SUSS | IAL INSTITUTE FOR ADULT LEARNING SINGAPORE

SKILLS LEARNABILITY INDEX

A data-driven index that measures the ease of learning different skills, providing insights to guide training and workforce development strategies.

October 2025

SRI MANIKANTAN

SILIN YANG

SIMON FREEBODY

Publisher's note

The views and analyses presented in this document are those of the authors. The contents are intended for discussion and generating ideas, and are not necessarily the views or policy prescriptions of the Institute for Adult Learning (IAL) or the Singapore University of Social Sciences (SUSS).

Please cite this publication as: Manikantan, S., Yang, S., & Freebody, S. (2025). *Skills Learnability Index.* Institute for Adult Learning, Singapore University of Social Sciences.

ISBN: 978-981-94-4256-0 (digital)
CSFP Analytics Report 1 (Oct 2025)

CONTENTS

WHAT IS SKILLS LEARNABILITY INDEX?

The rapid evolution of the labour market makes continuous skills development more critical than ever. Demographic shifts, digital transformation, and the green transition are actively shaping the types of work available, the skills required, and the pace at which workers must adapt. Ageing populations, for instance, are creating higher demand for jobs in healthcare and social support sectors while also requiring older workers to reskill in order to remain active in the labour market (OECD, 2019). Digital transformation is altering nearly every occupation, with new technologies boosting productivity but also increasing the risk of displacement for those unable to adapt (Acemoglu & Restrepo, 2020). Likewise, the green transition is giving rise to entirely new industries and occupations, each with distinct and evolving skills demands (OECD, 2024a). Together, these forces are accelerating the pace at which skills are changing, making skill adaptability essential.

Reflecting these transitions, the Skills Compass Report (Burning Glass Institute & Coursera, 2023) found that 37% of top skills required for U.S. jobs have changed in just five years—underscoring the urgency of skills adaptation. This challenge is compounded by the shrinking half-life of skills, which has fallen from around 30 years in 1984 to just five years today (Infosys, 2021). This shows that workers can no longer rely on static qualifications obtained early in life; continuous skill development has become essential to maintaining employability and ensuring that economies can meet emerging needs.

Yet despite this urgency, most workforce tools and career resources still primarily focus on labour market signals like job demand, salaries, and skill transferability. They rarely provide actionable insights into how learnable a particular skill is—information that is critical for planning meaningful skill development journeys. This omission hampers individuals' and organisations' ability to make informed decisions about the opportunity cost to invest in a skill. The OECD's Skills Strategy Framework (2024b) likewise emphasises that actionable skills information is crucial for navigating evolving job demands and supporting continuous learning.

Understanding how learnable a skill is therefore central to effective skill development. While there is no single, universally accepted definition of learnability, the concept is consistently linked to an individual's ability to acquire new skills and adapt to change. In workforce and policy contexts, it is described as a core employability trait—the ability to learn new job or task-specific competencies in order to remain relevant in evolving labour markets (International Labour Organization [ILO], 2018; World Employment Confederation [WEC], 2018). In industry and management research, it is framed more broadly as the desire and capability to continually grow one's skillsets across working life (Chamorro-Premuzic, 2018; Infosys, 2020). Taken together, these perspectives largely approach learnability from the individual's point of view—their motivation or learning capacity. In this project, however, we shift the lens to the skills themselves, treating learnability as a property that can be assessed and compared across different skills. We therefore introduce the concept of *Skill Learnability*, which refers to how difficult or easy a skill is to learn, independent of individual variation.

Building on this foundation, this methodological note presents the **Skills Learnability Index**—a data-driven tool designed to operationalise this concept. The Index quantifies the relative learnability of different skills, offering a structured way to assess and communicate how easy or challenging skills are to learn. By incorporating this dimension alongside traditional labour market signals, the Index provides actionable insights to help users plan and prioritise skill development pathways—ensuring that the skills they pursue not only align with labour-market demand but are also realistically attainable.

WHAT DOES THE INDEX MEASURE?

DIMENSIONS AND INDICATORS

The Skills Learnability Index is based on the understanding that skill learnability is a latent construct—an underlying factor that cannot be observed directly. To estimate it, we developed the Skills Learnability Framework (see Figure 1), which breaks this concept into distinct components that can be measured through specific indicators. Together, these indicators provide an indirect but systematic way to assess the ease of learning a skill. Drawing on insights from related theories and research, the framework clarifies the scope of the Index and the rationale for including these domains.

