Job seekers' learning attitudes in the face of digital disruptions and the COVID-19 pandemic: Investigating an upskilling programme in Singapore

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Paper prepared for presentation at the
"7th Conference of the Regulating for Decent Work Network"
Virtual Conference, International Labour Office Geneva, Switzerland
6-9 July 2021

Abstract

Due to the COVID-19 pandemic and rapid technological advancement, more workers face transitions in their work conditions. Furthermore, many face job uncertainty as economies become more disrupted. Although many economies have begun to see shifts in employment in recent years due to the challenges and opportunities brought on by Industry 4.0, the pandemic has accelerated many of these changes. Individual learners must upskill and reskill to acquire the competencies demanded by advanced technologies. While states can invest in support measures for job seekers, learners' attitudes, and expectations towards participating in skills training and upskilling programs are integral to their success. Recent research has found that attitudes towards learning and skills-upgrading, such as self-efficacy (i.e., confidence in learning) and adaptability, play a role in workplace learning and the transfer of training to job outcomes (Blume et al., 2009, Ford et al., 2018). Moreover, differences in learning attitudes and perceptions could make some workers more vulnerable than others to job market shifts (Gorlitz and Tamm, 2016). This paper focuses on a recent upskilling programme under Singapore's SkillsFuture policy initiative that emphasises lifelong learning. We study the SGUnited Skills (SGUS) programme launched in 2020 as part of the SGUnited Jobs and Skills package to help Singaporean job seekers, especially those affected by the COVID-19 situation, to access new job opportunities and improve their job-related skills and capabilities. The programme offers certifiable courses designed to help trainees obtain industry-relevant skills while unemployed due to the pandemic. We studied 91 job seekers as they participated in the SGUS programme at two tertiary institutions in Singapore. We found that self-efficacy in completing the course has correlations with the learners' attitudes towards skills upgrading. After considering learners' adaptability and self-efficacy, we discovered that mid to late career learners reported more positive attitudes towards skills upgrading than early-career learners, although the results were not statistically significant. Participants' feedback also indicates that while policy initiatives like the SGUS programme aim to cater to workers across the workforce, there is a need for differentiated support that is tailored to the different career stages of workers entering the programme.

Keywords: digitalization, human capital, reskilling, SkillsFuture Singapore, upskilling

Introduction

The combined effects of rapid technological advancement and the COVID-19 pandemic are leading to global disruptions in the labour market. Many economies were already facing challenges in upskilling large sections of the workforce due to increasing technological change, otherwise known as the Fourth Industrial Revolution or Industry 4.0 (Acemoglu and Autor, 2011; Arntz et al, 2017; Schwab, 2017). Globally, the COVID-19 pandemic is accelerating existing digitalization trends and leading to increased workforce and industry transformation (Rani et al, 2021). Hence, many workers are facing transitions in their job arrangements and work conditions with vulnerable workers, such as those in less secure jobs and informal work arrangements, disproportionately impacted by the pandemic (Boone, 2020; Tamin et al, 2021).

Like other industrialised nations, Singapore is facing challenges of job disruption, further exacerbated by the pandemic. In a bid to ensure long-term recovery from the COVID-19 scourge, there was a concerted effort by the Singapore government to provide upskilling programmes as a key labour market intervention for job seekers affected by sudden economic downturn. These initiatives draw on recent efforts to further develop Singapore as a Smart Nation, through efforts to advance innovation and productivity in the digital economy (Woo, 2018). Alongside the Smart Nation initiative, Singapore is investing in human capital development through increased focus on upskilling and reskilling in the context of technological disruption, including its flagship programme SkillsFuture Singapore and other lifelong learning initiatives. This includes increased focus on Vocational Education and Training (TVET), including updating current programmes to meet the need for digital skills in the context of Industry 4.0 (see Nair et al, 2021 for a recent summary). Alongside government investment in support programmes for job seekers, learners' attitudes and expectations for workers participating in skills training and upskilling programs are integral to the success of such policy interventions and their capacity to improve employability.

Investing in human capital in response to skills-biased technological change: the case of Singapore

According to human capital theory, investing in education, skills and training is a key form of production within capitalist systems, creating value in the labour market (Becker, 1962; Mincer, 1958). Human capital theory proposes that an economy does not need vast natural resources and physical capital to experience economic growth. Instead, by focusing on the skilled human capital within an economy, it can serve as an effective means to achieve greater productivity (Becker, 1962). This theory is built on the functionalist idea that for society to run efficiently, achievements must be appropriately rewarded. Educated workers who possess greater educational qualifications can draw higher earnings (Becker, 1975, Mincer, 1975). Individuals can invest in their own human capital, which should lead to greater opportunities in the labour market (Schultz, 1961). While such arguments seem logical and compelling, one critique of human capital theory is that it oversimplifies the complex nature of production and differential opportunities in schooling and labour market outcomes (Bowles and Gintis, 1975, Marginson, 2019). Indeed, key issues such as how to adequately measure human capital (Fix, 2018), alongside issues in labour market segmentation, income inequality, unemployment, and underemployment, remain largely unresolved in human capital theory and practice (Dickens and Lang, 1988, Livingstone, 1999). Furthermore, recent technological advancements have created new challenges in developing human capital in the digital age. In such a context, theories of skill-biased technological change (Brown et al, 2010; Goldin and Katz, 2009) that place greater emphasis on the role of advanced technologies in boosting the demand for skilled and educated workers may be even more pertinent than human capital theory.

