologies became more deeply embedded in work in Singapore. Yet this technological deepening did not translate straightforwardly into better jobs. The clearest gains in digital complexity accrued to managers; professionals recorded more partial gains, while the work of associate professionals and technicians weakened. Workers further down the occupational hierarchy saw little or no increase in digital complexity of their work. Digitalisation was spreading, but its developmental benefits remained stratified.

This is the report's central finding: **more technology does not necessarily mean better work.** But better work is certainly possible. The study identifies two distinct routes through which better outcomes were achieved: knowledge-work augmentation and technical-dexterity augmentation. Despite their different foundations, both pathways produced a common outcome: jobs were preserved or upgraded at higher levels of complexity, while wage gains were distributed relatively evenly across workers – suggesting a strong foundation for social inclusion with technological change. These pathways demonstrate that augmentation is not an abstract aspiration. It already exists within Singapore's economy and provides practical evidence of how technology can support both stronger firms and better work, if harnessed.

But augmentation was not the only pathway observed. The study also identifies the pathway of degradation of knowledge work, in which technological change increased the digital complexity demands of the jobs, but did not create the need for continuous learning nor complex tasks, and in fact reduced coordinating responsibilities embedded in jobs. This pathway is especially consequential because it shows that knowledge-work is not inherently protected from technological degradation. The pattern of highly-stratified distribution of wage gains in such firms holds an important warning of the risks of deep dislocation if such approaches proliferate.

Generative AI brings these findings to the centre of the policy debate because it reaches directly into knowledge work. It could deepen augmentation by extending workers' judgement and problem-solving, or accelerate degradation by fragmenting cognitive work, standardising judgement and shifting control away from workers. Yet Singapore's augmentation strategy cannot be confined to AI or knowledge work. Technical-dexterity augmentation requires the use of technologies beyond generative AI that can enhance physical dexterity and specialised technical work.

A further finding is that Singapore cannot rely solely on the markers historically associated with good jobs. Large foreign corporations and high-value-added sectors will remain important, but they cannot be assumed to generate augmentation automatically—or at sufficient scale. Steering augmentation therefore requires continuous, data-driven monitoring to identify where different patterns of technological change are emerging and whether they are producing better firms and better work.

The policy frontier is therefore no longer technology adoption alone. It is the deliberate production of better work through technology. Singapore must build the capability to steer, discover and observe this transformation: steer enterprises towards business, technology and workforce strategies that produce augmentation; systematically discover and diffuse the practices through which augmentation is achieved; and observe outcomes for firms, jobs, wages and workers so the AI transition is productive and inclusive.

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