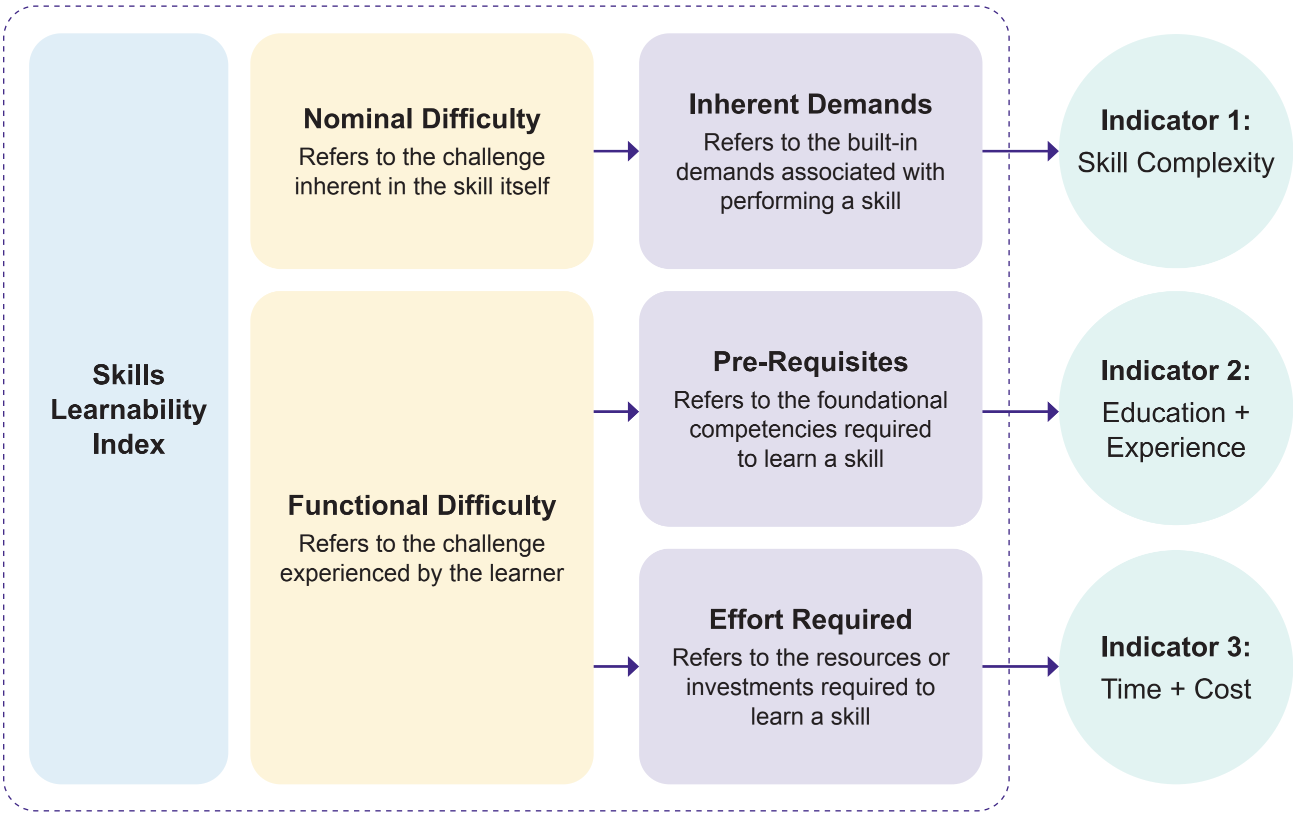

Figure 1: Skills Learnability Framework

It is important to note that the index focuses on the properties of the skill itself, rather than the characteristics of individual learners, making it a tool for comparison and planning at the skill level. In addition, the index is also intended to focus on learning a new skill, and not mastering or deepening existing skills that a learner may already possess.

FRAMEWORK ARCHITECTURE

To measure the ease of learning a skill, the framework first distinguishes between nominal difficulty and functional difficulty. **Nominal difficulty** reflects the intrinsic complexity of a skill — the inherent demands involved in performing it, entirely independent of the learner. While the learner cannot influence this dimension, it signals the level of challenge likely to be encountered during the learning process. **Functional difficulty**, by contrast, captures the more extrinsic factors that shape the learner's experience of acquiring a skill, such as the effort, resources, or pre-requisites required. Unlike nominal difficulty, these elements depend more directly on the learner's circumstances.

This distinction matters because the challenge of learning a skill arises from both the nature of the skill itself and the external conditions surrounding the learning process. This also parallels the distinction made in the skill acquisition literature between nominal and functional task difficulty (Guadagnoli & Lee, 2004). By integrating both perspectives, the Index provides a more balanced and realistic measure of what it takes to learn a skill.

KEY DOMAINS AND INDICATORS

Domain 1: Inherent Demands

This domain captures the **intrinsic barriers** to learning—the inherent demands of a skill that determine how easy or difficult it is to acquire. It reflects what is embedded in the nature of the skill itself rather than what depends on personal circumstances. This matters for skill learnability because skills differ widely in their level of challenge: some require only basic cognitive effort, while others involve integrating multiple mental and physical processes, sustaining attention, or applying advanced problem-solving. The greater these inherent demands, the more difficult it is to learn a skill, regardless of how motivated or well-prepared the learner may be.