Singapore's approach to skills development aligns broadly with human capital theory, especially with the advent of the digital economy. As a small country with limited natural resources, Singapore has long invested in its workforce to drive productivity and economic growth, with human capital being one of its most important resources given the city-state's dearth of other natural resources (Osman-Gani, 2004). Like other advanced economies, Singapore is facing challenges such as an ageing population and low birth-rates, which is leading to a range of labour market challenges in securing labour, including new forms of skills and training urgently needed in the digital economy. Human capital investment, including government focus on strengthening and restructuring the economy to support innovation in the context of digital disruption, remains a key priority (Nair et al, 2021). For example, the SkillsFuture Singapore scheme was launched in 2016 and subsidises a wide range of courses with the aim of worker upskilling and reskilling, as well as supporting industry-specific digital workplace programmes. In 2014, the Singapore Workforce Development Agency established a Lifelong Learning Council to encourage more Singaporeans to view learning as a continuous journey over their lifetime. Together, these policy shifts reflect how the national discourse is shifting towards ensuring that workers stay competent and employable by embracing a lifelong learning mindset (Nair et al, 2021).

Labour market interventions to tackle digital disruption and the COVID-19 pandemic: SG United (SGUS)

Launched under the broader framework of the country's SkillsFuture Singapore scheme, Singapore introduced a major training and job support scheme specifically to assist Singaporeans affected by COVID-19. Named the SGUnited Skills (SGUS) programme, it was launched in July 2020 by

SkillsFuture Singapore which is overseen by the Ministry of Manpower. SGUS is a full-time training programme ranging from 6 to 12 months, targeting over 20,000 jobseekers. The SGUS consists of certifiable courses delivered by various Continuing Education and Training (CET) Centres in Singapore, which include universities, polytechnics, and technical institutes, and provides a monthly training allowance of S$1200 and career advisory support. The training is modular in format, allowing trainees to flexibly exit if they find jobs during the training programme. Apart from courses provided by CET Centres, the SGUnited Mid-Career Pathways Programme comprises courses provided by companies in key sectors that are aimed at jobseekers aged 40 to 60, with a monthly training allowance of S$1500. The course fees are subsidised and, like SGUS, are aimed at increasing the employability of jobseekers. These programmes complement existing efforts such as the Professional Conversion Programme that helps mid-career PMETs move into new occupations and sectors that have good prospects and opportunities for progression through industry-recognised skills- conversion training. Nearly 7200 trainees had enrolled under the SGUnited Skills Programme (as of December 31, 2020). The sectors that received high enrolments were ICT and media, professional services, manufacturing, and healthcare.

These SkillsFuture Singapore initiatives also aim to aid Singaporeans in transiting towards a future-ready workforce by equipping them with industry-relevant skills that can improve their employability. These programmes and initiatives do not just stop at keeping Singaporeans employed and protecting their livelihoods. They aim to ensure that workers benefit in the long-term, not only recovering from the immediate impacts of the crisis but ultimately preparing them for the future jobs landscape. However, current measures of the efficacy of such programmes predominantly centre around job outcomes. While this is necessary in the short-term to ensure workforce stability and resilience, the long-term effects of reskilling programmes should focus on shifting the attitudes of learners towards upskilling given that extant research has demonstrated its importance (Baldwin and Ford, 1988; Blume et al., 2009; Grossman and Salas, 2011). Since the SGUS programme caters to participants from a wide range of backgrounds with varying levels of work experience, it provides an excellent opportunity to study differences in attitudes, expectations, and motivations of different profiles of job seekers regarding upskilling.

Motivation, Learning Adaptability and Resilience

Rising digitalization and the growth of new technologies are shifting the kinds of skills and competencies required in the workforce (Trenerry et al, 2021). This includes a growing demand for digital competencies, alongside technical and cognitive skills (Brunetti et al., 2020; Harteis and Goller, 2014; Sousa and Rocha, 2019). Notably, Osmundsen (2020) found that cognitive competencies such as a willingness to learn and openness to change were critical for developing digital capabilities.

Individuals' motivations and abilities to acquire new skills and their receptiveness to training are a key focus of recent research (Alvarez et al, 2004; Grossman and Salas, 2011). Reskilling or upskilling employees through workplace training is therefore seen as paramount to increasing productivity, reducing turnover, and having capacity to respond to technological and organisational innovations (Gorlitz and Tamm, 2016). Lifelong learning and CET have come into the spotlight because organization-wide digitalization necessitates that learning be undertaken continuously and consciously - employees become increasingly important assets that are closely monitored by organizations (Cascio, 2019; Chuang and Graham, 2018).

In the discourse of developing human capital and upskilling employees, a cohesive system must go beyond government and company-level interventions to encourage workers to take responsibility for their own learning. With the advancement of technology, there is an increasing need to promote individual responsibility for learning and performance improvement (Benson et al, 2002; Li and Herd, 2017). In many economies, motivation to learn continues to be one of the essential characteristics of lifelong learning: after completing compulsory schooling, continuing to develop skills and knowledge necessitates a desire and willingness to study and improve (OECD, 2005).

With work becoming less routine and rapidly changing, employees need a higher capability to adapt to and learn new work processes, especially technology-led tools (Billett, 2009). Employers also prefer employees that can adapt to change, the flexibility and willingness to learn and overcome substantial change in the workplace (CEDEFOP, 2010). Similarly, Ployhart and Bliese (2006) propose that learning is one of the eight dimensions that plays a key role in individuals' ability to adapt.

Motivations and Outcome Expectations

Motivation can be both a non-cognitive outcome e.g., the result of prior good experiences with training, or a predictor of other outcomes. In this instance, motivation is examined as the predictor to successful training and learning. Self-determination theory posits that a learner's motivation lies on a range, from not being motivated at all to being motivated by extrinsic motivation to becoming intrinsically motivated (Deci and Ryan, 2004). Recent studies have shown that motivation to learn is as important as, if not more than, cognitive ability in contributing to learning (Pintrich, 2003). Within motivation, we examine specifically how relatable the training is towards the individuals' ability to apply the training towards their career goals and future palace of employment (Baumeister and Leary, 1995). Outcome expectancy or the perceived usefulness of training as a measure to training success is first developed by Atkinson (1957) that achievement motivation is the result of the probability of success and the perceived difficulty of the task before being developed further as the Expectancy-Value Theory by Eccles (1983). A comprehensive framework of the internal processes and background factors that affect motivation based on this theory was developed, specifically highlighting how utility-value of the training plays a key role in the successful internalisation of the training (Barron and Hulleman, 2015; Wigfield et al, 2015).

