institute for adult learning singapore

Research Report

You and Your Work: Skills Utilisation in Singapore

Centre for Skills, Performance and Productivity Research

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The Institute for Adult Learning (IAL) aims to contribute to the competitiveness of Singapore by developing an effective, innovative and responsive Continuing Education and Training (CET) sector that is able to meet the needs of industries and the workforce. It achieves this by raising capabilities, catalysing innovation, and leading research in workforce learning.

Centre for Skills, Performance and Productivity Research, IAL

The research in this paper was conducted under the Centre for Skills, Performance and Productivity Research. This Centre focuses on the impact of skills at work, and the implications of this on policy and practice in CET. In particular, research will examine the role of skills in enterprises and the relationships between skills and a wide range of desirable workplace outcomes. These outcomes include productivity, innovation, learning, skills retention and the use of qualifications.

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Executive Summary

Traditional workforce research focuses on workers and their skills. However, when we examine issues such as productivity and how skills impact the workplace, it is also important to look at what skills jobs demand because it is through jobs that the impact of skills are transmitted to workplace performance. Job skills and worker skills are very different concepts. The former is a demand concept while the latter concerns the supply of skills.

In most countries, workforce policy is primarily supported by supply data. Job skills information tends to be overlooked because we assume that what is supplied will get 'used' in the workplace. This may not be true. Also, the methodology for collecting job skills data in large numbers had been relatively under-developed until recently.

The Skills Utilisation (SU) in Singapore project focuses on skills utilisation in jobs located in Singapore, how skills are distributed across industries and occupations, and how skills utilisation may be explained by other factors. As far as we know, no such data existed in Singapore until the current project. The benefits of creating skills utilisation data will help inform the appropriateness of the Continuing Education and Training (CET) supply strategy, the relevancy of Workforce Skills Qualifications (WSQ), especially the Employability Skills (ES) framework, and our knowledge concerning the extent of skill mismatches.

The data in the SU survey is derived from the Workforce Development Agency's (WDA's) main customers – workers who go for training and skills upgrading, and the information they give us about their jobs. The current report focuses on the survey results and general skills utilisation patterns. Future publications will cover specific topics such as the transferability of generic skills, the values of skills, skills impact of work practices, skills utilisation for low-wage workers and the professionals, managers, executives and technicians (PMETs) in much greater depth.

Summary of the Main Findings

- As in previous studies focusing on the minimum qualification required for the job, the SU data shows that there is still evidence for the continuing reliance on secondary education for jobs in Singapore.

- Across industries (and occupations), secondary education (as minimum required qualification to do the job) is featured strongly. The infocomm and pharmaceuticals & biologics industries are exceptions, as they mainly require their workers to have either diploma or degree qualifications. This may suggest that while the upgrading of workers' skills has been progressing well, the upgrading of job skills has been slow in responding.

- Most jobs in Singapore involve a lot of continuous learning. All industries have over a third of their jobs with 'frequent or ongoing' learning. This pattern may be due to the extensive CET provision in Singapore. In some industries, the figures are very high, for example, in the community & social services and healthcare industries, frequent or ongoing learning applies to 66.2% of the jobs; marine industry, 53.9%; aerospace & precision engineering industry, 50.0%, and so on. In contrast, only one in four jobs in the logistics & transportation and generic manufacturing industries contains frequent or ongoing learning.

- The pharmaceuticals & biologics industry has the highest average skills demanded, while the retail industry has the lowest. Also, most of the jobs in the pharmaceutical & biologics sector have a very high skill content compared with the sample as a whole.

- Job incomes are positively and significantly correlated to the skills content of jobs. In terms of the various job skills measures, job incomes are strongly correlated to the minimum qualification required for the job and initial learning time for the job, but only moderately correlated to continuous learning time.

- In terms of the Broad Skills Index (BSI) – which contains the qualification required and two measures of job learning time – low-wage jobs are 35.9% below the median BSI score of the top wage jobs. This suggests that to move from a low-wage job to a high-wage job, substantial learning, training or attainment of higher qualifications will be required.

- Despite the label of 'generic skills', these skills are not utilised to the same extent in all jobs. Thus, different generic skills may create different impact in different jobs. Some generic skills, e.g. paying attention to details, dealing with people and working with a team of people, are regarded as 'very important' skills in over 70% of jobs in Singapore, while other generic skills, e.g. making speeches, delivering presentations and writing long documents are used by less than 20% of the jobs.

- While the majority of PMET jobs are utilising skills above the sample average, around one-third of PMET jobs are below the sample average line. The industries in which the median PMET BSIs are either close to or below sample average include the food & beverage (F&B), retail, logistics & transportation industries.

- PMET jobs generally exercise more generic skills than other occupations. There are only two generic skills in which PMET jobs are used below the sample average, namely physical skills and emotional labour. Whilst the need for physical skills is generally in decline in most jobs, the need for greater emotional labour utilisation is important for the effectiveness in PMET jobs, and more generally, for personal effectiveness in all other jobs.

- Generic skills such as teamwork skills, planning skills and especially problem-solving skills are utilised by most industries. Influencing and physical skills are applicable to jobs in fewer industries. Influencing skills are relatively 'new'. These skills have been identified as the most rapidly rising in similar studies from the United Kingdom (UK), though starting from a very low base. For greater team and personal effectiveness, influencing skills are clearly the one to develop in future CET policy.

- Across all occupations and in most industries, there is a very high level usage of computers and computerised equipment, reflecting the progress made over the years in terms of upgrading work processes and automation. However, for most industries, 'routine use' (printing invoices and receipts) and ‘basic use’ (for word-processing, and databases) form the bulk of the computer usage for most industries. When it comes to more advanced usage (analysis and programming) of computers and computerised equipment, huge industrial and occupational differences emerge. Here, the infocomm, pharmaceuticals & biologics industries are significant users of advanced usage by far, compared with other industries. In other industries such as security, estate management, logistics & transportation and, to some extent, community & social services, advanced usage of computers is very low or negligible.

- In Singapore workplaces, the levels of task discretion and employee involvement practices are highly and significantly related to the general skills content of jobs in Singapore. The same contextual factors also have similar positive and significant relationships with generic skills utilisation.

Policy Implications

The results of the SU survey provide a huge amount of job skills data which point to a number of policy implications. Many of these are consistent with analysis elsewhere but the use of job skills data has provided a different perspective to examining policy options. The following discussion will focus on some of the current policy concerns, namely low-wage jobs, the PMET community, productivity via improved job processes and contextualisation of generic skills training.

Firstly, the SU survey results show that low-skill job content is linked to low-wage jobs. Thus, to escape this low-pay ‘trap’, the low-wage worker would have to move to jobs with substantial increase in either the minimum required qualification or training content, or both. Alternatively, there is a need to re-design existing job content to upgrade the employee’s skills. The latter policy option appears to be more challenging and may take more time, as changing job skills content is the employers’ decision and there may be other considerations involved. However, public policy can still influence this area of change if we deliver the high job skills idea via the role of the PMET (see discussion below). To increase job mobility from low-skilled to higher-skilled jobs, this is where the CET system has a direct and effective way for policy intervention.

Secondly, the survey results show that PMET jobs utilise more skills almost in all areas (except physical skills and emotional labour) than non-PMET jobs. In the current policy effort to upskill PMETs, there are two areas which are relevant to the 'T' shape training for PMETs. Firstly, as many PMETs are in positions that influence how work (their own and others) is done or designed, their role is key to upskilling jobs as well as augmenting productivity. As such, a greater appreciation of operation and human resource management issues for high performance and productivity (also see discussion below on 'job environment and skills utilisation') will be vital. The second area concerns the PMET's own training. Although PMET jobs in general are already highly skilled, these jobs do not appear to be exercising new skills, e.g. emotional labour, to a high level. In deepening the skills of PMETs, it is important to identify other emerging new skills that are useful to equip them to lead industries and productivity change.

Thirdly, this study shows that skills utilisation is influenced by job environment. Jobs that are more autonomous with high involvement are also jobs that utilise more skills and in high job income groups. Currently, very little CET or WSQ training pays much attention to the link between job environment and job effectiveness. For example, only the Service Excellence Training Programme at the managerial level has some emphasis on the importance of job environment in relation to greater skills utilisation. This could be an issue to look at for future training syllabus. But this call for improvement in job environment may not only be emphasised across WSQ frameworks, it is more so in all PMET training programmes as they would be the gatekeepers to facilitate positive change and greater skills utilisation in the workplace through new practices and new processes.

Lastly, this study shows that generic skills are utilised in a very differential manner across industries and job roles (e.g. between PMET and non-PMET jobs). Thus, it may be useful for future versions of 'generic skills contextualisation' to take into account job skills content. The survey results also point to 'emerging' new generic skills, though from a very low base, e.g. influencing skills and emotional labour. To what extent are future generic skills training able to deal with future or emerging generic skills? Many of the emerging skills are not new but a reformulation of familiar components. The question is, therefore, how adaptable is the WSQ (or ES) system in evolving training content to cater for new needs?

Glossary of Terms

BCA	Building and Construction Authority
BEST	Basic Education for Skills Training
BSI	Broad Skills Index
CET	Continuing Education and Training
CREST	Critical Enabling Skills Training
DOS	Department of Statistics
EQ	Emotional labour
ES	Employability Skills
ESS	Employability Skills System
F&B	Food and beverage
FLD	Front Line Division (in WDA)
GSI	Generic Skills Index
HRM	Human Resources Management
IDA	Infocomm Development Authority
IT	Information technology
JA	Job analysis
KSAO	Knowledge, skills, abilities and other characteristics
LLEF	Lifelong Learning Endowment Fund
MOM	Ministry of Manpower
NBN	National Broadband Network
NParks	National Parks Board

NPF	National Productivity Fund
PET	Pre-employment training
PMET	Professional, manager, executive, technician
SMa	Singapore Manufacturers' Federation
SNEF	Singapore National Employers Federation
SSIC	Singapore Standard Industrial Classification
SSOC	Singapore Standard Occupational Classification
STEP	Skills Training for Excellence Programme
SU	Skills Utilisation
TDI	Task Discretion Index
TIP	Technology Innovation Programme
TMIS	Tourism Management Institute of Singapore
T-UP	Technology for Enterprise Capability Upgrading Initiative
WDA	Workforce Development Agency
WSQ	Workforce Skills Qualification

Section 1: Context and Objectives

Workforce skills are vitally important in Singapore. This importance is highlighted in the 2011 Budget Statement succinctly in four areas. First, skills are fundamental to growing future incomes for all Singaporeans. A target of raising real income by 30% by the end of this decade is ambitious. This target cannot be attained unless there is a substantial change in the skills of the workforce.

Second, the Budget Statement also points to the need to strengthen our society through enabling all citizens to contribute and take active part. One of the biggest challenges at present is the need to improve the position of low-wage and older workers through improvement in their skills. In this respect, skills also carry a major role in attaining social goals and 'better society' in Singapore.

Third, the need to boost productivity is a major driver for overall economic and social improvement. Productivity is targeted to rise from its current low base of 1% to 3% per annum. Under the National Productivity Fund (NPF), $800m has been allocated to help strengthen the links between skills and productivity by 2015 with more increases expected after that. Funding such as NPF will transform the skills content of training and deepen job skills, as highlighted by the example of a new apprenticeship scheme, designed jointly by the National Parks Board (NParks) and WDA, to deepen trade skills.

Fourth, efforts are already underway to increase support for continuing education and training (CET) for specific groups. These include the low-wage and older workers. In addition, (PMETs, who now make up more than half of our workforce, are also accorded significant support to upgrade and deepen their skills. The above CET enhancement is expected to cost $30m every year. This is to be boosted by a further $500m top-up into the Lifelong Learning Endowment Fund (LLEF), increasing the LLEF to $3.6b, as well as complementing future annual spending on CET.

There is no doubt that these various national efforts will augment the human capability of Singapore in terms of its skills base. However, in order to know more about how these efforts are converted into impact on skills and how the activities of the CET system are making a difference to productivity via skills, we would need more information about the so-called ‘demand’ side. In other words, we need information that reflects skills utilisation at work. The basic question is “We train a lot, but do we know if skills are used?” Policy makers would want to know what and how skills are used in the workplace after skills training in the CET system, and in what ways skills are making an impact.

We tend to believe that we do know a lot about skills in Singapore. After all, we know the yearly and future output of various qualifications from the PET and CET sectors. We have quite accurate data on the qualifications that the existing workforce holds. However, in skills research, there is a difference – a huge difference – between skills that the workforce holds and skills required for a job to be done, even if we do not question the link between qualifications and skills. In fact, what we know a great deal about is the former, while our knowledge of the latter is rather thin.

The CET system examines the skills of jobs from time to time, especially when it starts introducing WSQ qualifications in the respective industries. We notice that there is still a significant difference between the broad competencies that we identify for WSQ purposes and what are actually used in a job on a day-to-day basis. Skills research concerns the latter and seeks to identify not only skills that are used, but also the relative importance of those skills from the job activities perspective. This perspective allows us to construct a scan on the skills content of Singaporean jobs.

The Skills Utilisation (SU) in Singapore project focuses on skills utilisation in jobs located in Singapore, how skills are distributed and how skills utilisation may be explained by other factors. Unlike previous studies which tended to examine the skills of the workers, this study focuses on the skills of a job. The methodology is constructed around job activities that take place in a job. As far as we know, no such data existed until the current project. The benefits of creating skills utilisation data will help inform the appropriateness of the CET supply strategy, the relevancy of WSQ qualifications (especially the ES framework) and the extent to which skills may be mismatched. With the creation of various skills indices, we can also compare skills across jobs and measure changes in skills utilisation, when the survey is repeated over time.

The current report focuses on the survey results and skills utilisation patterns. It has the following specific objectives:

- To provide skills utilisation mapping across key sectors and other domains (e.g. occupation, firm size etc.) in Singapore
- To construct key summary indicators such as the BSI and various Generic Skills Index (GSI) that form a multi-dimensional measure for job skills
- To construct other indicators that will enhance the analysis of skills utilisation, e.g. Workplace Involvement Index, Task Discretion Index, and Worker Commitment Index
- To identify workplace factors that are likely to enhance skills utilisation
- To provide the baseline skills measurements in order to measure job skills change over time.

Section 2: Skills Utilisation and Measurement

In order to understand the thinking and strategy behind the SU survey, it is important to have an appreciation of the complexity of the concept of skills and its measurement. One of the best ways to get a quick grasp of the issues involved is to look at the various skill theories and their implications.