To operationalise this domain within the Index, we use skill complexity as the indicator. Complexity is defined as "the degree to which there is a need to integrate complicated interactions among different mental and physical aspects of a task" (American Psychological Association, n.d.). Research shows that higher complexity increases the demands placed on learners' cognitive resources, which is known to constrain learning capacity (Daneman & Carpenter, 1980; Martini et al., 2020; Ninomiya et al., 2024). In practice, higher complexity also elevates emotional load such as anxiety (Derakshan & Eysenck, 2009; Klein et al., 2019) and creates greater instructional demands, requiring more feedback, practice, and opportunities for exploration (Laguna, 2008; Matovu et al., 2024).

In measuring skill complexity, the Index draws on the association of skills with job-level complexity. Our working assumption is that skills which occur more frequently in complex jobs are themselves more complex—and therefore less easily learned. This assumption is not only intuitive but also supported by recent research: a 2024 Scientific Reports study found that high-complexity jobs are characterised by requiring many high-complexity skills, while low-complexity jobs rely mainly on basic skills (Aufiero, De Marzo, Sbardella & Zaccaria, 2024). While this may not fully capture every dimension of inherent difficulty, it offers a systematic way of estimating skill complexity using available data. By including intrinsic difficulty in the framework, the Index ensures that the baseline challenges built into a skill are taken into account, providing a more realistic estimate of the ease of learning.

Domain 2: Pre-Requisites

Alongside these inherent challenges, pre-requisites reflect the **structural barriers** that learners must meet before they can begin learning a skill. They represent the baseline competencies or preparations required at the entry point of learning. In practice, these preparations most often take the form of formal education and prior work experience, which establish the minimum knowledge and familiarity needed to make skill acquisition possible. Some skills can be pursued with minimal preparation, while others demand years of study or extensive practice before competence is attainable. These requirements shape not only the feasibility of pursuing a skill pathway but also the opportunity costs learners face along the way, making pre-requisites a key external factor that influences the ease of learning.

Research underscores that formal education and prior experience significantly influence skill acquisition by providing essential cognitive foundations and practical familiarity (Haith & Krakauer, 2018; Tynjälä et al., 1997). Learners with these pre-requisites in place can progress more smoothly, while those without them encounter steeper barriers to entry. In this sense, education and experience act as thresholds that directly affect how learnable a skill is, determining both the starting point for learners and the level of challenge they are likely to face.

In measuring this domain, the Index uses indicators such as the typical education level and work experience required for specific skills, based on job postings data. While this approach does not directly measure an individual's precise prior knowledge or abilities, it serves as a practical proxy for estimating the foundational preparation typically needed to learn a skill. Incorporating these measures ensures that the Index reflects not only the inherent difficulty of a skill but also the structural entry barriers that shape its ease of learning.

Domain 3: Effort Required

Beyond structural barriers, this domain captures the **situational demands** that arise during the learning process—the resources learners must commit in order to learn a new skill. In practice, these resources most often take the form of time and financial cost, both of which strongly influence a learner's ability to pursue skill development. Even when a skill is intrinsically less complex and has minimal pre-requisites, high time demands or prohibitive costs can make it significantly harder to learn in practice. In this sense, effort required reflects the practical constraints that shape how learnable a skill is.

Time is a central element of this domain. Effective time management has been shown to be a crucial component of successful learning outcomes (Kitsantas, Winsler & Huie, 2008), yet research highlights that learners often underestimate the actual time needed to complete training (Buehler & Griffin, 2015). Such underestimation can lead to frustration, dropout, or poor performance. Encouragingly, interventions that improve learners' forecasting of time demands have been shown to support better outcomes (Follmer, Patchan & Spitznogle, 2022).

Financial cost is equally critical. Training costs vary widely depending on the mode of delivery—for example, between traditional classroom settings, laboratory-based learning, and online provision (Achuthan & Murali, 2015; Hartzler et al., 2023). Moreover, financial constraints are consistently cited as one of the most significant barriers to adult learning (MacKeracher, Suart & Potter, 2006). High costs can deter participation entirely, making cost estimation a necessary component in understanding skill learnability.

To operationalise these indicators, the Index draws on course data to estimate the typical time commitment and financial costs associated with learning specific skills. While such measures cannot capture the full range of situational differences learners face, they provide a consistent proxy for assessing the relative effort required across skills. By including effort required as a domain, the Index ensures that the index also reflects the practical resource demands that determine whether skill acquisition is realistically achievable.

HOW IS THE INDEX MEASURED?

METHODOLOGY

Our Skills Learnability Framework is built on three complementary indicators, each capturing a different dimension of how difficult a skill is to learn. These are:

Indicator 1
Skill Complexity

Indicator 2
Education and Experience

Indicator 3
Time and Cost

Skill Complexity (Indicator 1) is rescaled to a 1–100 scale, where higher values indicate greater complexity. *Education and experience* requirements are each normalised to the same 1–100 scale and then averaged to form Indicator 2, where higher values indicate more demanding pre-requisites. Similarly, *time and cost* are normalised to 1–100 and averaged to form Indicator 3, where higher values represent greater learning effort.