Perceptions of Self-efficacy

Self-efficacy was originally defined by Bandura as the 'self-belief in one's capabilities to exercise control over events to accomplish desired goals' (Wood and Bandura, 1989, p. 364). Studies have shown that self-efficacy has a strong relationship with individuals' pre-training motivation to learn (Chiaburu and Marinova, 2005; Colquitt et al, 2000; Phillips and Gully, 1997; Quiñones, 1995). Within the Singaporean context, Lim and Chan (2003) also assessed that self-efficacy affects the motivation for skill upgrading. Zimmerman found that individuals' perceptions of self-efficacy is distinct from other predictors of training performance as even in multiple regression analyses, it has shown to have discriminant validity in predictiveness of outcomes (2000).

Research Aims

Through our focus on the afore-mentioned SGUS programme, we study three key areas: the participants' predisposition and perceptions towards learning in general, their perceived usefulness of upskilling and finally, the self-efficacy in completing the programme. Understanding the participants for whom these training programs were developed, as well as any potential mismatch in participant expectations with program design objectives, requires an analysis of learning attitudes and expectations from training programs. We examined the differences between such expectations across participants with varying work experience. The present paper is part of an ongoing research to study the effectiveness of the SGUS programme and will focus on the initial phase of this programme when trainees first embarked on the training.

Methods

We studied 91 job seekers who were participating in the SGUS programme at two universities in Singapore. They completed the survey at the start of their programme, which lasts between 6 to 9 months, as part of an ongoing evaluation of the effectiveness of the SGUS programme in helping individuals reskill and/or upskill.

This survey included measures of adaptability, attitude towards skills upgrading and self-efficacy. The I-ADAPT framework developed by Ployhart and Bliese (2006) was used to measure adaptability. We used one of the eight dimensions that undergird adaptive performance of major tasks and adapted the 10-question scale about learning adaptability, which is necessary for effectiveness in a complex environment such as one experienced during the pandemic and exacerbated by digital disruption. Two additional measures were used to examine attitude towards the usefulness of skills upgrading and self-efficacy towards upskilling. They were adapted from the respective scales developed by Lim and Chan (2003) respectively. For all three measures, the participants were asked to present their responses on a 5-point Likert Scale (where 1 represented "strongly disagree" and 5 represented "strongly agree"). In addition, the survey collected sociodemographic information and details about the trainees work history and the course that they are embarking on.

Findings

As the study is ongoing, the findings and discussions are based on the preliminary analysis of the participants at the beginning of the programme.

Profile of trainees

The profile of the trainees in the study is presented in Table 1. Out of the 91 participants, close to sixty percent were male. The trainees were further categorised into two groups based on where they are in their careers. The first group comprised "early career" trainees who had up to 10 years of work experience. The second group of "mid to late career" trainees had more than 10 years of work experience. While the proportion of males to females in the "early career" group was equal, the number of males in the "mid to late career" group is almost three times that of females.

Table 1

Characteristics of Sample by Work Experience

Factor	Total Sample (n = 91)	Early Career (n = 48)	Mid to Late Career (n = 43)
Gender			
Male	58.2	47.9	70.0
Female	37.4	47.9	25.3
Prefer not to say	4.4	4.2	4.7
Marital Status			
Single	38.5	50.0	25.6
Married	50.6	41.7	60.5
Divorced / Separated	3.3	0.0	7
Prefer not to say	7.7	8.3	7
Number of Dependents (under 18 years old)			
No dependent	77.9	86.7	69.1
1 dependent	14.0	6.8	21.4
2 dependents	4.7	2.3	7.1
3 dependents	3.5	4.6	2.4
Number of Dependents (above 65 years old)			
No dependent	44.0	54.2	32.6
1 dependent	20.9	14.6	27.9
2 dependents	33.0	31.3	34.9
3 dependents	1.1	0.0	2.3
4 dependents	1.1	0.0	2.3
Last attended skills training (Govt-supported schemes e.g. SkillsFuture, e2i/PCP/WSG, R3)			
In the last 6 months	20.9	16.7	25.6
In the last 12 months	4.4	4.2	4.7
In the last 2 years	12.1	12.5	11.6
Longer than 2 years	8.8	8.3	9.3
Have not attended any	53.9	58.3	48.8
Last attended skills training (Company-led in-house job training)			
In the last 6 months	3.3	4.2	2.3
In the last 12 months	6.6	6.3	7.0
In the last 2 years	14.3	16.7	11.6
Longer than 2 years	13.2	4.2	23.3
Have not attended any	62.6	68.8	55.8
Last attended skills training (Massive Online Open Courses e.g. Coursera, Udemy etc.)			
In the last 6 months	29.7	35.4	23.3
In the last 12 months	8.8	10.4	7.0
In the last 2 years	0.0	0.0	0.0
Longer than 2 years	2.2	2.1	2.3
Have not attended any	59.3	52.1	67.4

Note: The figures represent the percentage of participants for each demographic.

The “late career” group naturally consisted of a higher percentage of married individuals (60%) while half of the “early career” group were singles. The “mid to late career” group reported a higher number of dependents of both under the ages of 18 and above the ages of 65, with 31% reporting dependent(s) under the age of 18 and two-thirds of the group having dependent(s) above the age of 65. This is vastly different compared to the “early career” group where 13% have dependent(s) under the ages of 18 and 45% have dependent(s) above the age of 65. Broadly, people in Singapore with children and elderly parents to support are referred to as the ‘sandwich class’ and experience great pressure to remain economically active and employable to meet their hefty financial commitments (Tan, 2021). Our “mid to late career” group participants would largely come under the ‘sandwich class’ and their motivation for upskilling can be understood in that light.