2.1 The Meanings of Skills

The basic question is “What is skill?” This simple question turns out to be rather difficult to answer, and it has been highly contested by various research disciplines. For example, economists and employers frequently associate the skills required by a job in terms of the ‘expected’ education qualification(s) and/or relevant job experience. These often do not provide an accurate description about the actual skills that are used. Instead, they may reflect the kind of ‘desirable workers’ whom we hope to recruit. Thus, some employers use education qualifications and/or relevant job experience as proxies for desirable characteristics that they expect of their workers. In practice, a common definition of skills does not exist across various research disciplines. The answer depends on what, where, how and how far one wants to identify skills.

Paul Attewell’s (Attewell, 1990) classic paper serves to highlight the conceptual complexity and the very different approaches to analysing skills. Indeed, since its publication 20 years ago, many of the epistemological issues remain unresolved. However, it is in the policy and practice arenas, significant progress has been made. For example, in the policy arena, there is an increasing recognition of ‘skills sets’ that include soft skills, generic skills and pro-employment characteristics such as initiatives, dependability and so on. In the practice arena, widespread use of job analysis and the competency-based approach to learning (and qualifications) reflect the need to embrace a multi-dimensional concept of skills.

So what exactly are the issues? Attewell (1990) attributes the different epistemological concerns to a result of competing theoretical traditions yielding very different ways of ‘knowing’ what skill is and therefore how to measure it. For example, is the concept of ‘skill’ a value-laden term – e.g. being ‘skilled’? So when we talk about skills, are we referring to someone who is already ‘skilled’ in excellence terms, or are we referring to a full spectrum of being skilled, including entry levels of competence? Again, when we talk about skills, do we refer to the job or to the worker? Ashton et. al. (1999) rightly pointed out that whilst the early disciplines had been useful, they were not ideal in studying skills utilisation and skills change over time. For example, the human capital approach tends to treat skills in a relatively ‘unproblematic’ manner. This is reflected in the standard use of education qualifications and experience as proxies for the skills of individuals. And from that, the skills of the individuals are deemed to be largely similar to, if not the same as, the skills content of the job associated with that worker. It is not difficult to see that there are too many assumptions made here. Whilst there is clearly a relationship between the worker’s own skills and the skills content of the job that he/she does, the two are not synonymous.

Another well-known problem concerns the issue of signalling. Employers may use qualifications as a filtering device to screen in the ‘better’ candidates. This problem becomes more pronounced where credentialism is practised widely. If this is the case, qualifications become an important tool for structuring the job market and society, but are less relevant as a measure of job skills. However, one of the most useful learning points from the economic approach is that qualifications can act as a practical device for signalling ‘trainability’ for a particular job, irrespective of qualifications being used as a measure of skills or a screening device.

Most sociological approaches largely ignore the quantitative approach of labour economics. Sociologists tend to focus on investigating how skills are socially constructed, and therefore for them, skills are very difficult to measure (or it may not be meaningful to do so) depending on the context in which skills are recognised (Spenner, 1990). For example, jobs that involve authority over others are often perceived as ‘skilled’, irrespective of the actual skills content of the job. This perspective suggests that a ‘high-skilled’ position may have skills and experience content, but in many instances, these are confused with the status that society accords to those jobs. Thus, Sung and Ashton (2012) found that “a skilled worker could be someone with power over others or with the ability to exercise some task discretion and the power to define their job as skilled and have employers and other workers accept that definition". In the social context, we sometimes conflate the position of skill with the position of power. Likewise, the effect of 'closed shop' – e.g. unions or professional bodies' exclusion of others – can also 'enhance' the perceived level of skills involved (Form, 1987). A useful learning point from the sociological perspective is that our perception of what is skilled and what is less skilled may well be the consequence of other factors and not necessarily the actual skill content itself.

Do we recognise a skill only because it is in high demand? Manual skills are often in high demand, yet they are not seen as 'high skills' because most societies tend to accord a low status to these skills. In other words, there are many skills around us. But we may fail to recognise them because they are either not in short supply or not recognised. In a similar way, for skills that we all can do so well, e.g. walking, standing or speaking, do we tend to overlook them when they may be very relevant to the performance of a task? The latter question concerns whether something, no matter how complex, that we manage to 'routinise' is something 'unskilled'.

But these questions can get more complex as we dig deeper. For example, we are increasingly defining a skilled outcome as one that we can expect a particular standard or a greater certainty of outcome. Thus, in competence-based training, a skilled worker is one who can perform the required outcomes. Being able to produce a consistent standard is the hallmark of being skilled. However, in many professions with high esteem in society, this is just one outcome that they cannot guarantee. For example, engineers cannot provide certainty that a highly complex engineering device will always work in space. Likewise, lawyers cannot predict the outcome of a legal dispute; a surgeon may fail in a complex medical operation. In all these cases, the status of being 'highly skilled' coexists with significant uncertainty in terms of outcome and performance.

So far, the discussion seems to focus on the skill of the worker. However, for many questions concerning the performance of a job, one might want to focus on the job (Vallas, 1990). As mentioned, many research projects do not make such a distinction, preferring to make the assumption that they are more or less the same thing. But are they? Whilst the current project is not about defining what skills are, it is sufficient to remind ourselves that these conceptual uncertainties can give rise to huge difficulties when it comes to measurement and our understanding of the impact of skills.

2.2 How Does the Concept of Skills Affect Measurement?

Until the launch of the first Skills survey in the UK in 1997, our knowledge of skills was hitherto informed by a mixed set of disciplines such as labour economics, industrial sociology and occupational psychology. The main concerns of labour economics focus on returns to education, income inequality and occupational mobility. Skills are often an 'inferred' concept as proxied by qualifications, years of schooling, years of experience, or a combination of all three. Industrial sociology focuses on organisations being a social system within which skills are one of the outcomes. Industrial sociologists argue that our perception of what is skilled or otherwise may be influenced by other factors such as convention, social esteem or the result of political processes.

Psychologists are more likely to accept a very broad definition of skills because they tend to examine skills as an integrated component within the wider 'learning' processes. They are more likely to accept that things connected with the utilisation of skills are part of skills themselves. This explains occupational psychologists' proposal to incorporate attitudes and other personal characteristics, e.g. dependability, self-motivation, attention to details and so on, as part of the skill set relevant to jobs.

The discussion so far reflects the complexity of doing a skills survey. Not only do we need to know what to measure, we also need to know how. The arrival of the Skills Surveys in the UK created the first ever large-scale research focusing on skills and skills utilisation (Felstead et al., 2002a, Felstead et al., 2007, Ashton et al., 1999, Felstead et al., 2002b). The approach of the Skills Surveys was to re-examine all the pointers that we just discussed. By using a 'work activities' approach, the UK studies design different measures and combinations of measures that reflect the variable meaning of skills, as seen from the different approaches. The current SU survey follows this interdisciplinary methodology.

Whilst not dismissing the usefulness of other disciplines, the psychology perspective is perhaps the most relevant to the concept of skills utilisation. There has been a long tradition in the 19th century in studying the principles of learning theory and human behaviour in relation to job performance. Training featured in some of this research especially in psychomotor and experimental psychology. More recently, further progress was made when occupational psychologists use the term ‘skills’ referring specifically to workplace cognitive and motor skills (Fleischmann and Mumford, 1988, Fleischmann and Mumford, 1989).

One promising strand of research was the proposal to examine skills in a more holistic manner in order to understand what skills are contained in a job. In particular, Gatewood and Field (1987) suggest the need to focus on ‘worker attributes’ such as knowledge, skills, abilities and other characteristics (the so-called KSAO approach). Although this is a very useful formulation for skills utilisation research, it is not without operational problems. For example, Ashton et. al. (1999) point out that there may be different interpretations as to whether ability is entirely cognitive, or whether skills are always psychomotor-related. Despite the fact that much of Gatewood and Field’s writing actually refers to workers’ attributes while our attention is ‘job skills’, their approach gives a very helpful pointer to skills utilisation research.

To implement the concept of KSAO, occupational psychologists often employ some form of ‘job analysis’. Job analysis (JA) can be worker or job oriented. In the former, JA is used to identify appropriate workers’ attributes for ‘personal specifications’. In the latter, it is a methodology that is ideal for skills utilisation research. Although there is quite a variety of JA, the principles are very similar in that JA is a systematic approach to collecting tasks performance (or job activities) required for a job.

The current SU survey, like the UK Skills Surveys, is informed by all the major approaches that we discussed so far. In the following section, we will explain how these approaches influence the design and measurements of our survey.

2.3 The Methodology

By drawing upon different disciplines, the objective of the SU survey is to develop an interdisciplinary approach to identifying job skills via a large-scale survey in order to answer a range of practical as well as policy-relevant questions that our current knowledge is limited. Also, we would like to develop measures of job skills that can provide a baseline for future research on skill changes.

The first challenge of the SU study is the conceptualisation of ‘skills’. For the questionnaire to be viable, the measures of skills have to be useable in all work contexts and in different industries. The previous discussion suggests that the different approaches to skills have very different notions of skills. However, learning from them, the design of the SU questionnaire is to adopt an inclusive skill concept that covers worker characteristics, personal attributes, abilities, attitudes and competencies that are regarded as important in carrying out various tasks.

In addition, going beyond the narrow confine of skills, we recognise that we have to incorporate a wider range of factors that are likely to influence skills utilisation. This means that we have to include in the survey organisational factors such as work practices, organisational culture, and personal characteristics such as motivation and commitment orientation.

In general, the job analysis literature suggests that in order to identify skills utilisation, we need to focus on tasks that individual workers have to perform in order to achieve the job objectives. However, in order that the questionnaire can be used by workers from different industrial settings, we avoided the use of any specific competencies that might only be relevant to some specific jobs and not others so that the questionnaire can be used by workers from different industrial settings. This means that, for example, the SU questionnaire includes a wide range of generic competencies that can be answered by managerial, non-managerial, technical and non-technical workers. As such, the skills questions cover the following broad areas:

- Intellectual skills (e.g. literacy, numeracy, problem-solving, planning etc)
- Interpersonal skills (e.g. communication, teamwork, leadership etc)

- Physical skills (e.g. hands dexterity, need to stand, walk or move objects etc)
- Knowledge (e.g. IT, technical etc)
- Motivation (e.g. attention to detail, initiative, discretionary effort etc)

These are to be supplemented by other traditional measures such as basic qualifications required for the job, initial learning time, and the extent of continuing learning.

2.3.1 Approach to Survey Measurement

There were a number of fairly important constraints on the operation of the survey. Firstly, the resources available – time and finances – meant that the project was not in a position to support vast numbers of researchers to poll respondents directly via a face-to-face type of interview, or to carry out some psychometric type of tests with respondents. This also meant that that we had to do a self-reported type of questionnaire. Under these constraints, it was also impossible to have ‘professional raters’ to evaluate the extent to which a certain skill was used in a particular job. Self-rating was adopted.

There are of course well-known issues concerning the use of a self-reporting methodology. For example, the standard of self-referencing, the impact of social desirability and the use of memory re-call in answering survey questions can significantly affect the reliability of the data. But by following the design of the UK Skills Survey, we designed questions that steered away from many of those problems. For example, instead of asking questions that could be interpreted as the competence of the worker, the questions were carefully worded to ask the respondent to comment on the extent to which the skill is used in his/her job. An example of this is as follow:

> “In your job, how important is … [planning others’ activities]?”

The respondent was given a Likert scale type of response choice, ranging from “Not important at all” to “Very important”. Other tasks (e.g. instructing, training or teaching people etc) were polled in a similar fashion, so that the questions were asked in a consistent manner.

We also followed the strategy of the UK study by developing careful, concrete and behaviourally worded questions so that the respondent would be encouraged to focus on the actual work and performance requirements. We also avoided the ‘halo’ effect.

In a detailed job analysis, there would be opportunities to verify the responses though an interviewer, but the resources and time that we had meant that this was not possible. The main strategy was that by asking the job-holder about the job that he/she was doing, we argued that the best informant of a job is the job-holder, and the job-holder knows what is needed to do the job.

At the testing stage, we learned a great deal about the constraints that we faced if we were to succeed in getting a reasonably large number of returns, given the time and resources available. So in the subsequent designs, some questions were left out, e.g. some measures of the skills of the workers. This would have enabled some form of ‘skills-matching’ analysis from the data. In other areas, the format of the responses was made more consistent to speed up response. In some cases, the range of responses was reduced, which was not ideal.

2.3.2 Consultation

WDA is the funding body for the project, and the targeted jobs are those that WDA has to deal with[1]. As a result, we consulted all the frontline divisions (FLDs) of WDA during the design stage. The purpose was to ensure that we could find access to workers to conduct the survey, and we had a good idea about the industrial contexts within which the jobs were located. Through the FLDs, we were put in touch with various CET centres where workers went for training. Not all the CET centres were approached. We initially contained our effort to just three large sectors in which they employed significantly more workers than others. The idea was that we would focus on the sectors that WDA worked with most and those sectors that

[1] The focus of the current study covers jobs that are the immediate attention of WDA. A national sample that goes beyond WDA’s immediate audiences is currently being designed, and it is expected to take place in late 2011/early 2012.

would matter more in employment terms (also see more discussion on the ‘Sample’ later).

The discussions with CET centres were also useful in ascertaining possible skills issues for the sector. At the same time, we could ascertain what kind of workers may be attending CET classes throughout the year and their levels of occupation. In that respect, although we randomly sampled the workers, we had a good idea of the kind of workers and the sectors they came from.

Other key agencies in government were also consulted, e.g. the Ministry of Manpower (MOM) and Department of Statistics (DOS), to ensure that there was no duplicated effort or data. These meetings were useful for other purposes too. For example, we included data that we might be able to examine skills in the context of low pay, as a result of the discussion with MOM.

Section 3: The Survey

This section covers the conduct of the survey itself, the questionnaire and the sample used.

3.1 The Questionnaire

The basic design of the SU questionnaire follows the three sweeps of Skills Surveys in the UK. However, we found that the practical engagement time with the respondent in Singapore is much shorter, compared with that in the UK. As a result, the questionnaire used in Singapore is a much shorter too, compared with its predecessors. The space constraint also means that we have to focus mainly on the skills questions. Many of the extended questions in the UK questionnaire, e.g. worker's own background, job/skills details of a job three years ago and so on, are not included.

Thus, the SU questionnaire contains the following areas of core questions:

- Job background information
- Job analysis of tasks/skills
- Use of computers or computerised equipment
- Job autonomy
- Minimum qualifications required for the job
- Initial and continuing learning time required for the job
- Worker commitment/motivation/effort
- Workplace involvement
- Nature of job
- Job income

- Industry and occupation classification
- Workplace information
- Brief personal background

The questionnaire was self-reported. It was a compact 3-page design and took an average of 30 minutes to complete. A facilitator was available in the majority cases to help out with queries. On a few occasions, a Chinese language version of the questionnaire was used.