To make interpretation more intuitive, the final Skills Learnability Index is inverted (using the transformation 101 – *score*) so that higher values will indicate greater ease of learning. For consistency, all analysis is conducted at the skill as the unit of analysis (rather than the job or task). Skills represented in fewer than 30 job postings are excluded to ensure statistical confidence in the results.

OVERALL INDEX

The overall Skill Learnability Index is calculated as the simple average of the three indicators, with equal weights (⅓ each) ensuring that all dimensions contribute equally to the final measure. This produces a single composite score (1–100) for each skill, where higher values reflect skills that are easier to learn.

For a particular skill *s*:

$$\text{Skills Learnability Index}_s = \tfrac{1}{3}(\text{Skill Complexity})_s + \tfrac{1}{3}(\text{Pre-Requisites})_s + \tfrac{1}{3}(\text{Effort Required})_s$$

Indicator 1: Skill Complexity

This indicator is designed to capture the relative complexity of skills, based on the assumption that skills more frequently associated with complex jobs can themselves be considered more complex.

We construct this indicator using 2024 job postings data, comprising over 6.8 million postings. Each posting is tagged to a job role under the Singapore Standard Occupational Classification (SSOC) and linked to the skills mentioned in the posting. For analysis, we aggregate these data into occupation–skill pairs: for each occupation, we record how often a given skill appears in its job postings. This covers more than 2,000 distinct skills and captures the frequency of each skill's demand across occupations.

To control for the size of each occupation, we first calculate the *Skill Incidence Rate* for each occupation-skill pair. This expresses skill demand as a proportion of occupation postings, ensuring that occupations with large posting volumes do not dominate the results.

$$\text{Skill Incidence Rate}_{s,o} = \frac{\text{Count of postings requiring skills } s \text{ in occupation } o}{\text{Total postings for occupation } o}$$

Next, to measure job complexity, we draw on the SSOC Broad Job Levels[1] (Singapore Department of Statistics, 2024). Each occupation is assigned a Job Complexity Score ranging from 1 (least complex) to 4 (most complex), based on the Broad Job Level associated with its SSOC 1-digit classification[2]. Level 1 covers occupations with the simplest tasks, while Level 4 represents those with the most complex and wide-ranging responsibilities.

We acknowledge that the Broad Job Level approach, as defined in the SSOC framework, primarily only reflects cognitive complexity. While this is the only standardised categorisation of job complexity currently available, it provides a consistent and comparable basis for our analysis. Accordingly, our measure of skill complexity should be interpreted as reflecting this dimension of complexity. In future iterations, additional dimensions of job complexity (e.g. physical demands) could be incorporated to provide a more holistic view.

For each skill, we then calculate a *Skill Complexity* Score by weighting the job complexity of each occupation by the skill incidence rate within that occupation:

$$\text{Skill Complexity}_{s} = \frac{\sum_o(\text{Skill Incidence Rate}_{s,o} \text{ X Job Complexity Score}_o)}{\sum_o \text{Skill Incidence Rate}_{s,o}}$$

[1] Broad Job Level is defined as a function of the complexity and range of the tasks and duties to be performed in an occupation.

[2] Broad Job Level is not defined for SSOC Group 1. Based on the occupational definitions, we assigned this group the highest complexity level (Level 4) to reflect the wide-ranging responsibilities of jobs within this category.

An incidence-weighted average is used so that occupations where a skill is more commonly required exert greater influence on its overall complexity score. Weighting by incidence also controls for differences in posting volumes across occupations, preventing larger occupations from dominating the results simply because they have more job postings. Using this approach rather than a simple mean prevents rare associations (e.g. when a skill appears only once in a very complex job) from disproportionately inflating the score, and anchors the measure in the relative frequency of skill demand.

Through this method, we produce a single Skill Complexity Score for each skill. A higher score means the skill is more commonly associated with higher complexity occupations.

Indicator 2: Education and Experience

This indicator estimates the baseline competencies that learners typically need before effectively learning a skill, focusing on two dimensions: education level and work experience.

This indicator is constructed using job postings data from 2022 to 2024. The analysis period was extended to over three years to enhance data coverage. Each posting is tagged to a job role under SSOC, from which we extract the minimum education and minimum experience requirements stated by employers. Postings with missing requirements were excluded, and duplicates were removed where possible.

To enable analysis, education and experience requirements were mapped into standardised zones shown in Figure 2 below. These categories represent structural thresholds of preparation typically expected of job seekers.