Regarding their past experiences with upskilling, both groups saw similar trends, with many not having attended any training before, and those that have attended having did so within the last 6 months. 54% of the participants reported that they had not attended any other government-supported training, 63% had not attended any company-led training and 59% had not attended courses offered by Massively Open Online Courses (MOOCs) such as Udemy and Coursera. Interestingly, of those in the “mid to late career” group who had attended government-supported training, half of them had attended such training within the last six months. Naturally, more than half of “mid to late career” participants who attended company-led training did so more than 2 years ago, whereas close to 90% of “early career” participants who attended company-led training did so within the last 2 years. There was a high uptake of MOOCs in the last six months – where several participants in the “early career” and “mid to late career” groups reported that they had attended such courses within the last six months (35% and 23% respectively).

The trainees also come from a wide variety of sectors – of which more than 20% comprised participants who were working in the financial services, and close to 17% were in the Information Communications and Technology (ICT) and Media sectors. Other notable sectors included the Education sector (8%), Healthcare and Community Care (7%), Construction or Facilities Management (6%), Oil & Gas, Marine & Shipping (6%), Transport and Logistics (6%), Retail (4%), Advanced Manufacturing (4%) and Human Resources (4%). Other sectors that represented a smaller number of participants included Wholesale Trade, Aerospace Engineering, Security, Electronics, Tourism and Social Services. 30% of “mid to late career” participants worked in growth areas such as ICM and Advanced Manufacturing as compared to “early career” participants (13%). The detailed breakdown of the sectors is presented in Table 2.

Table 2

Sector and Industry breakdown of Sample by Work Experience

Sector / Industry	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
Financial services	20.9	18.8	23.3
ICM (ICT & Media)	16.5	10.4	23.3
Education	7.7	8.3	7.0
Healthcare & Community care	6.6	8.3	4.7
Construction / facilities management	5.5	6.3	4.7
Oil & Gas, Marine & Shipping	5.5	6.3	4.7
Transport and Logistics	5.5	6.3	4.7
Retail	4.4	4.2	4.7
Advanced Manufacturing	4.4	2.1	7.0
Human Resources	4.4	4.2	4.7

Note: The figures represent the percentage of participants who reported their sectors.

Shifting to growth areas

63% of the participants identified that they are undertaking a programme in a different sector from the one they were currently in. There was a greater proportion of participants in the "mid to late career" group (67%) that said that they were moving to a different sector as compared to participants in the "early career" group (58%). These breakdowns and the new sectors of the courses taken are represented in Table 3.

Table 3

Breakdown of Participants undertaking course in different sector by Work Experience

	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
Undertaking SGUS Programme in a different sector			
Yes	62.6	58.3	67.4
No	37.7	41.7	32.6
New Sector Breakdown (Yes)			
n	57	28	29
Fintech	36.8	39.3	34.5
Data Science	19.3	25.0	13.8
Prefer not to say	14.0	17.9	10.3
Advanced Manufacturing	12.3	7.1	17.2
ICM	8.8	3.6	13.8
Digital Marketing	5.3	3.6	6.9
Digital HR	3.5	3.6	3.4

Note: The figures represent the percentage of participants who reported their sectors unless otherwise stated.

The programmes that were offered included skill-based courses such as data science (tracks included both programming and non-programming); digital human resources (HR); digital marketing (which included a choice of an advertising or social media track); and courses focusing on professional services such as financial technology (FinTech), ICT & Media and advanced manufacturing. 37% of the participants who identified that they were taking a course in a different sector than the ones they were in were taking the FinTech course. Data Science (19%) and Advanced Manufacturing were the next two courses in terms of uptake rate. The percentage of "early career" participants transiting toward doing data science is almost double of that of "mid to late career" participants while conversely, the percentage of "mid to late career" participants doing a course in advanced manufacturing is almost double that of "early career" participants. Table 4 highlights the variety of backgrounds of participants making transitions by taking a course that was in a different sector from their current career.

Table 4

Participants undertaking course in different sector by Current Sectors

Advanced Manufacturing	7
Aerospace Engineering	2
Construction/ facilities management	1
Human Resources	1
ICM (ICT & Media)	1
Oil & Gas, Marine & Shipping	1
Security	1
Data Science	11
Aerospace Engineering	1
Construction/ facilities management	1
Education	1
Financial services	4
Healthcare & Community care	1
Oil & Gas, Marine & Shipping	1
Retail	1
Transport and Logistics	1
Digital HR	2
Human Resources	1
Transport and Logistics	1
Digital Marketing	3
ICM (ICT & Media)	1
Tourism	1
Transport and Logistics	1
Fintech	20
Advanced Manufacturing	1
Construction/ facilities management	1
Education	2
Electronics	1
Financial services	5
Healthcare & Community care	2
ICM (ICT & Media)	5
Oil & Gas, Marine & Shipping	1
Transport and Logistics	1
Wholesale Trade	2
ICT and Media	5
Education	1
Healthcare & Community care	1
ICM (ICT & Media)	1
Retail	1
Tourism	1

Factors towards Course Participation

Motivations for Upskilling

The participants were given a list of choices to select as the top three reasons for their motivation for participating in the SGUS programme. The aim of these questions was to identify what contributed to them deciding to participate in a programme like SGUS. The top reasons showed that the key motivation to participate in such a programme was mostly around the changing landscape of work and how it has impacted their career aspirations. As seen in Table 5, the top four reasons were: learning new skills in growth sectors of the future (23%), personal interest in the topic (20%), relevance to the career they want to pursue (18%) and the ability of the course in aiding them move into a new industry (13%). It is evident that participants of such programmes are driven by intrinsic and extrinsic motivations, to increasing ability and relevance to the changing dynamics of the workforce. Both the “early career” and “mid to late career” groups have similar motivations, with percentages deviating only slightly.