3.2 The Survey

One of the biggest challenges for the SU survey was to get sufficient number of workers to take part in the survey. Interviewing workers at work would pose a few obstacles. We would need employers' permission for a start. Secondly, this might take workers off their work. This, too, would raise the possibility of employers' refusal.

We also considered using other methods, e.g. using a similar method like the one in the UK (i.e. calling upon the respondents through random sample grids), or using a telephone or postal survey. However, the research team decided against those approaches, as they would be expensive, time-consuming or have low response rates.

In the final analysis, the SU survey adopted an unusual approach to surveying workers in Singapore. The SU survey took advantage of the time when workers went for training at one of the CET centres who were away from their normal work environment and would be more likely to have time and space to take part in a three-page questionnaire. We also thought that this would be an appropriate channel as the survey's target groups would coincide with MOM or WDA's policy interest, and can be accessed in large numbers. The approach turned out to be very useful, as refusals were very rare.

The survey focused on three main sectors in Singapore – manufacturing, retail and hotel & tourism. However, the survey later included workers in other sectors for contrast, e.g. the public sector, logistics, social services, infocomm and so on. Thus, the survey was administered at various CET centres such as Tourism Management Institute of Singapore (TMIS), Building and Construction Authority (BCA), Singapore National Employers Federation (SNEF), Singapore Manufacturers' Federation (SMa) and many more. Over 12 months, we randomly sampled batches of workers who attended training at CET centres. These training centres provided a ready pool of workers from different industries and of different working levels. As there is generally a bias for larger organisations to send their workers for training at CET centres, we also approach business associations, which were well connected with local small businesses, in order to tap into their network of small businesses and workers working for them. Thus, we also conducted the survey via various local social or business networks, especially those amongst the housing estates.

At the end of the 12 months, 2293 questionnaires were collected. Data collection began in October 2009 and ended in September 2010. The survey was piloted in September 2009 to small groups of workers. Refinements were made to the choice of words, presentation and the length of questionnaire. Reliability scales were tested which consistently reflected the similar reliability as that in the UK surveys.

The majority of the surveys were administered by at least one member of the research team. Respondents were briefed on the purpose of the survey before they began. On a few occasions where this was not possible, the questionnaires were distributed with the research project information sheet which had contact details that respondents could call upon in order to clarify doubts.

To qualify for the survey, respondents had to be in a job based in Singapore for at least three months. This is the case because the unit of analysis is primarily the job, and not the person, as such. If they were unemployed at the time of survey, respondents could refer to their previous job. A 'lucky draw' (for 50 NTUC shopping vouchers worth $50 each) was included in the study to encourage participation. Respondents were required to indicate only their email and/or contact phone number at the end of the questionnaire if they were interested to participate in the lucky draw. The phone or email details were purely for the prize draw purposes in the event that they won. Otherwise, the survey was anonymous.

The data collected was entered in a FileMaker Pro database for ease of data entry and easy data checking. The data was subsequently exported to SPSS and STATA for further analysis. The data cleaning process was an extensive exercise with many rounds of discussions with regards to the classification of data and checking to ensure that answers in the questionnaires were entered accurately and consistently. The data on industry and occupation were coded based on the Singapore Standard Occupations Classification (SSOC) 2010 and the Singapore Standard Industrial Classification (SSIC) 2010, both published by the Singapore Department of Statistics.

3.3 The Sample

There were a total of 2293 individuals surveyed. Table 3.3.1 shows the profile of the SU data. We cross-classify all the jobs in the sample in terms of occupation, industry, contract type, firm size, job income and gender (job holder).

Table 3.3.1. SU Sample Profile

Category	Sub-groups	%	N	Total
Occupation	Professional, Managerial, Executive & Technical	46.4	1060	2285
	Clerical & Related Worker	7.4	169	
	Service, Shop Worker & Sales Worker	35.2	804	
	Production, Craftsman & Related Worker	5.8	132	
	Plant, Machine Operators & Assembler	2.8	65	
	Cleaner, Labourer & Related Worker	2.4	55	
Industry	Aerospace & precision engineering	3.3	72	2166
	Logistics & transportation	8.7	189	

Category	Sub-groups	%	N	Total
	Pharma & biologics	2.5	55	
	Construction	6.3	136	
	Chemicals/petrochemicals	3.8	82	
	Electronics/electrical engineering	3.5	75	
	Marine	3.6	78	
	Retail	22.7	492	
	Security, estate management & services	1.3	28	
	Infocomm	2.5	55	
	Hotels, tourism, events & attractions	5.1	111	
	Community & social services, healthcare	6.8	148	
	Food & beverage	7.9	172	
	Landscape	2.8	60	
	Government & other public service	15.0	324	
	Generic manufacturing	4.1	89	
Gender	Male	55.5	1208	2175
	Female	44.5	967	
Establishment Size	Less than 10	14.6	330	2262
	Between 10 and 49	18.9	428	
	50 or more	66.5	1504	

Category	Sub-groups	%	N	Total
Contract Type	Permanent full-time	83.9	1864	2221
	Fixed-term contract	6.8	151	
	Self-employed	2.7	60	
	Temp/part-time contract	6.6	146	
Income	Less than $1,200	19.3	427	2213
	$1,200–$2,999	54.6	1209	
	$3,000–$4,999	19.1	423	
	$5,000–$7,999	4.9	109	
	$8,000 or more	2.0	45	

Through discussions with WDA Frontline Divisions and various CET centres, we have prior information regarding the types of training that were taking place throughout the months ahead of the survey. We also knew the level of personnel and the industries that might be involved. We used this information to stratify the sample before we started to randomly sample the respondents. The choice of using CET centres as a vehicle for survey was also influenced by the need to examine jobs of those who participate in CET. As a result, when we compared our sample with employment profile statistics from the MOM, we saw some differences, though the overall patterns are similar.

Table 3.3.2 shows that the manufacturing sector in the SU data accounts for 20.8% of the sample. This is somewhat higher than the national manufacturing employment of 15.7%. The SU sample 6.3% on construction is also of a higher percentage compared with the national figure of 6.1%. Correspondingly, the percentage of SU service respondents (57.8%) is lower than the national percentage (77.1%). Additionally, we included a sample of public sector jobs (15%)

for contrast. However, it is important to note that the MOM breakdown does not separate the public sector jobs, and these are included in the service category. Thus, if we were to combine the service and public sector jobs in the SU data, the SU and MOM data would be very close.

Table 3.3.2. Comparison between SU Data and National Profile (%)

Category	SU Data Profile	SU Data Profile	MOM Employment Profile (2009)
Industry Sector	Manufacturing	20.8	15.7
	Construction	6.3	6.1
	Services	57.8	77.1
	Public Sector	15.0	- -
Occupa-tion	Professional, Managerial, Executive & Technical	46.2	52.0
	Clerical & Related Worker	7.4	12.7
	Service, Shop Worker & Sales Worker	35.1	11.1
	Production, Craftsmen & Related Worker	5.8	4.75
	Plant, Machine Operator & Assembler	2.8	8.5
	Elementary Worker	2.4	7.5
	Occupation not classified	0.3	3.3
Contract Type	Permanent full-time	83.9	87.2
	Fixed-term contract	6.8	- -
	Self-employed	2.7	- -
	Temporary/part-time contract	6.6	- -

Whilst the CET centre strategy was efficient in conducting a survey of this size with a very low refusal rate, there were some minor issues to note in some cases. For example, in the government and public services sample, the respondents were mostly administrative and managerial staff. Very few senior officers participated in the survey. However, for other sectors, e.g. manufacturing and services, the CET centre strategy presented the opportunity to capture a wider range of workers, generally covering different levels of job roles.

Section 4: The Distribution of Skills at Work in Singapore

One of the first skills indices that policy makers and CET practitioners would find useful is a general measure of the skills content of a job. Adapting from the UK studies, we use three components – i.e. the minimum qualifications required for the job, initial learning time and continuous learning time – in the general skills measure, also known as the Broad Skills Index (BSI). Thus, the three components reflect the respective roles of prior education, basic training, and skills development necessary for performing a job in a competent manner.

The role of 'minimum qualification required' is important. The justification for using this as a proxy is that it does provide important information about the level of general knowledge required for the job. In this sense, the role of qualifications (and therefore the role of formal education) in measuring the skills of a job cannot be overlooked. Thus, in the SU survey, we ask "What minimum qualification, if any, would someone need in order to get the type of job that you have now?" The logic behind this approach is that, in general, the jobholder should be the most reliable source about the content of his/her job. We use the word 'minimum' to emphasise to the respondent that we are looking for the absolute base-line requirement and not a desirable level of qualifications which may reflect 'screening' objective among employers for higher quality of candidates. The latter does not help to measure skills used in a job.

The second component concerns initial learning time required for a job. In many jobs, especially where vocational skills are frequently employed, the 'scope' of skills is often reflected in the amount of initial training time required. This measure takes into account of skills that are nurtured through taking up a job. So it is closely related to job specific skills. In some cases, this measure also has the advantage of recognising non-certifiable skills that are important to the job. This would be reflected in the amount of learning time required. In addition, this component may indirectly reflect the complexity of skills required for a job because different workplaces may organise themselves differently. Thus, we may expect a workplace that emphasised ‘quality’ or teamwork to spend more time in initial learning, even though we may be comparing two very similar jobs.

Although initial learning time is a very useful measure for the BSI, there may exist some ambiguity, as pointed out by the UK studies (Ashton et. al., 1999). For example, a very ‘quick learner’ may happen to be a ‘better educated’ person in non-manual jobs. In this case, the initial learning time would be under reported. So a longer learning time may be a negative rather than positive measure of skills. To ascertain this, we ran a test to see if learning times are positively related to other skills indicators. If our assumption was correct that learning time is a positive measure of skills, then it should be positively correlated to other skill indices. Indeed, our test confirms that learning time is positively correlated with leadership, problem-solving, planning skills, ICT skills, minimum qualifications required for the job and continuous learning time.

The third component covers continuous learning that is required for the job. This measure therefore refers to skill development after the worker is able to hold down the job. This is one of the most frequently overlooked items in most empirical analyses. Conventional approaches could be criticised of being overly ‘front-end’ focused by only examining what qualifications are required or using job experience as a proxy for job-related learning when we really do not know the extent of continuous learning. By measuring the extent to which continuous learning is required for the job, we get some idea about the ‘depth’ of skills involved. Hence, this third measure is closely related to the concept of skills deepening.

The above discussion leads to a formulation of the BSI consisting of the following components:

BSI = Min. Qualification Required + Initial Learning Time + Extent of Continuous Learning

With the BSI, we will be able to summarise the skills content of any job in the sample. We can then compare the skills of different jobs and between different industries. We can identify skills utilisation issues subject to contextual factors (see later chapters). When the exercises are repeated over time, as in the case of the UK, we will be able to map out skills changes in jobs.

4.1 Findings on the Distribution of Minimum Qualifications Required

Before we examine the BSI scores, we look at the distribution of the components of the BSI. Table 4.1 shows that gender differences are negligible in terms of minimum qualifications required for their jobs. However, occupational differences are huge[2]. For example, 45.8% (17.1% + 28.7%) of all PMET jobs require a polytechnic diploma or above qualifications while only 7.3% (2.7%+4.5%) of service jobs would require similar qualifications[3]. However, it is important to note that amongst PMET jobs, there is a wide range of minimum qualifications required, and not just degrees or above. This reflects the nature of the PMET group that PMET jobs can be found in a variety of job roles with different levels of skills demand.

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[2] Occupational classification here broadly follows SSOC 2010. PMET comes from categories 1, 2 and 3. Category 6 (agricultural & fishery) is not included in the SU sample.

[3] WDA has a 'working definition' for PMET – i.e. those who have diploma qualifications or higher. This definition largely reflects the funding requirement of CET training. The SU data can be constructed to reflect such a definition via the minimum qualification required for the job. However, this report adopts the original self-reported occupational status because of the need to look at PMETs in general and not just those who are qualified for PMET training subsidies.

Elementary occupations[4] have the highest proportion of jobs that do not require any qualification at all (28.3%). However, other than PMET jobs, all other occupations utilise secondary education as the minimum qualifications for their jobs. In the cases of clerical, administrative staff, services, shop, sales workers, plant and machine operatives, the proportions of their jobs that utilise no higher than secondary education exceed 60%. For most jobs, a secondary level of education still forms the most important starting point in Singapore. Previous studies identified that the bulk of the Singapore workforce possessed mainly secondary education qualifications reflecting the relatively low skill content required at the time, and the SU data shows that there is still evidence for the continuing reliance on secondary education in jobs in Singapore.

Table 4.1 also shows that of all the different contract types, 28.2% contract jobs demands the highest skills content in terms of minimum qualification required while 27.3% (10.2%+17.1%) of all permanent jobs require diploma or above qualifications while only 17% (5.9%+11.1) of all part-time or temporary jobs would require such qualifications. The most interesting one is 'self-employed'. It appears that high-level qualifications are not important for self-employed jobs. Only 7.0% of self-employed jobs required a degree or above as a minimum qualification for their jobs, the lowest amongst different job contract types. However, as seen in later tables 4.2 and 4.3, this is more than made up by the huge amounts of initial and continuous learning times that are required for self-employed jobs.

Also, when combined with the results in later table, it also shows that the skills of the self-employed are largely learning on the job, both on starting up and continuously.

[4] For convenience, we refer the 'Cleaner, labourer & related worker' category as 'Elementary Worker or occupation' throughout the discussion from here on.