Education Level	Zone
Post-Secondary	1
Diploma	2
Bachelor’s Degree	3
Graduate Degree	4

Experience Level	Zone
≤ 2 years	1
3-5 years	2
6-8 years	3
≥ 9 years	4

Figure 2: Classification of Education and Experience Level into Zones

To reduce variation across postings, we assign each SSOC job role a single baseline requirement for education and experience. This is defined as the modal value — the zone that appears most frequently across postings for that role. For example, most postings for Software Developer (SSOC 25121) minimally require a Bachelor's degree and 3–5 years' experience, corresponding to Education Zone 3 and Experience Zone 2. In cases of ties, the lower requirement was selected to represent the conservative baseline.

To link skills to these requirements, we identified the 10 most important skills associated with each SSOC job role. *Important skills* are defined as those that are most frequently highlighted by employers for a given job role, while being distinctive to that role rather than generic across all occupations. For example, for *Software Developers*, key skills include *Applications Development* and *Software Testing*. Readers who would like to explore the technical details of how such skills are derived can refer to the *Consolidated Skills Requirements* section of SkillsFuture Singapore (SSG)'s Career Transition Insights methodology page.

To establish baseline requirements for each skill, we aggregated education and experience zones across all the occupations in which the skill appears. For each skill, the modal education zone and modal experience zone — the zones that appear most frequently across postings — were then identified. For example, if *Data Engineering* appears mainly in technical roles such as Data Engineers and Data Scientists, and the majority of postings require a Bachelor's degree and 3–5 years' experience, then the baseline requirements for *Data Engineering* are set as Education Zone 3 (Bachelor's) and Experience Zone 2 (3–5 years). The final output is a set of baseline education and experience zones for each skill, reflecting the dominant expectations of the labour market.

We acknowledge that this approach is constrained by the information employers choose to report in postings. Not all postings specify education or experience requirements, and those that do may reflect hiring norms rather than the absolute minimum needed to learn a skill. Nevertheless, this framework provides a consistent way of comparing the relative baseline requirements typically associated with different skills. In future iterations, complementary measures (e.g. industry-specific requirements, or self-reported learner data), if there is available data, could be incorporated to provide a more holistic view of skill pre-requisites.

Indicator 3: Time and Cost

This indicator measures the time and financial resources typically required to learn each skill. We construct this indicator using the universe of SSG-funded courses active in 2024, which include both Workforce Skills Qualifications (WSQ) and non-WSQ certified courses. In total, we analysed over 6,000 courses mapped to about 2,000 skills. Each course is mapped to one or more skills in the SSG Skills Framework, either through SSG's skill extraction algorithm or by training providers via manual updates and validation.

We acknowledge that the dataset does not capture the full range of training courses available in the market. However, given data availability, we focus on SSG-funded courses as a starting point. This provides a comprehensive and standardised foundation, with scope to expand coverage in future iterations.

Since this index focuses on the learning of new skills rather than the deepening of existing ones, we limit our analysis to focus only on introductory or basic level courses for that skill and exclude courses that are primarily accreditation-based. Courses with missing or zero values for duration or fees are also excluded to avoid distortion.

Some courses are multi-skill, meaning they cover more than one skill within the same sitting. Since information on the exact distribution of time and cost by skill is not available, we allocate these equally across the skills covered. For example, a 30-hour course costing $600 that covers three skills is treated as 10 hours and $200 per skill. This simplifying assumption ensures comparability across courses, while recognising that future iterations could refine the approach if more detailed data become available.

For each skill, we calculate the median course duration and the median course fee across all relevant training programmes. We treat each course equally, regardless of provider or enrolment size, to reflect the supply of training options rather than learner demand. We use the median rather than the mean because of the characteristics of our dataset: most skills are represented by only one or two courses, where the median simply reduces to the observed value or the midpoint of the two. For skills with larger numbers of courses, the median provides a more robust estimate than the mean, as it is less sensitive to extreme outliers (e.g. unusually long or costly programmes). This ensures that the indicator reflects the typical resource requirement for skill acquisition while minimising distortion from atypical courses.

$$\text{Skill Time}_s = \text{median}\left(\frac{\text{Course Duration}_i}{k_i}\right), \quad \text{Skill Cost}_s = \text{median}\left(\frac{\text{Course Fee}_i}{k_i}\right)$$

where k_i is the number of skills taught in course i

This indicator provides a practical and comparable lens on the training resources typically required to learn different skills. It should be interpreted as a proxy for learning requirements based on the available supply of training options, rather than as an absolute measure of all possible pathways to skill acquisition.

HOW CAN STAKEHOLDERS USE THE INDEX?

The Skills Learnability Index is designed to provide actionable insights that go beyond labour market signals. By quantifying how easy or challenging different skills are to acquire, the Index enables stakeholders to plan, prioritise, and sequence skill development more effectively. While the data underpinning the Index are technical, its applications are practical: individuals can decide which skills to pursue, employers can design targeted training, career coaches can provide tailored guidance, and policymakers can align education and training systems with realistic learning trajectories. The following examples illustrate how different groups might use the Index in practice.