Table 5

Top 5 motivation for programme participation by work experience

Motivations for participating in SGUS Programme	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
Learn new skills in growth sectors of the future	22.8	21.7	24.0
Personal interest in the topic	19.5	17.5	21.7
Relevance to the career I want to pursue	18.0	18.2	17.8
To move into a new industry	12.9	14.7	10.9
Provision of a monthly stipend	10.7	9.8	11.6

Note: The figures represent the percentage of participants who reported the motivation.

As seen in Table 6, when participants were asked about their attitudes towards upskilling, the results of the response provided by the participants were slightly above average, with the overall average of these sets of questions being 3.50 (where 3 is neutral and 4 is agree). Only the average response by the "mid to late career" group to question 4 "upgrading of skills is not important in my job" reported a score that is above 4 (4.07). Even though the survey was administered to participants who were already participating in an upskilling programme, their attitude towards upskilling is not overwhelmingly positive. A reverse-scoring was carried out for the last two questions as they were negatively phrased - this was to ensure the consistency of the analysis. A multivariate analysis of variance (MANOVA) was carried out for the two groups ("early career" and "mid to late career") to identify if there was a statistically significant difference between the attitudes towards upskilling of both groups for each set of questions. There was no significant difference in the attitudes across both groups, Wilks' Lamda =0.94, F (5, 85) = 1.16, p = 0.33).

Table 6

Attitudes towards upskilling by work experience

Attitudes towards Upskilling	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
My job should be more secure if I upgrade my skill level	3.54	3.63	3.44
Skills upgrading will improve my chances of promotion	3.45	3.56	3.33
My pay will increase if I upgrade my skills	3.27	3.40	3.14
Upgrading of skills is not important in my job*	3.89	3.73	4.07
Skills upgrading may not make my job any easier*	3.36	3.29	3.44
Total Average	3.50	3.52	3.48

Note: Scores are mean scores. Responses were on a 5-point Likert scale, ranging from 1 'Strongly disagree' to 5 'Strongly agree'.

Learning Adaptability and Resilience

The results of the responses for the questions around the perceptions towards learning are generally trending positive, with most results close to 4.0 (agree). This shows that the participants of the programme generally have a positive perception of learning. While there was not a significant difference between the scores of the "early career" and "mid to late career" group, the results of all the questions were reported higher for the "mid to late career" group than the "early career" group, an average increase of 0.2. This shows that "mid to late career" participants have a slightly more positive outlook on learning than "early career" participants. MANOVA was carried out for the two groups ("early career" and "mid to late career") to identify if there was a statistically significant difference between the general perception towards learning of both groups for each set of questions. There was no significant difference in the perceptions across both groups, Wilks' Lamda =0.92, F (9, 81) = 0.76, p = 0.66).

Table 7
Breakdown of Learning Motivations by Work Experience

Perceptions towards Learning	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
I take responsibility for acquiring new skills	4.33	4.25	4.42
I enjoy learning new approaches for my work	4.24	4.10	4.40
I take action to improve my work performance deficiencies	4.10	4.02	4.19
I often learn new information and skills to stay at the forefront of my profession	4.02	3.83	4.23
I quickly learn new methods to solve problems	3.89	3.73	4.07
I train to keep my work skills and knowledge current	4.01	3.83	4.21
I am continually learning new skills for my job	3.91	3.77	4.07
I take responsibility for staying current in my profession	4.03	3.88	4.21
I try to learn new skills for my job before they are needed	3.90	3.73	4.09
Total Average	4.05	3.91	4.21

Note: Scores are mean scores. Responses were on a 5-point Likert scale, ranging from 1 'Strongly disagree' to 5 'Strongly agree'.

Perceptions on Self-Efficacy

Similarly, the results of the responses for the questions around the participants' self-efficacy towards learning were trending positive, where most average scores were higher than 4.0. The differences between the individual responses of the "early career" group and the "mid to late career" group are mixed, where some questions reported higher results for "early career" group and some for "mid to late career group". Overall, learners' perceptions of self-efficacy were found to be higher in "mid to late career" participants than "early career" participants. A reverse scoring was carried out for fifth, sixth and seventh questions for the scale as they were negatively phrased - this was to ensure the consistency of the analysis. MANOVA was carried out for the two groups ("early career" and "mid to late career") to identify if there was a statistically significant difference between their self-efficacy towards completing the programme of both groups for each set of questions. There was no significant difference in the self-efficacy across both groups, Wilks' Lamda = 0.87, F (9, 81) = 1.32, p = 0.24).

Table 8
Perceptions on Self-Efficacy by Work Experience

Perceptions on Self-Efficacy	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
I will have no problem learning new skills	4.14	4.15	4.14
I will have the capability to handle the demands of SGUS training	4.16	4.10	4.23
I am sure I will be able to complete SGUS training	4.24	4.25	4.23
I am confident of picking up the skills taught in SGUS training	4.30	4.27	4.33
I may not be able to keep in pace with the class in SGUS training*	3.44	3.27	3.63
I am too old to keep in pace with the other students in SGUS training*	3.10	4.13	4.07
As a person gets older, he/she will find it harder to learn new skills*	3.43	3.27	3.60
I am fully committed in giving my best to learn well throughout SGUS training	4.42	4.46	4.37
I am confident that SGUS training will help me secure a job	3.24	3.25	3.23
Total Average	3.97	3.92	4.03

Note: Scores are mean scores. Responses were on a 5-point Likert scale, ranging from 1 'Strongly disagree' to 5 'Strongly agree'.