Table 4.1. Minimum Qualifications Required for the Job (%)

		No qualification	Secondary level	Post-secondary or non-tertiary	Polytechnic diploma	Degree or PG	N
Gender	Male	8.0	51.7	15.1	8.9	16.2	1144
	Female	5.3	51.9	14.7	11.2	16.8	926
Occupa-tion	Professional, managerial, executive and technical	3.5	31.8	18.9	17.1	28.7	1025
	Clerical & Related Worker	3.8	64.4	19.4	7.5	5.0	160
	Services, shop worker and sales worker	9.2	74.6	9.0	2.7	4.5	753
	Production, craftsmen & related	12.8	64.8	12.8	3.2	6.4	125
	Plant, Machine Operator & Assembler	10.3	62.1	17.2	5.2	5.2	58
	Elementary worker	28.3	50.0	10.9	4.3	6.5	46
Contract Type	Permanent	5.6	52.1	14.9	10.2	17.1	1780

		No qualification	Secondary level	Post-secondary or non-tertiary	Polytechnic diploma	Degree or PG	N
	Contract	11.3	43.7	16.9	12.7	15.5	142
	Self-employed	21.1	47.4	17.5	7.0	7.0	57
	Part-time/ Temporary	11.9	60.0	11.1	5.9	11.1	135
Industry	Aerospace & precision engineering	1.4	43.5	27.5	11.6	15.9	69
	Chemicals/ petrochemical	4.9	34.6	19.8	16.0	24.7	81
	Community & social services, healthcare	3.0	59.0	6.0	5.2	26.9	134
	Construction	12.2	48.0	11.4	9.8	18.7	123
	Electronic/ electrical engineering	5.7	31.4	12.9	21.4	28.6	70
	Food & beverage	20.9	57.1	12.3	4.9	4.9	163

	No qualification	Secondary level	Post-secondary or non-tertiary	Polytechnic diploma	Degree or PG	N
Generic manufacturing	6.0	48.8	9.5	9.5	26.2	84
Government/ public service	4.2	43.2	15.5	17.4	19.7	310
Hotels, tourism, events & attractions	6.7	61.0	15.2	5.7	11.4	105
Infocomm	3.9	25.5	27.5	21.6	21.6	51
Landscape	5.6	53.7	18.5	13.0	9.3	54
Logistics & transportation	8.2	71.7	12.5	2.2	5.4	184
Marine	1.4	52.1	24.7	11.0	11.0	73
Pharma & biologics	1.8	18.2	20.0	16.4	43.6	55
Retail	7.2	61.9	14.7	6.1	10.1	475

		No qualification	Secondary level	Post-secondary or non-tertiary	Polytechnic diploma	Degree or PG	N
	Security, estate management & services	3.6	78.6	10.7	3.6	3.6	28
Job Income	Less than $1,200	15.7	68.1	8.9	3.1	4.2	382
	$1,200–$2,999	6.3	60.1	15.2	8.3	10.1	1158
	$3,000–$4,999	2.4	28.2	20.6	17.0	31.8	412
	$5,000–$7,999	1.8	19.3	16.5	21.1	41.3	109
	$8,000 or more	4.4	24.4	8.9	20.0	42.2	45
Size of Company	Less than 10	11.8	62.2	8.3	8.0	9.7	288
	Between 10 and 49	9.5	46.5	18.8	11.0	14.2	409
	50 or more	5.1	51.6	15.3	10.0	18.0	1455

Across industries, the reliance on secondary education qualification is featured strongly, except in three industries namely, electronic/electrical engineering (31.4%), infocomm (25.5%) and pharmaceuticals & biologics (18.2%) which require mainly either diploma or degree qualifications. This shows that most of the jobs in different industries and occupation only require a minimum qualification of secondary education. This may imply that the current jobs across industries do not really require a huge amount of higher qualification, and 'screening' for desirable workers appears to explain the discrepancy between what is observed here and what employers normally call for.

The community & social services and healthcare industries present an interesting case. There are two 'peaks' in the distribution. The first is the use of secondary education qualifications – 59% of all jobs in this sector require this relatively low level of qualifications. The second peak is at the top end of qualifications – 26.9% require degrees or above. Generic manufacturing has a similar pattern to community & social services too. There are also other industries that have a 'two-peak' pattern of minimum qualification requirement, though those peaks may be not as pronounced. These are construction and government & other public services.

The hotel & tourism, retail, security & estate management, logistic & transportation, landscape and F&B industries comprise jobs that mainly require secondary or no qualifications. Degrees in general are rarely required in these industries; most of the industries have less than 10% of the jobs, requiring degrees. Interestingly, infocomm has a fairly even spread of qualifications requirements, reflecting an even demand for different levels of qualifications in these industries.

In terms of job income, the pattern of minimum qualifications required reflects the prediction of the human capital theory – 83.8% (15.7% + 68.1%) of the very low paying jobs (those under $1,200 per month) require only secondary or no qualifications. Then as we move up the pay bands, the proportion of jobs that require a degree or above goes up. Thus, for those jobs earning $8,000 or more per month, 62.2% of those jobs require a diploma or above qualification. Pay, in general, is positively correlated to minimum job qualifications (χ^2=435.96, df=16, p=.000).

The pattern of minimum qualifications required is also related to company size[5]. Table 4.1 shows that 74% (11.8% + 62.2%) jobs in micro enterprises (less than 10 employees) require either no qualifications or secondary qualifications. For the larger companies the corresponding figures are 56% (9.5% + 46.5%) and 56.7% (5.1% + 51.6). This seems to support the popular view that micro enterprises tend to pay less attention to qualification requirement in terms of the jobs that they have, compared with larger ones. But it is equally likely that many micro enterprises are not able to hire highly qualified workers, because of their lower salaries, perceived prospects or individuals' preferences to work for larger companies. Likewise, 18% of the larger firms (50 or more employees) would require their jobs to have a degree or above, compared with less than 10% for the micro enterprises.

4.2 Findings on the Distribution of Initial Learning Time

Table 4.2 gives the distribution of initial learning time by gender. Here it clearly shows that jobs carried out by male workers tend to have a longer initial learning time, compared with female jobs – 26.1% of male jobs requiring 6 months or more training compared with 15.0% for female jobs. This seems to reflect the types of jobs that male and female workers tend to occupy. As the gender differences are very little in the other two components of the BSI – minimum qualification required and continuous learning time (see Table 4.3) – it would seem that women tend to occupy less skilled jobs than men, and the main differential comes from initial learning time of the jobs that female workers hold. Further analysis on the standardised BSI scores (combining all three components of BSI) shows that the

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[5] We have adopted fairly broad categories for firm size – i.e. 0-9; 10-49 and 50 or more employees – for two reasons. The first reason is that many employees do not know the exact size of their workplaces. The upper categories are often unreliable. Secondly, our definition reflects the different stages of formalisation of functions within organisations. Micro firms – 0-9 employees – tend to have little formalisation of job roles, e.g. sales, marketing, production etc. Employees tend to deal with a variety of tasks. Small firms – 10-49 employees – firms are beginning to form some rudimentary specialised functions. Firms that have 50 or more employees will have to organise themselves in various job divisions or roles.

median standardised BSI for male jobs is 0.5427 while the median standardised BSI for female jobs is 0.4562, resulting a broad skills differential between male and female jobs of 44%. At the other end of the scale, almost 1 in 2 (49.8%) female jobs take less than 1 month to learn. For male job, the figure is 35.4%.

Table 4.2. Descriptive Statistics of Initial Learning Time Required for the Job (%)

		Less than 1 week	1 week or < 1 month	1 month or < 3 months	3 months or < 6 months	6 months or more	N
Gender	Male	13.6	21.8	25.9	12.6	26.1	1197
	Female	18.0	31.8	23.4	11.8	15.0	958
Occupation	Professional, managerial, executive and technical	8.3	19.3	23.3	16.5	32.5	1045
	Clerical & Related Worker	22.9	39.2	24.1	7.8	6.0	166
	Services, shop worker and sales worker	23.1	32.8	28.0	6.9	9.2	796
	Production, craftsmen & related	13.0	23.7	24.4	16.0	22.9	131
	Plant, Machine Operator & Assembler	3.1	21.9	26.6	18.8	29.7	64
	Elementary worker	30.8	36.5	15.4	7.7	9.6	52
Contract Type	Permanent	13.3	25.6	27.0	13.1	21.0	1842
	Contract	18.7	31.3	20.0	11.3	18.7	150
	Self-employed	13.3	11.7	16.7	10.0	48.3	60
	Part-time/Temporary	36.4	35.7	11.2	3.5	13.3	143

		Less than 1 week	1 week or < 1 month	1 month or < 3 months	3 months or < 6 months	6 months or more	N
Industry	Aerospace & precision engineering	6.9	18.1	15.3	12.5	47.2	72
	Chemicals/petrochemicals	2.5	17.3	28.4	17.3	34.6	81
	Community & social services, healthcare	9.3	27.1	28.6	14.3	20.7	140
	Construction	17.0	16.3	15.6	11.1	40.0	135
	Electronics/electrical engineering	5.4	24.3	31.1	14.9	24.3	74
	Food & beverage	18.1	33.9	21.1	12.3	14.6	171
	Generic manufacturing	12.4	19.1	28.1	12.4	28.1	89
	Government/public service	14.4	29.1	24.1	15.3	17.2	320
	Hotels, tourism, events & attractions	13.6	24.5	25.5	9.1	27.3	110
	Infocomm	12.7	36.4	12.7	14.5	23.6	55
	Landscape	6.8	25.4	20.3	22.0	25.4	59
	Logistics & transportation	9.0	21.7	46.6	10.6	12.2	189

		Less than 1 week	1 week or < 1 month	1 month or < 3 months	3 months or < 6 months	6 months or more	N
	Marine	11.7	16.9	23.4	20.8	27.3	77
	Pharma & biologics	1.8	18.2	23.6	14.5	41.8	55
	Retail	28.2	32.4	21.6	9.2	8.6	490
	Security, estate management & services	14.3	32.1	28.6	3.6	21.4	28
Income	Less than $1,200	28.6	31.4	20.2	9.3	10.5	420
	$1,200–$2,999	14.7	30.1	28.7	11.6	14.8	1201
	$3,000–$4,999	8.4	16.5	24.1	14.8	36.3	419
	$5,000–$7,999	1.9	10.3	11.2	19.6	57.0	107
	$8,000 or more	8.9	6.7	13.3	13.3	57.8	45
Size of company	Less than 10	15.1	32.1	20.4	11.4	21.0	324
	Between 10 and 49	17.2	26.4	21.0	13.4	21.9	424
	50 or more	14.7	25.2	26.7	12.1	21.2	1492

In terms of occupation, PMETs, plant machinery operators and assemblers have the greatest proportions of their jobs needing six months or more initial training time – 32.5% and 29.7%, respectively. These two occupations also have the lowest proportion of their jobs that require less than one week training. Only 3.1% of plant, machinery operators and assemblers require less than one week training while 8.3% of PMET jobs require such a short duration of training.

In general, there seems to be a pattern of the technical occupations taking more initial learning time than the non-technical ones. Here, production, craftsmen and related jobs have a similar pattern of initial training time to that of plant, machinery operators and assemblers – each has a relatively high percentage of initial learning time beyond six months, 22.9% and 29.7%, respectively. However, for the remaining three occupations, high proportions of their jobs seem to have rather short initial training time. For services, shop workers etc, 23.1% of their jobs require less than one week training. Likewise, clerical workers (22.9%) and elementary workers (30.8%) also have very high proportions of their jobs that can be learned within a week.

In terms of contract type, we have already mentioned that self-employed jobs seem to have the highest initial learning time. 48.3% of self-employed jobs need six months or more to learn. This compares with contract and part-time work – often referred as 'non-standard' form of work – only 18.7% and 13.3% of their jobs can be learned with at least six month. Part-time jobs also have the highest proportion of their jobs which take less than one week to learn.

There are huge industrial differences in initial learning time. In general, the technical industries take longer initial learning time than other sectors. For example, over 40% of pharmaceuticals & biologics and aerospace & precision engineering jobs take six months or more to learn. In contrast, in retail, only 8.6% of its jobs would take that long to learn. Discussions with industries suggest that the length of initial training time in some industries such as pharmaceuticals & biologics is heavily influenced by the extent of safety regulations and stringent work practices that leave very little room for deviations from expected work behaviour or standards. As discussed previously, the measure of initial learning may reflect job complexity and the influence of environmental factors. The case of pharmaceuticals & biologics jobs seems to support this view.

Alternatively, if we look at the learning time less than 1 month, three industries have over 50% of their jobs requiring an initial learning time of less than 1 month. These include the retail (60.6%), F&B (52.0%), chemicals and petrochemical (19.8%) and infocomm (49.1%) industries. These stand in contrast with pharmaceuticals & biologics. The latter industry only has 20.0% of its jobs which require less than one month initial learning.

Surprisingly, firm size makes very little difference to initial learning time (r=.023, n=2240, p=.285). Job incomes correlate positively with initial learning time (r=.344, n=2192, p=.000). Jobs with high job incomes are also jobs with longer learning time. Thus, 57.8% of jobs earning $8,000 or month per month need six months or more initial learning. This compares with around 10% of the low-wage (less than $1,200 per month) who may require six months or more training.

4.3 Findings on the Distribution of Continuous Learning Time

Table 4.3 provides a very interesting general picture. Most jobs in Singapore involve a lot of continuous learning. For example, jobs that require ‘very frequent; almost ongoing’ learning are the highest proportions of jobs in all occupations. This is not as big a surprise as it was first thought, and it seems to make sense in today’s fast changing environment and the intensity of competition.

Amongst PMET jobs, almost 50% of all PMET jobs require frequent and ongoing learning. Even amongst clerical and related workers, who have the largest proportion of their jobs with very little continuous learning (28.5%), the same proportion (28.5%) of clerical and related workers have frequent and almost on-going continuous learning. More unexpectedly, amongst elementary workers, one-third (32.1%) claim to have frequent and ongoing learning within their jobs. Perhaps this is not a big surprise, as we refer to continuous learning as any form of learning that is relevant to the job. This includes informal as well as formal learning.