Individuals: Deciding which skills to pursue

The Index helps individuals make informed choices about which skills to develop, not just based on wages or labour market demand, but also on how feasible the learning process will be. For example, a mid-career warehouse assistant considering whether to move into scheduling coordination or entry-level cybersecurity can use the Index to see that scheduling requires shorter training with fewer pre-requisites, while cybersecurity involves more advanced preparation and longer study. With this knowledge, the individual can set realistic expectations about time, cost, and effort, and plan a pathway that balances aspiration with practicality.

Employers: Designing Effective Skill Development Programmes

Employers can use the Index to anticipate workforce upskilling and reskilling needs and structure training programmes more effectively. Consider the transformation of a Financial Executive into a Financial Analyst. Index results may highlight that acquiring data analysis skills requires a higher level of learning effort compared to other financial competencies. With this insight, employers can design staged training pathways, starting with foundational data literacy, then advancing to statistical techniques and analytical tools. In this way, the Index helps employers forecast training investments, sequence learning more efficiently, and support smoother role transitions.

Career Coaches: Providing Tailored Guidance for Learners

Career coaches can draw on the Index to provide evidence-based guidance and personalised roadmaps. Consider a displaced clerical worker choosing between becoming a Human Resources (HR) Assistant or a Payroll Officer. Payroll typically demands more specialised technical training, which takes longer and may involve higher costs, while HR assistant roles can be accessed more quickly and affordably through shorter upskilling courses. By highlighting these differences in skill complexity, time commitment, and training investment, the Index enables coaches to recommend realistic entry points—such as beginning in HR—and map out progressive steps toward more advanced roles like payroll over time.

Policymakers: Aligning Training Systems with Feasible Pathways

Policymakers can use the Index to design training and education systems that reflect not only skill demand but also the feasibility of learning those skills. For instance, if digital skills are in high demand but difficult for many learners to acquire quickly, governments may choose to fund bridging programmes or modular pathways that lower barriers. Conversely, if certain green-transition skills are both in demand and relatively straightforward to learn, policymakers might prioritise scaling training provision rapidly to meet urgent workforce needs. In both cases, the Index helps ensure that investments in training translate into accessible and achievable opportunities for learners.

CONCLUSION

Technological disruption, demographic shifts, evolving employment structures, and climate transitions have intensified the demand for continual upskilling and reskilling. Yet existing workforce tools and career resources provide little information about how easy/difficult it is to learn a new skill. The Skills Learnability Index represents an important step forward to address this gap by providing a more structured, data-driven approach to measure the ease of learning different skills. At the same time, several measurement limitations must be acknowledged.

Learnability as a Latent Construct

First, the concept of learnability is a latent construct, which means it cannot be observed directly. The index must therefore rely on indirect indicators and proxies to estimate ease of learning. While these proxies provide useful signals, they introduce approximation errors and may not fully reflect an individual's actual readiness or the true resources required. For example, course cost as a proxy for learning effort overlooks opportunity costs such as foregone income or personal commitments, which vary substantially across learners.

Omission of Key Learning Factors

The current framework does not capture several crucial factors known to influence learning outcomes. Factors such as cultural context, social support, motivation, and confidence, all of which research shows play a significant role in shaping learning ease, are excluded due to difficulty to capture in available data. The omission of these dimensions limits the Index's ability to reflect the full spectrum of what makes a skill easier or harder to acquire.

Aggregation of Indicators into a Composite Index

As with any composite measure, there are constraints of aggregation. Reducing a multifaceted learning process into a single score entails loss of nuance, and results may be sensitive to methodological choices like weighting or indicator selection.

Data Source and Coverage Limitations

The Index is constrained by the availability and scope of current data sources. Two of the indicators rely on Singapore's job posting data, which reflects employer-demanded skills but omits other valuable learning approaches, such as informal or non-formal learning. Another indicator is drawn solely from SSG-funded courses, which do not represent the full range of training options available to learners. These limitations restrict the comprehensiveness of the Index and surface the need to broaden data inputs over time.

FUTURE RESEARCH

At present, the Index is calculated uniformly across all learners, overlooking the substantial variation in learning ease that arises from differences in prior knowledge, skills and experience. Addressing this gap is a key priority for Phase 2 of the study, which will introduce a personalised individual-dependent score, integrating individual specific factors for more tailored career guidance and skill development.

No dataset or analysis is perfect. We welcome feedback and are already working to refine the methodology in subsequent editions of the Skills Learnability Index. Even with these constraints, providing a more structured, data-driven approach to measure the ease of learning different skills is a vital place to start. The Index seeks to empower the individuals, employers, career coaches and policymakers a much-needed yardstick for understanding the ease of learning a skill, and with it a stronger foundation to make informed decisions on skill development, upskilling, and targeted career guidance for effective workforce and career planning.

ACKNOWLEDGEMENTS

This methodological note was made possible through the support of several individuals and teams. We gratefully acknowledge their contributions, which were critical in providing data, guidance, and expert feedback that strengthened this work.