Factors towards Course Success

The participants were given a list of choices to select from as the top factors they believed would contribute to their successful completion of the course. The top reasons chosen selected were the presence of practical takeaways (16%), difficulty of the course (15%), alignment between course content and their career goals (13%) and available time for completing course requirements (11%). The full results are presented in Table 9.

Participants gave feedback regarding the challenges they face with the programme, and they can be categorised into two key themes: the applicability of the programme and the difficulty of the programme. The first theme revealed that participants were concerned about whether such courses have practical takeaways that are relevant to the work they will be doing in the future. One participant shared that while the programme was a good platform to learn new skills, there seemed to be a lot of theory and there needs to be more time for practical aspects. Another participant suggested that to enable greater practical application and facilitate career transition, there should be an option to be attached to an employer as part of the programme. Separately, a participant felt that the content, which was tailored for undergraduates, was not suitable as most of the participants are working professionals and the theoretical nature of the content was not relatable.

The second theme was on the difficulty of the programme. Participants were anxious about how difficult the course might be and whether they had adequate time to complete the course. This was especially so given that participants came from a variety of backgrounds and are at vastly different starting points. One participant suggested that it will be helpful to provide a more accurate gauge of the difficulty level of the course so as not to result in a mismatch in expectations / workload with the capabilities of the students. One example given could be to provide a minimal academic or working IT knowledge experience prior to registration for the course. Some participants felt that they struggled more than others, and some thought they were not adequately informed of the difficulty level of the course beforehand. Another participant highlighted that as students within each course have different calibre and motivations for taking the course, it is difficult to maximise learning for everyone. One way to resolve such an issue, as suggested by participants, is to have courses at varying levels (e.g., beginner, intermediate, advanced etc.) to allow the classes to be more cohesive and efficient, having more classes but reducing class sizes to allow each individual to learn better and faster with a more targeted approach.

Table 9

Top factors of success for programme completion by work experience

Factors of success in programme completion	Total Sample (n = 91)	Early Career (n = 48)	Mid to late career (n = 43)
Presence of practical takeaways	18.4	13.2	15.9
Difficulty of the course	14.9	14.7	14.8
Alignment between course content and career goals	14.2	11.6	13
Available time for completing course requirements	11.3	10.9	11.1
Familiarity with studying after long hiatus	9.9	9.3	9.6
Family commitments	5.7	9.3	7.4
Availability of job offer mid-training	2.8	9.3	5.9
Experience with online learning tools	7.8	3.9	5.9
Presence of conducive study environment due to COVID-19	5	6.2	5.6
Presence of peer support	3.5	5.4	4.4
Presence of psychological and emotional support	3.5	4.7	4.1

Note: The figures represent the percentage of participants who reported the factors of success.

Discussion and conclusion

This paper presents preliminary, baseline findings of participants undertaking a skill upgrading programme in Singapore. The study found that while participants came from a range of industries, many are transiting to growth sectors such as Fintech, Data Science, Advanced Manufacturing and Digital Marketing/HR, among others. This is encouraging and aligned with the aims of the SGUS programme to reskill workers and help them to transition into new sectors. This also indicates a willingness among participants to transition from sectors that are being disrupted by digital technologies and the COVID-19 pandemic. Though the changing dynamics of the landscape is a key extrinsic motivation to programme participation, this seems to have been internalised as participants see the need to learn new skills and take personal interest in growth skills. Furthermore, participants recognise that learning is crucial to development of their "human capital" - taking ownership and responsibility for upskilling as avenues towards career goals (new career pursuit / industry). This is a promising sign that as the wider policy pushes for workers to seek opportunities in upskilling, workers are taking ownership in upgrading themselves. A broader area of future research would be on how people are motivated to move towards new careers or industries.

Despite this, we also identified that "mid to late career" participants have very different needs and considerations than "early career" participants – this is consistent with research proposing adult learning for the mature-aged to consider their unique circumstances such as financial needs (OECD, 2019). More than half of the participants reported that they had not attended any training before – this is potentially an area of concern given the current push for greater upskilling and reskilling in Singapore as the economy and industries transform. Nevertheless, this suggests that the SGUS programme had managed to reach out to this group of workers and provided them with an opportunity to reskill and make transitions into a new sector. In particular, we observed that more "early career" participants were transiting toward doing data science than "mid to late career" participants while conversely, the percentage of "mid to late career" participants doing a course in advanced manufacturing is almost double that of "early career" participants. This might suggest that a difference in programmes preference across trainees who are at different stages of their careers.

Relatedly, the self-efficacy in skills upgrading was high and the perceptions of skills training were positive across both early and mid to late career participants. However, the attitudes towards upskilling and its perceived outcomes are not overwhelmingly positive. While examining the differences between "early career" and "mid to late career" participants, the study found that "mid to late career" participants reported greater learning adaptability and self-efficacy than early-career participants. This is different from existing studies which show that mature workers tend to have lower learning adaptability and perceptions towards their self-efficacy (Bowman and Kearns, 2007). Pavlova and Maclean (2007) found that a barrier to learning for mature workers is their attitude towards learning and that a culture which encourages learning in older people is key to supporting effective skill development. Consistent with other research on age-related differences to motivation of learning such as in Kormos and Csizér (2008), various factors play a different role at different life stages and therefore it is challenging to draw conclusions that generalises across age groups. Comparing the attitude towards skill upgrading, it suggests that there might be differences between early and mid to late career participants though this needs to be investigated further. These findings suggest that there might be opportunities for policy makers to manage and improve the expectations of programme outcome to achieve greater training performance.