Table 4.3. Descriptive Statistics of Continuous Learning Time Required for the Job (%)

		Very little or negligible	A few days	More than a few days but less than 2 weeks	Very frequent; almost on-going	N
Gender	Male	17.7	16.1	25.1	41.2	1183
	Female	17.3	16.1	22.2	44.4	928
Contract Type	Permanent full-time	16.7	16.1	24.0	43.2	1799
	Fixed-term	14.2	14.2	31.1	40.5	148
	Self-employed	19.0	15.5	17.2	48.3	58
	Temp/part-time	27.3	21.0	18.9	32.9	143

		Very little or negligible	A few days	More than a few days but less than 2 weeks	Very frequent; almost on-going	N
Occupation	Professional, Managerial, Executive and Technical	13.4	12.9	24.1	49.7	1033
	Clerical & Related Worker	28.5	20.0	23.0	28.5	165
	Service, Shop Worker and Sales Worker	18.8	18.8	23.0	39.5	762
	Production, Craftsmen and Related Worker	26.2	15.4	27.7	30.8	130
	Plant, Machine Operator & Assembler	15.6	15.6	23.4	45.3	64
	Elementary worker	24.5	26.4	17.0	32.1	53
Industry	Aerospace & precision engineering	20.8	11.1	18.1	50.0	72
	Chemicals/ petrochemicals	17.1	13.4	25.6	43.9	82
	Community & social services, healthcare	8.5	6.2	19.2	66.2	130
	Construction	15.9	16.7	23.5	43.9	132
	Electronics/ electrical engineering	20.8	15.3	26.4	37.5	72
	Food & beverage	13.3	15.2	25.5	46.1	165
	Generic manufacturing	25.0	11.4	29.5	34.1	88
	Government/public service	12.1	13.7	28.9	45.4	315
	Hotels, tourism, events & attractions	19.1	20.0	20.9	40.0	110
	Infocomm	20.4	22.2	18.5	38.9	54
	Landscape	10.2	22.0	25.4	42.4	59

		Very little or negligible	A few days	More than a few days but less than 2 weeks	Very frequent; almost on-going	N
	Logistics & transportation	25.5	13.6	24.5	36.4	184
	Marine	11.8	14.5	19.7	53.9	76
	Pharma & biologics	16.4	16.4	20.0	47.3	55
	Retail	20.6	21.6	22.5	35.3	476
	Security, estate management & services	14.8	18.5	29.6	37.0	27
Income	Less than $1,200	21.1	19.4	19.6	40.0	403
	$1,200–$2,999	19.1	16.7	24.1	40.1	1181
	$3,000–$4,999	12.1	14.0	26.1	47.8	414
	$5,000–$7,999	15.1	8.5	27.4	49.1	106
	$8,000 or more	6.8	18.2	29.5	45.5	44
Size of company	Less than 10	20.6	13.5	18.3	47.6	311
	Between 10 and 49	22.8	18.5	22.8	36.0	417
	50 or more	15.4	16.1	25.3	43.3	1468

This very high level of continuous learning on the job is also observed across industries. All industries have over a third of their jobs with frequent and on-going learning. In some industries, the figures are very high indeed. For example, in community & social services and healthcare sectors, frequent and ongoing learning applies to 66.2% of the jobs; marine, 53.9%; aerospace & precision engineering, 50.0% and so on. Interestingly, in the F&B industry, which is known for its low minimum required qualifications and relatively short initial learning time, 46.1% of F&B jobs have frequent and ongoing learning. For some of these industries, high continuous learning may reflect the need to update regulatory knowledge while in others, such as the F&B industry, continuous learning may be a way of life within their jobs. So for a variety of reasons, there is a lot more continuous learning than we would normally perceive.

To contrast this very high level of continuous learning, some industries still have a high proportion of their jobs that involve little continuous learning, e.g. logistics & transportation (25.5%), generic manufacturing (25%), electronics/electrical engineering (20.8%), hotels and tourism (19.1%) and retail (20.6%). It is also a surprise to see 20.4% of the jobs in infocomm having very little continuous learning. This may reflect the very diverse types of jobs that are part of the infocomm sector.

In terms of job income, all job income groups have a high proportion of their jobs claiming frequent and ongoing learning. However, the proportion of very little continuous learning is the highest amongst lowest job income group (21.1%). Only 6.8% of jobs in the highest job income group report very little continuous learning. This is consistent with other skills indicators in the BSI.

The effect of firm size is mixed. Micro-organisations (less than 10 employees) have both the highest proportion of jobs to have frequent and ongoing learning (47.6%), but at the same time, they also have one of the highest proportions of jobs having very little ongoing learning (20.6%).

4.4 Findings on the Distribution of BSI

Previous discussions explain how a broad measure of skills content can be derived from three components in the data – i.e. minimum qualification required, initial learning time and continuous learning time. Following the methodology employed by the UK study, we applied Principal Component Analysis to the three measures of job skills in order to extract the first principle component that correlates closely with the three measures.

The three components of broad skills were found to be 'consistent'[6]. We were successful in creating a single BSI for every job in the sample. The BSI reflects the skills demanded from the job. It has a sample average of zero. Positive figures represent above average skills demanded from the job within the sample. Likewise, negative figures represent below average skills demanded.

The BSI therefore enables us to compare the skills content of every job in the sample. By cross-tabulating these jobs by occupation or by industry, we can get a picture of how the demand for skills vary by different criteria.

Table 4.4.1 shows the BSI by industry. The index is ranked from the highest to the lowest. As each job in the sample has its own BSI score, the table contains the median BSI scores for the industries that they refer to. Thus, all the industries from landscape and above represent the median BSI scores above the sample average. The average jobs in these industries have skills demanded greater than the average jobs in others. Most of the technical industries fall into this category. However, non-technical industries such as community & social services, government and other public services, infocomm and landscape also have skills demand greater than the sample average.

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[6] Kaiser-Meyer-Olkin measure of sampling adequacy is 0.58. Bartlett's Sphericity Test: $\chi^2 = 275.9$, df = 3, Sig. = .000

For easier interpretation, we also derive a 'normalised' score for BSI with values ranging from 0 to 1. So the lowest score in the sample has a value of 0 and the highest in the sample has a value of 1. All other jobs fall between these two.

Table 4.4.1 thus shows that pharmaceuticals & biologics have the highest average skills demanded of their jobs, and retail has the lowest, compared with all others. The skills differential is about 36% points (.7239 – .367). Alternatively, the skills demanded in an 'average' pharmaceuticals & biologics job is about twice as high as that in retail.

Table 4.4.1. Broad Skills Index (Median) by Industry

Industry	BSI	Normalised BSI
Pharma & biologics	1.0606	.7239
Chemicals/petrochemicals	.6226	.6386
Electronics/electrical engineering	.6021	.6346
Aerospace & precision engineering	.5884	.6320
Generic manufacturing	.1572	.5481
Infocomm	.1571	.5481
Construction	.1436	.5454
Marine	.1436	.5454
Community & social services, healthcare	.1436	.5454
Government & other public service	.1436	.5454
Landscape	.1298	.5428
Security, estate management & services	-.3150	.4562
Hotels, tourism, events & attractions	-.3150	.4562

Logistics & transportation	-.3288	.4535
Food & beverage	-.3288	.4535
Retail	-.7735	.3670

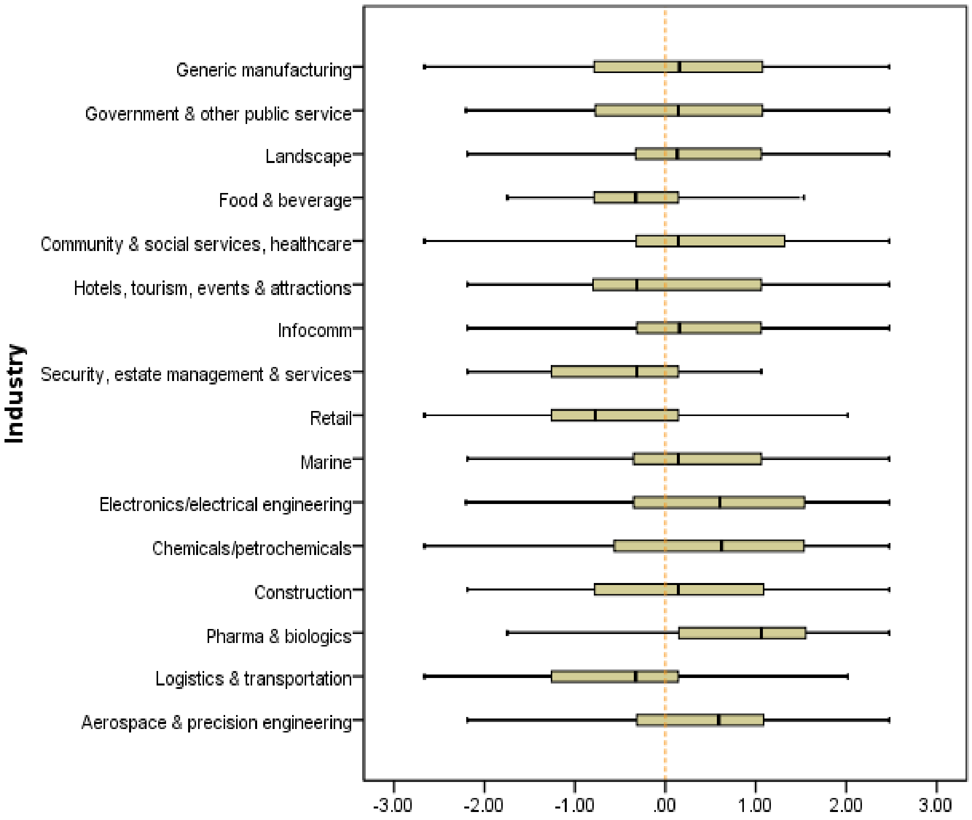
Our discussions with industries provide a useful reminder that we ought to interpret these comparisons with caution. For example, it is pointed out that in the 'technical' industries, there is a lot of formalised training which tends to score highly within the formulation of the BSI. In the non-technical industries, e.g. retail, there is a lot of training too. However, much of it is embedded within the day-to-day activities. A lot of the training may have happened without the worker noticing it. So arguably, there may be an in-built bias within the BSI formulation against the non-technical jobs.

Comparing the median is useful, but it does not convey all the information about the skills profiles across different samples. In the following section, we include three boxplot figures in order to highlight some of the more subtle aspects of the data[7].

In Figure 4.4.1, we can see the full range of the BSI for each industry in the sample. In pharmaceuticals & biologics, not only does the industry have the highest median BSI, its 25th percentile is above the sample average. In other words, over 75% of the jobs in the pharmaceuticals & biologics sector are above the sample average. This means that most jobs in this sector have very high skill content, compared with the sample as a whole.

[7] There are five elements in a boxplot. The first is the median score (which is the line inside the box). Then the right boundary of the box represents the top 75% of the sample group. The left boundary of the box is the low 25%. The two ends of the 'whiskers' represent the maximum and minimum values in the groups. The boxplot provides much more information than the simple reporting of the median scores. For example, construction jobs in the figure have a similar median score to that of Marine jobs. However, the 75% mark of construction jobs is much further to the right, compared with marine jobs, suggesting that a greater skills utilisation amongst construction jobs.

Figure 4.4.1. Boxplot of BSI by Industry



The use of the boxplot makes interesting comparisons across industries. For example, hotels & tourism, F&B, logistics & transportation and security & estate management have very similar median BSI scores, suggesting the skills content in the average jobs in these industries are very similar. However, if we are to take into consideration the 25th and 75th percentiles, we may have a different conclusion. Here, the 75th percentile of the hotel & tourism sector is much higher than the other industries. Likewise, the 25th percentiles for security & estate management and logistics & transportation are much lower than other two. Thus, by taking the median, the 25th and 75th percentiles together, one may be inclined to suggest that the bulk of the jobs in the hotel & tourism sectors require greater skills utilisation than the other three industries. This is a result that would not be apparent if we were to compare the median score only.

The BSI score of pharmaceuticals & biologics stands out compared with all other industries. As mentioned, this is very much the result of an industry that is heavily governed by safety regulations, and that most of the jobs are expected to go through huge amounts of training (and retraining). Some of the training is necessary for the immediate operation of the job, but some training is due to the precautionary nature of the industry. The implication of this is that skills utilisation may be augmented through the regulatory environment.

Table 4.4.1 also tells us where the low skilled industries are. Five industries – food & beverage, hotels & tourism, security & estate management, retail and logistics & transportation – have their median BSIs below the sample average. At the same time, the 75th percentiles of the four of these five industries (i.e. all except hotels & tourism) are very close to the sample average line. When we compare our results with national productivity data from DOS, hotels and restaurants, F&B, logistics and transportation are also sectors that have below average national productivity. There seems to be a tentative link here between low skilled workers and low productivity.

Next, we will examine the occupational differences of BSI. In Table 4.4.2, the data confirm our expectation that PMET jobs might have the highest demand for skills while clerical, shop & sales, cleaning & general labour jobs would have the lowest skills content. The median skills differential between the highest PMET and the lowest group is around .27 (or 27%).

Table 4.4.2. Broad Skills Index (Median) by Occupation

Occupation	BSI	Normalised BSI
Professional, Managerial, Executive & Technical	.616	.637
Plant, Machine Operator & Assembler	.130	.543
Production, Craftsman & Related Worker	-.343	.451
Service, Shop Worker & Sales Worker	-.357	.448
Clerical & Related Worker	-.773	.367
Elementary Worker	-.787	.364

However, as in the previous analysis on industries, comparing the median BSI misses out a lot of details. In Figure 4.4.2, clerical & related jobs and the elementary jobs (cleaning & general labour jobs) have almost similar BSIs, but the 75th percentile BSI for the elementary jobs is much lower – it is even below the sample average BSI – clerical & related jobs actually have greater skills content than elementary jobs. A similar comparison can also be made between production & related jobs and service & sales jobs.