We would like to thank the SkillsFuture Singapore (SSG) Team for providing access to the datasets used in this analysis, as well as for their valuable analytical support. We are also grateful to **Mr Edwin Tan** for his guidance throughout this project and for reviewing and refining this report.

We would especially like to acknowledge, with deep appreciation, the contributions of our expert reviewers, whose thoughtful feedback and advice were instrumental in shaping and validating this work:

- **Dr Bledi Taska**
- **Dr Glenda Quintini**
- **Dr Gog Soon Joo**
- **Professor Johnny Sung**
- **Associate Professor Randolph Tan**
- **Associate Professor (Practice) Terence Ho**

Their insights and careful reviews provided invaluable perspectives that strengthened the methodological approach and enhanced the quality of this note.

PROJECT TEAM

SRI MANIKANTAN

Analyst, Centre for Skills-First Practices, Institute for Adult Learning

Sri is an Analyst at the Centre for Skills-First Practices at the Institute for Adult Learning. She holds a Master's in Data Analytics from Carnegie Mellon University and brings over five years of experience in project management and data-driven decision-making. Her work focuses on transforming complex data into actionable insights that guide workforce strategies and shape skills policy.

SILIN YANG

Deputy Director, Centre for Skills-First Practices, Institute for Adult Learning

Silin is Deputy Director of the Centre for Skills-First Practices at the Institute for Adult Learning, where she oversees the analytics function at the centre. With nearly 20 years' experience, she translates data, behavioural insights, and trend forecasting into strategic workforce solutions. Silin also leads transformation initiatives, working with stakeholders to strengthen organisational and workforce agility. She is both the founding editor and an editorial board member of the *Singapore Labour Journal*.

SIMON FREEBODY

Associate Specialist, Centre for Skills-First Practices, Institute for Adult Learning

Simon Freebody is an experienced researcher with a demonstrated history of working in social policy and labour economics. He is skilled in data analytics, research design, policy evaluation, and project management. He has worked on numerous research projects in the area of workforce development and skills including the OECD "Survey of Adult Skills" (PIAAC), UNESCO's "Lifelong Learning Entitlements: from design to Impact" and the Institute for Adult Learning "Business Performance and Skills Survey".

ADVISORS

GOG SOON JOO

Fellow, Centre for Skills-First Practices, Institute for Adult Learning

EDWIN TAN

Director, Centre for Skills-First Practices, Institute for Adult Learning

REFERENCES

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labour markets. *Journal of Political Economy, 128*(6), 2188–2244. https://doi.org/10.1086/705716

Achuthan, K., & Murali, S. S. (2015). A comparative study of educational laboratories from cost and learning effectiveness perspective. In R. Silhavy, R. Senkerik, Z. Kominkova Oplatkova, Z. Prokopova, & P. Silhavy (Eds.), *Software engineering in intelligent systems* (Advances in Intelligent Systems and Computing, Vol. 349, pp. 143–153). Springer. https://doi.org/10.1007/978-3-319-18473-9_15

American Psychological Association. (n.d.). Task complexity. In *APA Dictionary of Psychology*. Retrieved September 6, 2025, from https://dictionary.apa.org/task-complexity

Aufiero, S., De Marzo, G., Sbardella, A., & Zaccaria, A. (2024). Mapping job fitness and skill coherence into wages: An economic complexity analysis. *Scientific Reports*, 14, 11752. https://doi.org/10.1038/s41598-024-61448-x

Buehler, R., & Griffin, D. (2015). The planning fallacy: When plans lead to optimistic forecasts. In M. D. Mumford & M. Frese (Eds.), *The psychology of planning in organisations: Research and applications* (pp. 31–57). Routledge. https://doi.org/10.4324/9780203105894

Chamorro-Premuzic, T. (2018, February 19). *Curiosity is as important as intelligence.* Harvard Business Review. https://hbr.org/2018/02/curiosity-is-as-important-as-intelligence

Coursera, & Burning Glass Institute. (2023). *Skills Compass Report 2023* [Report]. https://www.burningglassinstitute.org/research/2023-skills-compass-report

Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behaviour, 19*(4), 450–466. https://doi.org/10.1016/S0022-5371(80)90312-6

Derakshan, N., & Eysenck, M. W. (2009). Anxiety, processing efficiency, and cognitive performance: New developments from attentional control theory. *European Psychologist, 14*(2), 168–176. https://doi.org/10.1027/1016-9040.14.2.168

Follmer, D. J., Patchan, M., & Spitznogle, R. (2022). Supporting college learners' study time calibration: Relations to course achievement and self-regulated learning skills. *Journal of College Reading and Learning, 52*(2), 75–96. https://doi.org/10.1080/10790195.2022.2033646

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: A framework for conceptualising the effects of various practice conditions in motor learning. *Journal of Motor Behaviour, 36*(2), 212–224. https://doi.org/10.3200/JMBR.36.2.212-224