From the initial feedback of the SGUS programme, there are areas of concern that are worth considering for policymakers who are involved in the design of such programmes. Firstly, the applicability of the learning outcomes in such programmes to the industry needs and actual job requirements needs to be examined - while the programme may seek to provide knowledge and skills that are relevant to the course area, there is an opportunity for programme participants to have hands-on experience to increase the transfer of training. Adult internships or short industry attachments could be incorporated into the design of upskilling programmes to augment the training. Secondly, there are differences in the perceived difficulty of such training programmes. For participants who come from varying backgrounds, a more targeted approach might be required. Pre-requisite courses or bootcamps might also be helpful for participants who do not have the necessary skills required to thrive in such courses, such as programming-related skills. Automated self-assessment quizzes at the point of course selection could also be introduced to help participants gauge their competency levels as required by different courses. Course descriptions should also be more explicit in spelling out prior levels of knowledge that participants should possess.

The study presented here are part of an ongoing study of the effectiveness of the SGUS programme in helping workers reskill and transition to new careers. The above findings are the from the first stage of the study when the trainees first embarked on the training programmes and the study will continue to track the progress of these trainees after they have completed the programme to develop further insights into the effectiveness of the SGUS programme. The insights that we have gained from this first phase of the study indicates that the programme has provided workers with an opportunity to upskill and reskill in preparation to enter new sectors of growth as Singapore digitalizes and transforms its industry and economy. While the matching of the programme to the personalised needs of the workers could be improved, we observed that the trainees were motivated to undergo and complete the programme and had positive attitudes as well as a strong sense of self-efficacy as they embarked on the programme. This is an encouraging sign for policymakers who are exploring similar programmes to address the reskilling and training needs of their workforce.

References

Acemoglu, D. and Autor, D. (2011) ‘Skills, tasks and technologies: Implications for employment and earnings’, *Handbook of Labor Economics.* Elsevier.

Alvarez, K., Salas, E. and Garofano, C. M. (2004) ‘An integrated model of training evaluation and effectiveness’, *Human Resource Development Review,* 3**,** 385-416.

Arntz, M., Gregory, T. and Zierahn, U. (2017) ‘Revisiting the risk of automation’, *Economics Letters,* 159**,** 157-160.

Atkinson, J. W. (1957), ‘Motivational determinants of risk-taking behavior’ *Psychological Review,* 64**,** 359.

Baldwin, T. T. and Ford, J. K. (1988), ‘Transfer of training: A review and directions for future research’, *Personnel Psychology,* 41**,** 63-105.

Barron, K. E. and Hulleman, C. S. (2015), ‘Expectancy-value-cost model of motivation’ *Psychology,* 84**,** 261-271.

Baumeister, R. F. and Leary, M. R. (1995), ‘The need to belong: Desire for interpersonal attachments as a fundamental human motivation’, *Psychological Bulletin,* 117**,** 497-529.

Becker, G. S. (1962), ‘Investment in human capital: A theoretical analysis’, *Journal of Political Economy,* 70**,** 9-49.

Becker, G. S. (1975), “Investment in human capital: effects on earnings”, *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education, Second Edition,* NBER.

Benson, D. E., Haney, W., Ore, T. E., Persell, C. H., Schulte, A., Steele, J. and Winfield, I. (2002), ‘Digital technologies and the scholarship of teaching and learning in sociology’, *Teaching Sociology***,** 140-157.

Billett, S. (2009), ‘Changing Work, Work Practice: The Consequences for Vocational Education’, *International Handbook of Education for the Changing World of Work,* 175-187, Springer, Dordrecht

Blume, B. D., Ford, J. K., Baldwin, T. T. and Huang, J. L. (2009), 'Transfer of Training: A Meta-Analytic Review', *Journal of Management,* 36**,** 1065-1105.

Boone, L. (2020), 'Coronavirus: the world economy at risk. OECD interim economic outlook'

Bowles, S. and Gintis, H. (1975), 'The problem with human capital theory - a Marxian critique', *The American Economic Review,* 65**,** 74-82.

Bowman, K. and Kearns, P. (2007), *E-learning for the mature age worker*, Citeseer.

Brown, P., Lauder, H. and Ashton, D. (2010), '*The global auction: The broken promises of education, jobs, and incomes'*, Oxford University Press.

Brunetti, F., Matt, D. T., Bonfanti, A., De Longhi, A., Pedrini, G. and Orzes, G. (2020), 'Digital transformation challenges: strategies emerging from a multi-stakeholder approach', *The TQM Journal*.

Cascio, W. F. (2019), 'Training trends: Macro, micro, and policy issues', *Human Resource Management Review,* 29**,** 284-297.

CEDEFOP (2010), '*The skill matching challenge: Analysing skill mismatch and policy implications'*, Luxembourg.

Chiaburu, D. S. and Marinova, S. V. (2005), 'What predicts skill transfer? An exploratory study of goal orientation, training self-efficacy and organizational supports', *International Journal of Training and Development,* 9**,** 110-123.

Chuang, S. F. and Graham, C. M. (2018), 'Embracing the sobering reality of technological influences on jobs, employment and human resource development: A systematic literature review', *European Journal of Training and Development,* 42**,** 400-416.

Colquitt, J. A., Lepine, J. A. and Noe, R. A. (2000), 'Toward an integrative theory of training motivation: a meta-analytic path analysis of 20 years of research', *Journal of Applied Psychology,* 85**,** 678.

Deci, E. L. & Ryan, R. M. (2004), 'Handbook of s*elf-determination research',* University Rochester Press.

Dickens, W. T. and Lang, K. (1988), 'The reemergence of segmented labor market theory', *The American Economic Review,* 78**,** 129-134.

Eccles, J. (1983), 'Expectancies, values and academic behaviors' *In:* SPENCE, J. T. (ed.) *Achievement and achievement motives: Psychological and sociological approaches,* San Francisco, CA.

Fix, B. (2018), 'The trouble with human capital theory', *Working Papers on Capital as Power*.