Figure 4.4.2. Boxplot of BSI by Occupation

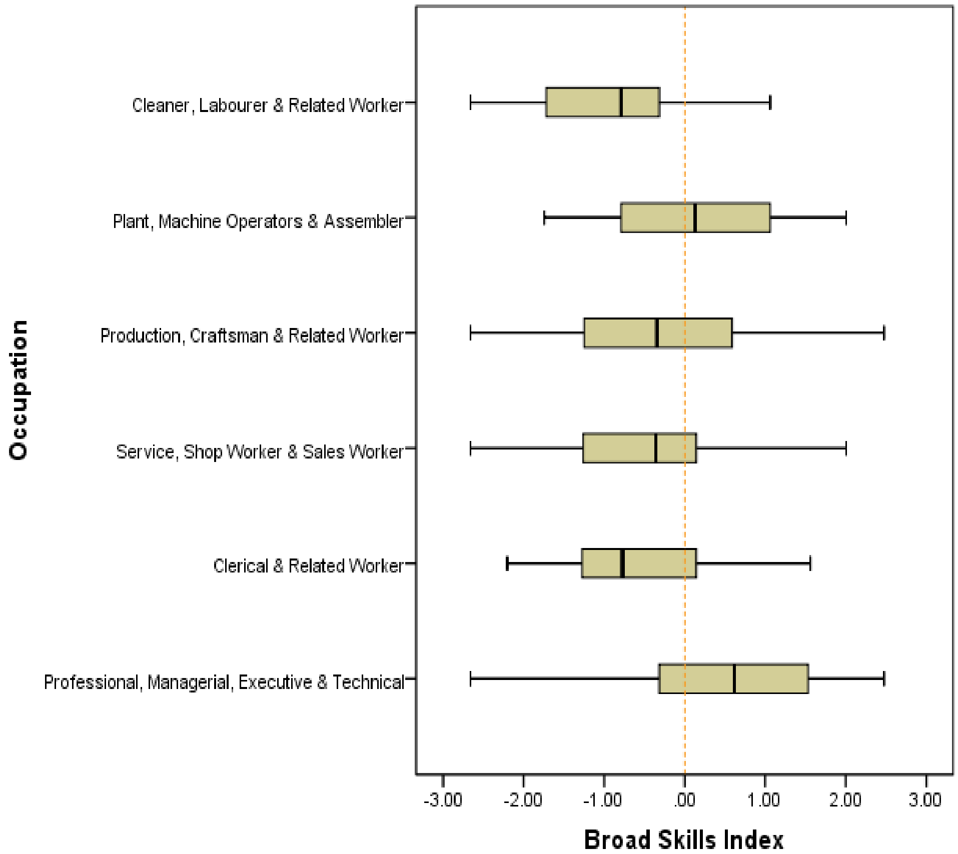
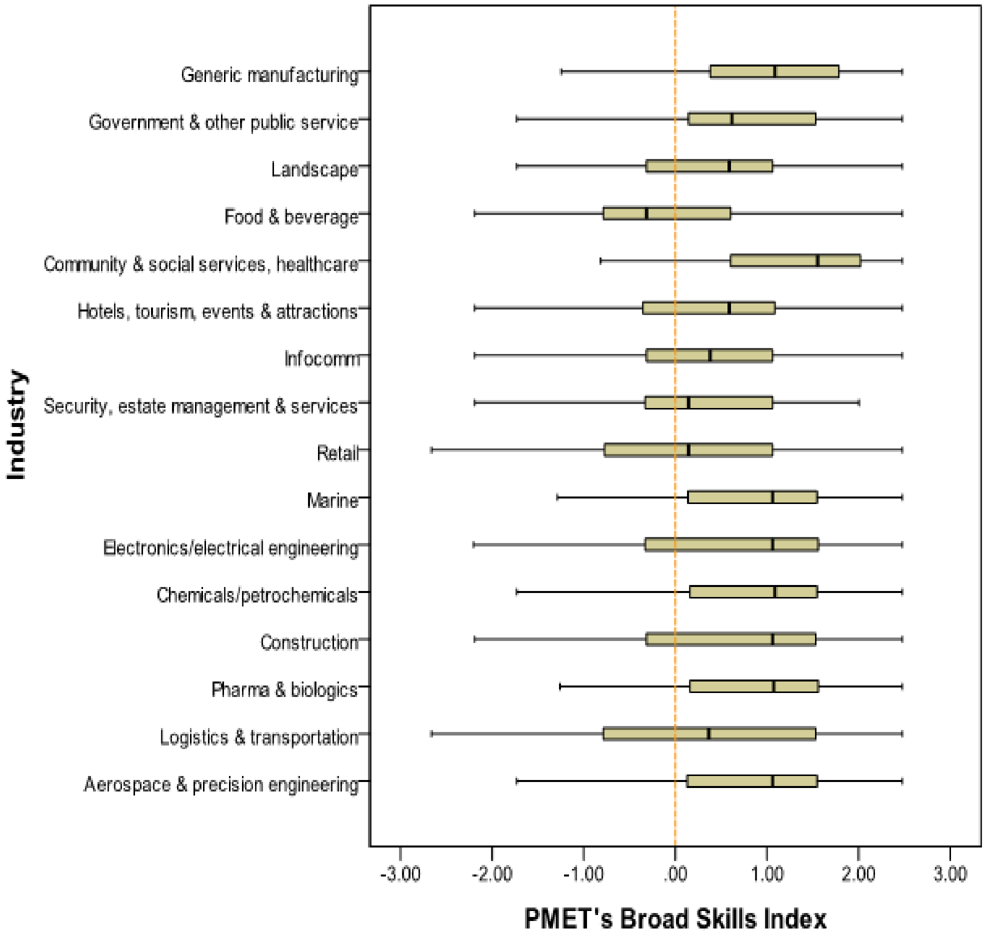


Figure 4.4.2 also suggests that not all PMET jobs are of above average skills. The data suggests that around one third of PMET jobs are below the sample average line. Figure 4.4.3 further differentiates the BSI scores by PMET and non-PMET status. It identifies the industries in which the median PMET BSIs are either close to or below sample average. These are F&B, retail and logistics and transport.

Figure 4.4.3. Boxplot of PMET's BSI



We examine one more aspect of the BSI via the boxplot figure. We saw in previous Tables 4.1, 4.2 and 4.3 that job incomes are positively related to minimum qualification required for the job, initial learning time and continuous learning time. These are all in line with the human capital type of prediction, even though the basic concept of human capital theory mainly refers to the worker's skills while the BSI measures the job's skills demand. This positive relationship between job skills and job income is reflected in Table 4.4.3 and Figure 4.4.4.

Table 4.4.3 shows that the difference in median (normalised) BSI of the low-wage jobs is massive – 35.9% below the median of the top wage jobs (.726 – .367)[8].

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[8] The cut-off point for 'low-wage' jobs ($1,200 per month) was designed back in Nov 2009. This figure may therefore be a little below the current low-wage mark of around $1,500.

Indeed, the median of the low-wage group coincides with the median BSIs of clerical & related jobs and elementary jobs (see previous Table 4.4.2). It seems to confirm that low-wage jobs are generally found in these occupational groups.

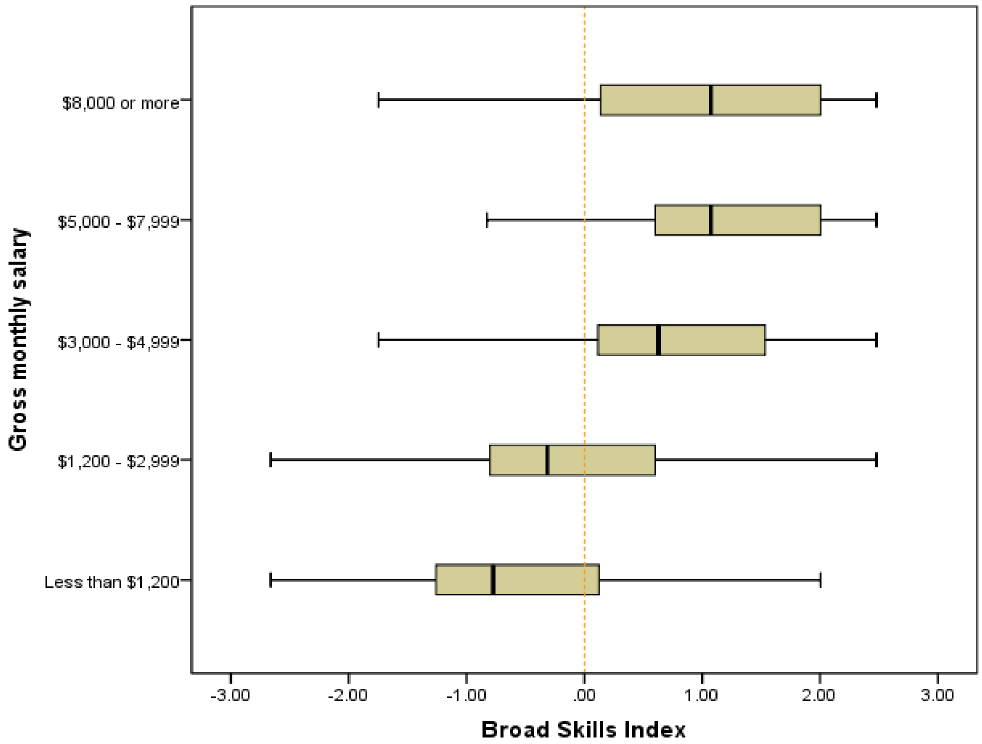
Table 4.4.3. Broad Skills Index (Median) by Job Income

Gross monthly income	BSI	Normalised BSI	Increase in BSI	Increase in BSI as a % of income group below
$8,000 or more	1.074	.726	.001	0%
$5,000–$7,999	1.074	.727	.087	13.52%
$3,000–$4,999	.629	.640	.184	40.28%
$1,200–$2,999	-.315	.456	.089	24.30%
Less than $1,200	-.773	.367	-	

The figures in Table 4.4.3 also suggest that to move from a low-wage job (less than $1,200 per month) to the next income jobs ($1,200–$2,999), the median BSI will need to increase by 9% points (.456 – .367), other things being equal. If we consider what this means in terms of the BSI components, this may mean moving into jobs that have either greater qualification requirements or greater training content. The biggest BSI jump is between $1,200–$2,999 and $3,000–$4,999. The median increase here is 18%. So the skills content transition is almost twice that the bottom two job income groups. This also means substantial learning or training will be required to do the move.

Figure 4.4.4 shows that the low-wage jobs have a huge disadvantage in the labour market as over 70% of the jobs are below average skills in the sample. However, it is clear from the figure that there are still quite a lot of jobs in $1,200-2,999 job income group that are below the sample average. In this sense, the low skill groups may include both less than $1,200 and more than half of the $1,200-2,999 group.

Figure 4.4.4. Boxplot of BSI by Job Income



Within this positive relationship between job income and job skills, Figure 4.4.4 shows that job income's relationship with minimum qualification required and initial learning time is much greater than continuous learning time, though all four variables are significantly related to each other.

Table 4.4.4. Correlations amongst Job Income, Minimum Qualification Required and Learning Times

	Gross Monthly Income	Minimum Qualification Required	Initial Learning Time	Continuous Learning Time
Gross Monthly Income	1	.410(**)	.344(**)	.096(**)
N		2106	2262	2148
Minimum Qualification Required	.410(**)	1	.240(**)	.150(**)
N	2106		2156	2117
Initial Learning Time	.344(**)	.240(**)	1	.198(**)
N	2262	2156		2200
Continuous Learning Time	.096(**)	.150(**)	.198(**)	1
N	2148	2117	2200	

** Correlation is significant at the 0.01 level (2-tailed)

In conclusion, the BSI and its sub-components have proved to be very useful concepts that link the skills content of a job to a range of employment related profiles. Much of this information cannot be derived via conventional studies. The weakness of the BSI approach is that it may favour the 'technical' industries in comparison to the 'non-technical' industries.

Section 5: The Utilisation of Generic Skills in Singapore

The concept of generic skills is not new, though the recent policy focus on lifelong learning has revived its popularity. This also creates a number of related debates that using similar terminologies, e.g. key skills, basic skills, key competencies and employability skills (Cornford, 2005).

Many of the existing studies on generic skills concentrate on how generic skills should be taught in school or developed in the workplace (Stasz et al., 1995). There have been very few attempts, other than the Skills Surveys in the UK, to investigate the extent of generic skills utilisation in jobs. Much of the research in this area assumes that generic skills are pretty much ‘generic’ as its name suggests. A further implicit assumption is that the extent of their relevance is also quite uniform across different industrial and occupational settings. Moreover, study carried out by Greatbatch et al (2004: 17) in the UK found that ‘employers are increasingly seeking generic skills alongside technical skills as a means of developing a workforce that is able to cope with increasing complex work practices, team working, reduced supervision, greater job flexibility, and rotation, and increased interaction with customers’. Despite these studies, there is still a lack research on generic skills utilisation. We still assume that all skills taught will be used at work. This may not be true.

At the macro level, public programmes on basic or generic skills have been used by many developed countries as an effective means to enhancing economic benefits to individuals as well as to employers. However, recent research on basic skills does not demonstrate consistent results concerning the impact of generic skills in terms of those benefits (Willmott, 2011, Ananiadou et al., 2004). One of the reasons for this inconclusive picture, we suspect, is that we are not sure about the extent to which generic skills are actually used in the workplace.

In Singapore, generic skills occupy an important position within the CET system as well as the WSQ qualification framework. However, its importance actually goes back before the birth of the CET system. In 1983, ‘basic skills’ were introduced under the BEST (Basic Education for Skills Training) Programme (Sung, 2006). Since then generic skills training went through a few transformations, and more recently, generic skills were reformulated into another programme called CREST (Critical Enabling Skills Training) in 1998. These early front-runners on generic skills tended to focus on specific general skills, e.g. numeracy or workplace English. CREST, while embracing a wider range of generic skills, was criticised for not being competency-based and not formally assessed (Willmott, 2011).

In 2003, generic skills training became a priority area of training when WDA was established. The Employability Skills (ES) System emerged in 2004 addressing generic skills needs at all levels of the workplace. ES continued to gather momentum in the years after its inception which eventually became the flagship programme to tackle low-wage problems. Willmott's (2011) study indicated that by 2010, employability skills training had become the single largest programme within the Workforce Skills Qualifications (WSQ) system with $82.2m allocated between 2008 and 2010.

By any measure, the central role of ES reflects the strategic importance of generic skills in enabling lifelong learning, workplace performance as well as individual employability and wage growth. However, there has been little research in this area. The most challenging task is to obtain appropriate data about generic skills at work. The nature of generic skills means that it is very difficult to identify and measure. The SU survey is the first in Singapore to examine the extent to which generic skills are used at work.

In this section, we will examine the extent to which various generic skills are used in Singaporean workplaces.

5.1 Measuring Generic Skills

The SU survey adopted a job analysis approach in which a series of detailed questions are put to the respondents about their jobs. There are a number of important advantages in taking this approach. Firstly, the questions were well tested in previous surveys in the UK, and have a high degree of reliability. Secondly, these questions are sufficiently flexible to handle jobs coming from a variety of industrial settings and job roles.

Respondents are asked “In your job, how important are the following tasks?” The response scale offered ranges from ‘not important at all’, ‘not very important’, ‘fairly important’ to ‘very important’. Examples of tasks include working with people, teams, use of literacy, numeracy, planning, handling resources and dealing with problems. These 42 tasks reflect the different types of generic skills involved in each task.

Table 5.1.1 shows the 42 tasks and percentage of jobs that reported a particular task is rated ‘very important’. The first most striking information from the table is that despite the label of ‘generic skills’, this does not mean that these skills are equally applicable in all jobs. Some generic skills, e.g. paying attention to details, dealing with people and working with a team of people, are regarded as ‘very important’ skills in over 70% of jobs in Singapore. Other generic skills that at least 50% of the sample find it very important include, listening carefully to colleagues, thinking solutions to problems, specialist knowledge or understanding, knowledge of health and safety at work, knowledge of particular products or services, spotting problems, errors or faults, managing your own feelings, working out the cause of problems or faults, organising your own time, collaborating with colleagues, managing the feelings of other people, reading written information.

At the other end of the scale, some generic skills are utilised by a much smaller proportion of jobs. For example, the skill needed for writing long documents is only regarded as very important by 16.3% of the jobs. Likewise, making speeches or conducting presentations is required by 21.0% of the jobs.