Haith, A. M., & Krakauer, J. W. (2018). The multiple effects of practice: Skill, habit, and reduced cognitive load. *Current Opinion in Behavioural Sciences, 20,* 196–201. https://doi.org/10.1016/j.cobeha.2018.01.015

Hartzler, B., Hinde, J., Lang, S., Correia, N., Yermash, J., Yap, K., Murphy, C. M., Ruwala, R., Rash, C. J., Becker, S. J., & Garner, B. R. (2023). Virtual training is more cost-effective than in-person training for preparing staff to implement contingency management. *Journal of Technology in Behavioural Science, 8*(3), 255–264. https://doi.org/10.1007/s41347-022-00283-1

Infosys Limited. (2021). *Learnability report: Learnability critical in the know-edge age* [PDF]. Infosys. Retrieved from https://www.infosys.com/products-and-platforms/wingspan/insights/documents/learnability-critical-knowledge-age.pdf Infosys

Infosys. (2020). *Learnability as a core competency.* World Economic Forum, Davos Agenda Insights. https://www.infosys.com/wef/2020/learnability-core-competency.html

International Labour Organization. (2018). *Skills and the future of work: Strategies for inclusive growth in Asia and the Pacific.* International Labour Organization. https://www.ilo.org/asia/publications/WCMS_650239/lang--en/index.htm

Kitsantas, A., Winsler, A., & Huie, F. (2008). Self-regulation and ability predictors of academic success during college: A predictive validity study. *Journal of Advanced Academics, 20*(1), 42–68. https://doi.org/10.4219/jaa-2008-867

Klein, E., Bieck, S. M., Bloechle, J., Huber, S, Bahnmueller, J., Willmes, K., & Moeller, K. (2019). Anticipation of difficult tasks: Neural correlates of negative emotions and emotion regulation. *Behavioural and Brain Functions, 15,* 1–13. https://doi.org/10.1186/s12993-019-0155-1

Laguna, P. L. (2008). Task complexity and sources of task-related information during the observational learning process. *Journal of Sports Sciences, 26*(10), 1097–1113. https://doi.org/10.1080/02640410801956569

MacKeracher, D., Suart, T., & Potter, J. (2006). *State of the field report: Barriers to participation in adult learning.* Canadian Council on Learning.

Martini, M., Marhenke, R., Martini, C., Rossi, S., & Sachse, P. (2020). Individual differences in working memory capacity moderate effects of post-learning activity on memory consolidation over the long term. *Scientific Reports, 10*(1), 17976. https://doi.org/10.1038/s41598-020-74760-z

Matovu, H., Won, M., Hernandez-Alvarado, R. B., Ungu, D. A. K., Treagust, D. F., Tsai, C.-C., Mocerino, M., & Tasker, R. (2024). The perceived complexity of learning tasks influences students' collaborative interactions in immersive virtual reality. *Journal of Science Education and Technology, 33*(4), 542–555. https://doi.org/10.1007/s10956-024-10103-1

Ninomiya, Y., Iwata, T., Terai, H., & Miwa, K. (2024). Effect of cognitive load and working memory capacity on the efficiency of discovering better alternatives: A survival analysis. *Memory & Cognition, 52*(1), 115–131. https://doi.org/10.3758/s13421-023-01448-w

OECD. (2019). OECD skills strategy 2019: *Skills to shape a better future.* OECD Publishing. https://doi.org/10.1787/9789264313835-en

OECD. (2024a). *Skills Summit 2024: Issues for discussion* [Background paper]. https://one.oecd.org/document/SKC(2024)1/en/pdf

OECD. (2024b). *OECD skills strategy framework and dashboard.* https://www.oecd.org/en/data/insights/data-explainers/2024/05/oecd-skills-strategy-framework-and-dashboard.html
Singapore Department of Statistics. (2024). Singapore Standard Occupational Classification 2024 [Report]. https://www.singstat.gov.sg/-/media/files/standards_and_classifications/occupational_classification/ssoc2024report.ashx

Singapore Department of Statistics. (2024). *Singapore Standard Occupational Classification 2024* [Report]. https://www.singstat.gov.sg/-/media/files/standards_and_classifications/occupational_classification/ssoc2024report.ashx

Tynjälä, P., Nuutinen, A., Eteläpelto, A., Kirjonen, J., & Remes, P. (1997). The acquisition of professional expertise: A challenge for educational research. *Scandinavian Journal of Educational Research, 41*(3–4), 475–494. https://doi.org/10.1080/0031383970410310

World Employment Confederation. (2018). *Activity report 2018.* World Employment Confederation. https://wecglobal.org/publication/activity-report-2018/

Institute for Adult Learning Singapore

11 Eunos Road 8
#07-04 Lifelong Learning Institute
Singapore 408601

(65) 6579 0300 CSP@ial.edu.sg www.ial.edu.sg