Ford, K. J., Baldwin, T. T. and Prasad, J. (2018), 'Transfer of Training: The Known and the Unknown', *Annual Review of Organizational Psychology and Organizational Behavior,* 5**,** 201-225.

Goldin, C. D. and Katz, L. F. (2009), '*The race between education and technology*, Harvard University Press.

Gorlitz, K. and Tamm, M. (2016), 'Revisiting the complementarity between education and training - the role of job tasks and firm effects', *Education Economics,* 24**,** 261-279.

Grossman, R. and Salas, E. (2011), 'The transfer of training: what really matters', *International journal of training and development,* 15**,** 103-120.

Harteis, C. and Goller, M. (2014), 'New Skills for New Jobs: Work Agency as a Necessary Condition for Successful Lifelong Learning', *Promoting, Assessing, Recognizing and Certifying Lifelong Learning.*

Kormos, J. and Csizér, K. (2008), 'Age-related differences in the motivation of learning English as a foreign language: Attitudes, selves, and motivated learning behavior', *Language learning,* 58**,** 327-355.

Li, J. and Herd, A. M. (2017), 'Shifting Practices in Digital Workplace Learning: An Integrated Approach to Learning, Knowledge Management, and Knowledge Sharing', *Human Resource Development International,* 20**,** 185-193.

Lim, G. S. and Chan, A. (2003), 'Individual and situational correlates of motivation for skills upgrading: an empirical study', *Human Resource Development International,* 6**,** 219-242.

Livingstone, D. W. (1999), 'Beyond human capital theory: The underemployment problem', *International Journal of Contemporary Sociology,* 36**,** 163-192.

Marginson, S. (2019), 'Limitations of human capital theory', *Studies in Higher Education,* 44**,** 287-301.

Mincer, J. (1958), 'Investment in human capital and personal income distribution', *Journal of political economy,* 66**,** 281-302.

Mincer, J. (1975), 'Education, experience, and the distribution of earnings and employment: an overview', *Education, Income, and Human Behavior***,** 71-94.

Nair, S., Lim, S. S., Trenerry, B., Chng, S., Wang, Y. (2021), 'Preparing for workforce transformation in Singapore: The Role of Technical and Vocational Education and Training', *The Next Digital Decade - Policy Approaches from Asia,* Germany: Konrad Adenauer Stiftung and Digital Asia Hub.

OECD (2005), 'Education Policy Analysis', OECD Publishing, Paris

OECD (2019), 'Working Better with Age, Ageing and Employment Policies', OECD Publishing, Paris,

Osman-Gani, A. M. (2004), 'Human capital development in Singapore: An analysis of national policy perspectives', *Advances in developing human resources,* 6**,** 276-287.

Osmundsen, K. (2020), 'Competences for digital transformation: insights from the Norwegian energy sector', In: *53rd Hawaii International Conference on System Sciences*.

Pavlova, M. and Maclean, R., (2007), 'Re-skilling for all? The changing role of TVET in ageing societies of developing countries', *International Handbook of Education for the Changing World of Work: Bridging Academic and Vocational Learning*, 28, Dordrecht: Springer Netherlands

Phillips, J. M. and Gully, S. M. (1997), 'Role of goal orientation, ability, need for achievement, and locus of control in the self-efficacy and goal--setting process', *Journal of Applied Psychology,* 82**,** 792.

Pintrich, P. R. (2003), 'A motivational science perspective on the role of student motivation in learning and teaching contexts', *Journal of Educational Psychology,* 95**,** 667.

Ployhart, R. E. and Bliese, P. D. (2006), ‘Individual adaptability (I-ADAPT) theory: Conceptualizing the antecedents, consequences, and measurement of individual differences in adaptability’, *Understanding adaptability: A prerequisite for effective performance within complex environments,* Emerald Group Publishing Limited.

Quiñones, M. A. (1995), ‘Pretraining context effects: Training assignment as feedback’, *Journal of Applied Psychology,* 80**,** 226-238.

Rani, U., Kumar Dhir, R., Furrer, M., Gőbel, N., Moraiti, A. and Cooney, S. (2021), *World Employment and Social Outlook: The Role of Digital Labour Platforms in Transforming the World of Work*, International Labour Organisation.

Schultz, T. W. (1961), ‘Investment in human capital’, *The American economic review,* 51**,** 1-17.

Schwab, K., (2017), *The fourth industrial revolution*. Currency.

Sousa, M. J. and Rocha, Á. (2019), ‘Digital learning: Developing skills for digital transformation of organizations’, *Future Generation Computer Systems,* 91**,** 327-334.

Tamin, J., Samuel, O., Suraya, A., Ebuenyi, I. D., Naicker, N. and Rajput-Ray, M. (2021), ‘Vulnerable workers and COVID-19: insights from a survey of members of the international commission for occupational health’, *International Journal of Environmental Research and Public Health,* 18**,** 346.

Tan, O. B. (2021), ‘Why the sandwich class feels the money squeeze’, *The Straits Times*.

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y. and Oh, P. H. (2021), ‘Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors’, *Frontiers in Psychology,* 12**,** 822.

Wigfield, A., Eccles, J. S., Fredricks, J. A., Simpkins, S., Roeser, R. W. and Schiefele, U. (2015), ‘Development of achievement motivation and engagement’, *Handbook of Child Psychology and Developmental Science: Socioemotional Processes, Vol. 3, 7th ed*, Hoboken, NJ, US: John Wiley & Sons, Inc.

Woo, J. J. (2018), ‘Technology and Governance in Singapore's Smart Nation Initiative’, *Ash Center Policy Briefs Series*.

Wood, R. and Bandura, A. (1989), ‘Social cognitive theory of organizational management’, *Academy of management Review,* 14**,** 361-384.

Zimmerman, B. J. (2000), ‘Self-efficacy: An essential motive to learn’, *Contemporary educational psychology,* 25**,** 82-91.