Table 5.1.1. Generic Skills Utilisation in Singapore Jobs

Generic Skills	Very Important (%)
Paying attention to details	77.3
Dealing with people	76.3
Working with a team of people	75.6
Listening carefully to colleagues	68.3
Thinking of solution to problems	66.4
Knowledge of health and safety at work	65.0
Specialist knowledge or understanding	64.2
Knowledge of particular products or services	63.4
Spotting problems, errors or faults	59.7
Managing your own feelings	57.2
Working out the cause of problems or faults	56.8
Organising your own time	55.2
Collaborating with colleagues	54.9
Managing the feelings of other people	52.8
Reading written info	51.9
Knowledge of how to use tools or equipment	49.7
Instructing, training or teaching people	47.0
Motivating the staff you manage or supervise	46.1
Reading short documents	45.8

Generic Skills	Very Important (%)
Coaching the staff you manage or supervise	44.6
Selling a product or service	44.3
Skills or accuracy in using hands or fingers	43.6
Counselling, advising or caring for customers or clients	43.5
Planning your own activities	43.4
Analysing complex work-related problems in depth	42.6
Writing materials such as forms, notices or signs	42.0
Adding, subtracting, multiplying or dividing numbers	41.9
Keeping a close control over resources	39.7
Negotiations	37.3
Physical stamina	37.0
Writing short documents	36.1
Persuading or influencing others	35.1
Calculating using decimals, percentages or fractions	33.7
Developing the career of staff you manage	33.2
Speaking another language or dialect fluently other than your Mother tongue and English	32.0
Making strategic decisions about the future of your organisation	30.8
Reading long documents	28.4
Physical strength	25.0

Generic Skills	Very Important (%)
Planning others activities	24.9
Calculating using more advanced mathematical or statistical tools	21.4
Making speeches or presentations	21.0
Writing long documents	16.3

Forty-two questions/variables are obviously too many to make sense of the basic structure of generic skills that are practised in Singaporean workplaces. Thus, we apply a statistical technique known as factor analysis to generate a smaller group of measures which are also known as 'factors' or 'dimensions' of generic skills. These factors are a weighted combination of the 42 variables that vary very closely together with the underlying generic skills concepts that the questions try to measure.

After factor analysis, factors emerge. These factors can be described as 'generic skills' types. A brief description of those generic skills is provided in Table 5.1.2.

Table 5.1.2. Generic Skills Derived from Factor Analysis

Generic Skills	Skills Content
Literacy skills	Reading and writing documents, memos, forms, reports etc.
Leadership skills	Coaching and motivating staff; developing career for staff, planning others' activities; making strategic decisions and managing resources
Physical skills	Physical strength, dexterity with hands and stamina
Problem-solving	Spotting and analysing problems, identifying causes and finding a solution
Influencing skills	Advising customers, persuading others, dealing with people, making speeches and presentations
Teamwork skills	Working in teams, listening to colleagues, paying attention to details
Planning	Organising and planning own activities and time
Numeracy skills	Working with numbers, using advanced mathematical and statistical tools
Emotional labour	Language skills, negotiation, managing others and own feelings

New scores for the nine groups of generic skills are derived from factor analysis for every job in the sample[9]. These new scores act as summary indices for the nine generic skill groups, which are referred to as 'Generic Skills Indices' (GSIs). Like the BSI, the GSIs have an average of zero across all the data. Thus, a negative value would indicate a particular generic skill has a less than average utilisation. Likewise, a positive value indicates an above average utilisation.

[9] In factor analysis, the new scores are actually based upon all 42 variables in the data set, but the activities that form the factors (as described in the table) are the most heavily weighted in the calculation of the factors.

Together with IT skills, there are 10 generic skills identified in the SU survey. IT utilisation will be looked at separately later.

5.2 The Distribution of Generic Skills

Recent discussion on the ES system focuses on the need to contextualise ES training in Singapore (Willmott, 2011). In order to further this discussion, it is important to have information on how generic skills are used at work. To some extent, the generic skills data in the SU survey can provide this information. However, the SU data is not ideal because it was not designed to support the ES training programme closely, and in particular, the questions have not been designed to fit the WSQ framework. The contribution of the current data is to map out the extent to which generic skills are indeed utilised very differently because of their varying needs across occupations and industries.

Table 5.2.1 contains the median GSIs by occupation. For easy comparison, median generic skill indices that are below sample average utilisation are marked purple. We can see here that PMET jobs generally exercise more generic skills than others occupations[10]. There are only two generic skills in which PMET jobs are used below the sample average, namely physical skills and emotional labour (EQ). The below average utilisation of EQ is a small surprise. We would expect the EQ index for PMET to be positive. However, EQ is still a very new 'skill' that did not receive much attention until the last few years. Perhaps this is an area for future PMET training.

[10] This discussion in this section only reports the median GSI. There are also detailed boxplot results which are not reported here.

Table 5.2.1. GSI by Occupation (Median)

	Literacy skills	Leadership skills	Physical Skills	Problem-solving skills	Influencing skills	Teamwork	Planning skills	Numeracy skills	EQ skills
PMET	.394	.829	-.363	.567	.185	.177	.526	.255	-.019
Clerical & related worker	.408	-1.823	-.146	-.381	-1.068	.255	-.144	.648	.106
Service, shop & sales worker	-.042	.499	.776	-.035	.746	.304	-.184	.040	.440
Production, craftsman and related worker	-.317	.717	1.413	.580	-1.523	.059	.084	-.054	-.129
Plant, machine operator & assembler	-.374	.680	1.799	.643	-1.201	.049	.076	-.167	-.084
Elementary worker	-.152	.688	1.175	.126	-1.083	-.012	-.008	-.626	-.204

The case of the clerical & related workers presents an interesting case. Table 5.2.1 shows that the average job in those occupations have below sample average utilisation in leadership skills, physical skills, problem-solving skills, influencing skills and planning skills. This seems to suggest that clerical and related jobs are relatively passive in their job environment. It also seems that these jobs tend to take instructions from others in their organisations. In Section 7 of this report, we will discuss a new measure for job autonomy and how that may be linked to skills. The Task Discretion Index for clerical & related workers is below other occupations, and is consistent with this conjecture. Also one surprising finding is the below sample average utilisation of problem-solving skills of the service, shop or sales workers, because as a service or sales worker, problem-solving should have been part of the day to day job in order to provide excellent or even just good customer service.

Influencing skills may not be all that useful to clerical & related jobs. They are not that frequently required by other occupations such as production & craftsmen, plant, machine operators & assemblers and elementary workers either. Again, this probably reflects their immediate job environment.

In comparison to PMET and clerical & related jobs, jobs in other occupations all have below average utilisation of literacy skills, especially the 'technical' occupations. Likewise, a similar pattern is found with numeracy skills, except for the service, shop & sales jobs (which have around average utilisation).

Leadership, problem solving and teamwork skills are relatively important and these are utilised to a larger extent in many of the occupations. Teamwork seems to be utilised by most jobs. However, other than clerical, service, shop & sales jobs, the teamwork GSI for other jobs tend to hang around the average, suggesting a very similar teamwork utilisation patterns for most jobs.

Like influencing skills, EQ is a relative new skill to be identified separately from other generic skills. It is a little surprise to find that PMET jobs do not utilise this skills much, compared with other occupations. EQ is also less used by jobs that have to work with machinery and plants. Thus, it is not a surprise to find that EQ is not used much by production, craftsmen, operators and assemblers. However, it is in the ‘people industries’ that EQ appears to be very important. Thus, service & sales jobs have the highest GSI score for EQ.

Table 5.2.2 reports GSIs by industry. Many of the patterns that we observe across occupations in the previous table carry over to Table 5.2.2. For example, teamwork skills, planning skills and especially problem-solving skills are utilised by most industries. Influencing and physical skills are applicable to jobs in fewer industries.

Other general patterns include EQ being mostly utilised by ‘service oriented’ and frontline types of jobs. It is also noticeable that a few industries utilise a wide range of generic skills above the sample average. These industries include marine, community, social and health care services, hotels & tourism, retail and F&B. Jobs in the marine industry do not use influencing skills as much as other generic skills while community, social services & healthcare, and food & beverage jobs do not use planning skills when all other generic skills are utilised to the above sample average level. The F&B case is interesting. We wonder if the widespread use of job scheduling tools is actually taking away the need for planning skills amongst F&B jobs.

Similarly, retail jobs underutilise problem-solving skills. But all other generic skills are utilised above average compared with other jobs. For community, social services & healthcare, the only generic skills that is underutilisation is planning skills, compared with other industries.

Table 5.2.2. GSIs by Industry (Median)

	Literacy skills	Leadership skills	Physical skills	Problem-solving skills	Influencing skills	Teamwork	Planning skills	Numeracy skills	EQ skills
Aerospace & precision engineering	-.460	.417	.259	.637	-1.223	.198	.133	.125	-.285
Logistics & transportation	-.451	-.194	.523	.674	.609	.113	.314	-.958	.207
Pharmaceuticals & biologics	.505	-.778	-.223	.996	-.711	.371	.878	.187	-.164
Construction	.426	.934	.194	.504	-.312	-.359	.327	.132	.247
Chemicals/petro-chemicals	.024	.286	-.140	.581	-1.471	.195	.543	.352	-.871
Electronics/electrical engineering	.180	-.249	-.314	.891	-.700	-.199	.363	.179	.174
Marine	.243	.903	.069	.680	-.902	.188	.511	.166	.114
Retail	.225	.817	.451	-.216	.802	.284	.011	.430	.314
Security, estate management & services	-.018	1.222	-.374	-.081	-.279	.276	.235	-.199	-.074

	Literacy skills	Leadership skills	Physical skills	Problem-solving skills	Influencing skills	Teamwork	Planning skills	Numeracy skills	EQ skills
Infocomm	-.169	-1.057	-.871	.773	-.094	.195	.585	-.313	.239
Hotels, tourism, events & attractions	.866	.908	-.339	.531	.874	.349	.111	.313	.254
Community & social services, healthcare	.467	.288	.410	.076	.707	.389	-.461	.288	.352
Food & beverage	.069	1.365	.668	.443	.658	.467	-.257	.449	.462
Landscape	.210	.475	.317	.334	-.494	.049	.562	-.326	.372
Government/public service	.605	.116	.163	.220	.396	.295	.280	-.104	-.081
Generic manufacturing	-.041	.414	.652	.641	-1.335	.169	.114	.274	-.072

For landscape and public/government sector jobs, there is also a wide range of generic skills utilisation. In landscape jobs, only influencing and numeracy skills are underutilised. In public/government jobs, EQ and numeracy skills appear to be not so important. Two industries, retail and security are the only two industries that showed underutilisation of problem-solving skills, and it quite surprising for the security and estate management jobs to under-utilise it as their jobs require them to solve problems of the estates.

In Table 5.2.3, we produce an overview identifying the industries that are either high users or low users of the nine generic skills in their jobs.

Table 5.2.3. High and Low Generic Skills Utilisation by Industry

Generic Skills	Top 3 Utilisation	Bottom 3 Utilisation
Literacy	• Hotels, tourism, events • Government • Pharmaceuticals and biologics	• Aerospace and precision engineering • Logistics and transportation • Infocomm
Leadership	• Food & beverage • Security, estate management & services • Construction	• Infocomm • Pharmaceuticals and biologics • Electronics/ electrical engineering
Physical	• Food and beverage • Generic manufacturing • Logistics and transportation	• Infocomm • Security & estate management • Hotels, tourism, events
Problem-solving	• Pharmaceuticals and biologics • Electronics/ electrical engineering • Infocomm	• Retail • Security & estate management • Community and social services
Influencing skills	• Hotels, tourism, events • Retail • Community and social services	• Chemicals/petrochemicals • Generic manufacturing • Aerospace & precision engineering
Teamwork	• Food & beverage • Community and social services • Pharmaceuticals & biologics	• Construction • Electronics/electrical engineering • Landscape
Planning	• Pharmaceuticals & biologics • Infocomm • Landscape	• Community and social services • Food and beverage • Retail
Numeracy	• Food and beverage • Retail • Chemicals/ petrochemicals	• Logistics and transportation • Landscape • Infocomm
EQ	• Food and beverage • Landscape • Community and social services	• Chemicals/ petrochemicals • Aerospace and precision engineering • Pharmaceuticals & biologics

Both Table 5.2.1 and 5.2.2 reflect the status quo of jobs and generic skills utilisation. Far from ‘generic skills’ being equally applicable in most jobs, the data show a very diverse patterns of generic skills used. The implication of these diverse patterns would suggest that if contextualisation of ES were to be explored, we would need more information about how job environment is linked to generic skills utilisation. Using the additional information, industry and CET stakeholders can either take the existing patterns and redesign ES delivery, or use the information to re-think and re-design the generic skills content of jobs.

We also examine whether the value of a job may have some connection with generic skills utilisation. In Table 5.2.4, we can see that the pattern of generic skills utilisation appears to be mediated between 'low' and 'high' job incomes. For example, the low-wage jobs (less than $1,200 per month) seem to under utilise generic skills that are the opposite case for other (higher) income jobs, except numeracy skills. For the $1,200–$2,999 income jobs, these jobs utilise all the generic skills above average utilisation, compared with other job income groups.

Table 5.2.4. GSIs by Income (Median)

	Literacy skills	Leadership skills	Physical Skills	Problem-solving skills	Influencing skills	Teamwork	Planning skills	Numeracy skills	EQ skills
Less than $1,200	-.204	-.120	.996	-.211	.338	.196	-.450	.078	.507
$1,200–$2,999	.185	.525	.414	.330	.365	.254	.225	.129	.120
$3,000–$4,999	.271	.812	-.443	.557	.040	.186	.532	.248	-.074
$5,000–$7,999	.745	1.407	-1.430	.740	.193	-.011	.923	.187	-.140
$8,000 or more	.212	1.688	-1.324	.537	-.223	-.452	1.069	.011	-.017

Then physical skills are generally less applicable to job income groups above $3,000 per month. Literacy, leadership, problem solving and planning skills are important to all job income groups, except the low-wage jobs.

The very top income jobs do not exercise influencing skills as much as jobs below them. This is an interesting and somewhat puzzling finding. One would imagine that influencing skills would be very important in high earning jobs. Likewise, teamwork skills for the top two income groups are less important than the jobs of lower incomes. EQ skills are utilised to a larger extent by the bottom two income groups. This is an interesting finding and we can make various conjectures about that.

The job income group ($1,200–$2,999) just above the bottom group makes interesting contrast, as these jobs seem to utilise all generic skills above the sample average. This may suggest that this category of jobs may have a fairly wide-ranging demand for generic skills, compared with others. Once we go into the higher income jobs, the nature of job changes again so that only certain generic skills are utilised more essentially than others.

Section 6: The Use of Computer and Computerised Equipment

Productivity is one of the most important policy targets in the current economic strategy in Singapore. Technology is often seen as a significant factor in enhancing productivity. Yet we know very little about the fundamental relationship between the use of computers, or more broadly the use of IT and automated equipment, and productivity in Singapore.

IT is one of the main leverages to improve productivity and business processes. The Singapore government has invested heavily in efforts that encourage technology adoption, e.g. providing the necessary infrastructure, incentives and training for adoption among businesses. The Infocomm Development Authority (IDA) spent $1b wiring up the country with Next Generation Nationwide Broadband Network (NBN) providing ultra fast internet connectivity to homes and businesses. This paved the way for an enhanced online experience allowing businesses to explore more online options to increase productivity such as expanded online services to customers and offering staff the flexibility of telecommuting. Spring Singapore is also managing various grants to encourage businesses to adopt technology to improve their productivity. Examples include the Technology Innovation Programme (TIP) and Technology for Enterprise Capability Upgrading Initiative (T-UP). Despite these substantial national efforts, the impact of technology in general and computer use in particular at the work level is largely known. Indeed, the picture of research in this area is mixed.

In the USA, there has been a long debate regarding the impact of computers and labour productivity. So far, the picture of the impact of computer use on productivity is 'mixed'. For example, Atrostic and Nguyen (2005) identified significant effect of using computers, computer networks on plant-level productivity in US manufacturing. Hyatt and Nguyen (2010) later confirm that the positive effect is particularly important for SMEs, but the effect is not so significant for larger organisations. Indeed, Jorgenson et al. (2008) reminded us that there was a long period in the US history that the adoption of computers and IT in the 1980s and early 1990s made little impact on productivity. The connection between computer use and productivity only began to pick up after mid-1990s. Research in this area calls it the 'computer productivity paradox'.

However, while the productivity debate is still going on, research in the last three decades shows that the introduction of computers and IT in general has made a lasting impact on the organisation of work as well as the mix of skilled and unskilled workers (Bresnahan, 1999, Felstead et al., 2002b). Although it is clear that the recent generations of workers are on average more IT literate than their previous counter-parts, there is a scarcity of data on how widespread computer usage is at workplaces in Singapore. We have very little information on how workers are coping with the use of IT and computers, how fast IT-related skills content is changing and what occupations are affected the most.

In the following sections, we examine the distribution of the use of computers and computerised equipment at work. Furthermore, we will examine the extent to which the use of computer and the internet may form a central part of our jobs.

6.1 The Complexity of Computer Use at Work

In much of the literature on the effect of computer use, the measure is often undifferentiated. This might not be a problem in the early days when computers were just being introduced and the role of computer use was relatively specialised. However, in today's environment, not only is the use of computer extended to many areas of work, its function has become well established as part of the skills set of many job roles. These different job roles require very different levels of knowledge and skills in order to use the computer or related IT equipment effectively.

To address these issues, the survey designs four levels of computer use in order to differentiate the different skill levels involved at work, as shown in Table 6.1.1.

Table 6.1.1. Four Levels of Computer Use

Level of Use	Detail
Routine use	Using a computer for routine procedures, e.g. printing out a receipt or an invoice
Basic use	Using a computer for word processing, spread-sheets, searching information online or using email
Complex use	Using a computer for analytical, designing or statistical purposes
Advanced use	Using a computer for programming

In Table 6.1.2, we differentiate the different uses of the computer. It is clear from the table that computer use in the workplace is widespread. Amongst the different occupations, PMET jobs tend to have high computer utilisation across the four levels of computer use. Noticeably, 39.6% of PMET jobs require computers for analytical purposes. Only 2.0% of jobs in the elementary occupations would require computer for analytical use. Indeed, for elementary jobs, all use of computer is generally low in comparison to other occupations.

Basic computer use is generally high ranging from 55.6% to 88.5% for all but one occupation (elementary jobs: 37.3%). The basic skills required for most jobs would include using the computer for word-processing, spread sheets, searching information and email. For routine use of the computer, only jobs in PMET, clerical, service, shop and sales tend to have high utilisation.

Table 6.1.2. Proportions of Different Levels of Computer Use by Occupation (%)

		Routine Tasks	Basic Use	Analysis	Programming
Occupation	PMET	64.2	88.5	39.6	9.7
	Clerical & Related Worker	77.2	88.3	19.1	4.9
	Service, shop & sales worker	65.9	55.6	13.4	3.9
	Production, craftsman and related worker	40.0	60.8	18.3	5.8
	Plant, machine operator & assembler	37.7	62.3	19.7	6.6
	Elementary worker	21.6	37.3	2.0	3.9

Table 6.1.3 reveals a picture of diverse use of the computer by industry. It is not a surprise that infocomm reports the highest level of programming use (30.9%) of the computer amongst different industries. Jobs in infocomm also have a very high level of basic (85.5%) and analytical (43.6%) use of the computer.

On analytical use of the computer, jobs in the pharmaceuticals & biologics industry seem to be the biggest users with 54.5% of jobs reporting this use. Closely behind are infocomm (43.6%), electronics/electrical engineering (38.7%) and hotel & tourism (34.5%).

Basic use of the computer is the most prevalent use of the computer across all industries. Also, the data show that most industries have higher basic computer use than routine use. However, community, social service & healthcare is the only exception with more routine use (92.3%) of the computer than any other usage. As such, there are more jobs in the community, social & healthcare using the computer for routine purposes than any other industry.

Table 6.1.3. Proportions of Different Levels of Computer Use by Industry (%)

		Routine Tasks	Basic Use	Analysis	Program-ming
Industry	Aerospace & precision engineering	51.4	77.1	31.4	10.0
	Logistics & transportation	47.8	59.3	17.6	3.8
	Pharmaceuticals & biologics	50.9	92.7	54.5	12.7
	Construction	41.7	70.9	20.5	7.9
	Chemicals/ petrochemicals	62.2	90.2	29.3	2.4
	Electronics/electrical engineering	53.3	85.3	38.7	12.0
	Marine	53.2	77.9	31.2	5.2
	Retail	72.0	60.2	19.3	3.5
	Security, estate management & services	53.6	75.0	7.1	3.6
	Infocomm	58.2	85.5	43.6	30.9
	Hotels, tourism, events & attractions	74.5	86.4	34.5	6.4
	Community & social services, healthcare	92.3	74.8	18.2	3.5
	Food & beverage	61.0	72.6	20.7	5.5
	Landscape	50.0	68.5	31.5	9.3
	Government/public service	66.0	81.6	30.5	6.3
	Generic manufacturing	39.5	69.7	26.3	7.9

6.2 The Centrality of Computer Use to Job Tasks and Job Skills

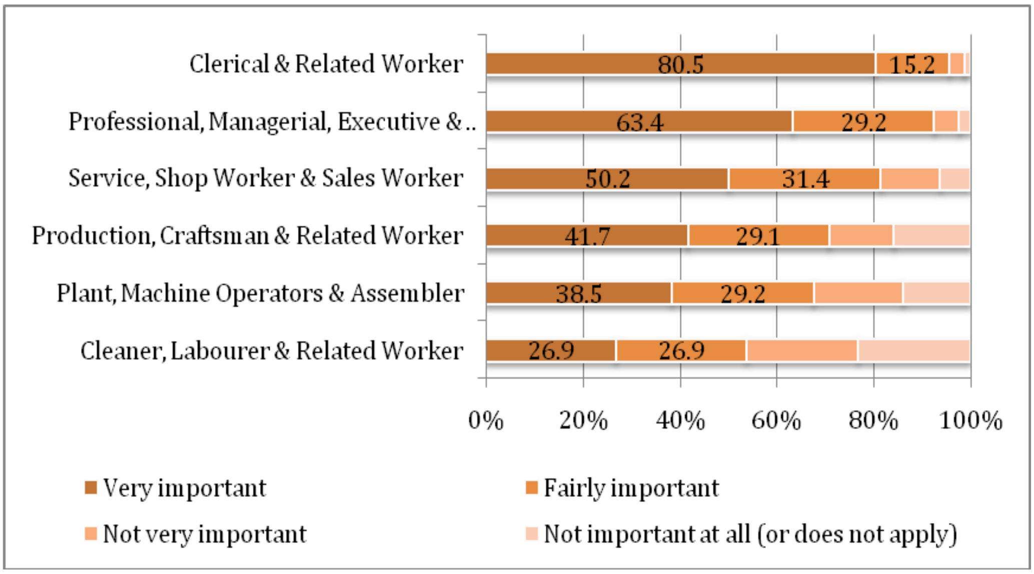
The measures discussed in the previous section highlight the very different levels of use of the computer or computerised equipment. It is clear from the results of that discussion that the use of computer has entered most tasks and is linked to the skills required by those tasks in most jobs. We may ask a further question “To what extent is the use of computer has become part of the tasks?” This question focuses on the centrality of computing to contemporary job tasks in the jobs that we cover.

In the SU survey, we have a question on “[In your job, how important is] … using a computer, ‘PC’, or computerised equipment?” This is to be supplemented by a further question on the internet – “[In your job, how important is] … using the internet?” The second question is to explore the extent to which IT is to support a wide range of task effectiveness, e.g. information search, problem solving, communication and co-working.

Both questions have four ratings from ‘very important’ to ‘not important at all’. We take the first two ratings – ‘very important’ and ‘fairly important’ – as indicators for the centrality of computer and IT use in the respondent’s job.

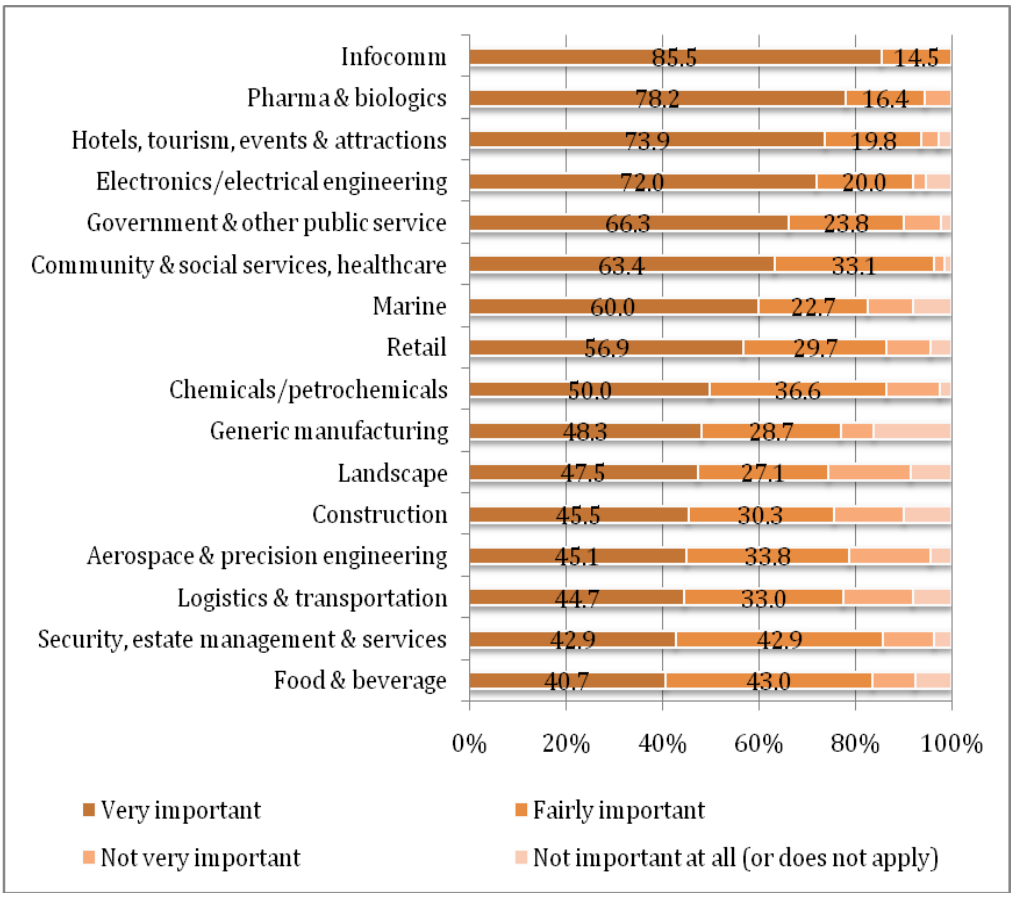
In Figure 6.2.1, the data show that in all but one occupation, the centrality of the use of computers and computerised equipment is at a very high level. Over two-thirds of these jobs have reported the use of computer and computerised equipment as either ‘very important’ or ‘fairly important’. Even in the elementary occupations, 53.8% of the jobs report either ‘very important’ or ‘fairly important use’ of the computer or computerised equipment. We do not have longitudinal data to track this rising importance, though we may expect this to rise, as up-skilling and new work processes continue to upgrade jobs because of the need to raise productivity in Singapore. Results in the UK Skills Surveys showed that the importance of the use of computers and computerised equipment has been rising in repeated surveys over time.

Figure 6.2.1. The Importance of Use of Computers and Computerised Equipment by Occupation (%)



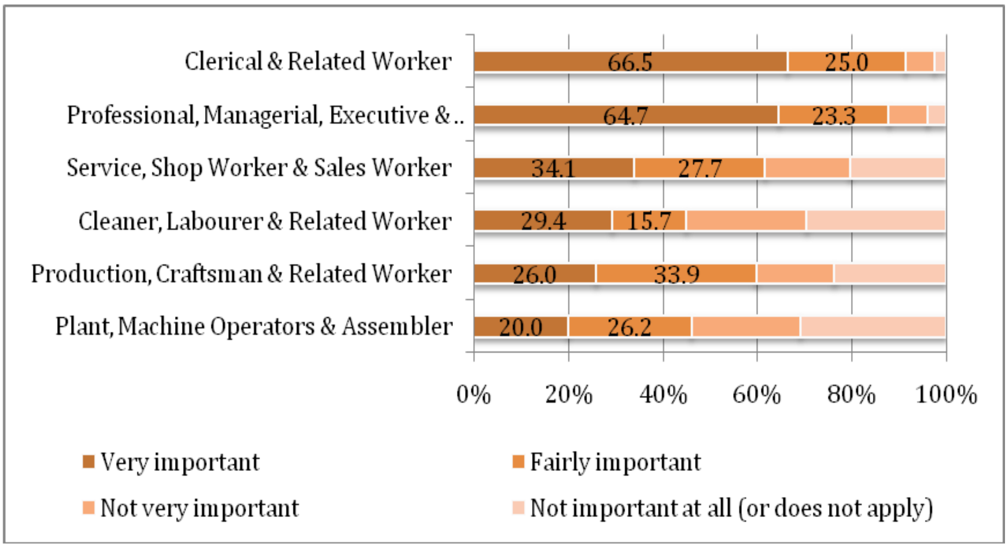
In Figure 6.2.2, we present the results on the use of computers and computerised equipment by industry. The picture is very similar to the previous table. Most industries have a very high level of computers and computerised equipment use – all exceeding 70% of their jobs, either as 'very important' or 'fairly important'. Although infocomm takes the obvious first rank in the table, the importance of computers and computerised equipment seems to be applicable to all industries, and there is little 'technology' and 'non-technology' divide.

Figure 6.2.2. The Importance of Use of Computers and Computerised Equipment by Industry (%)



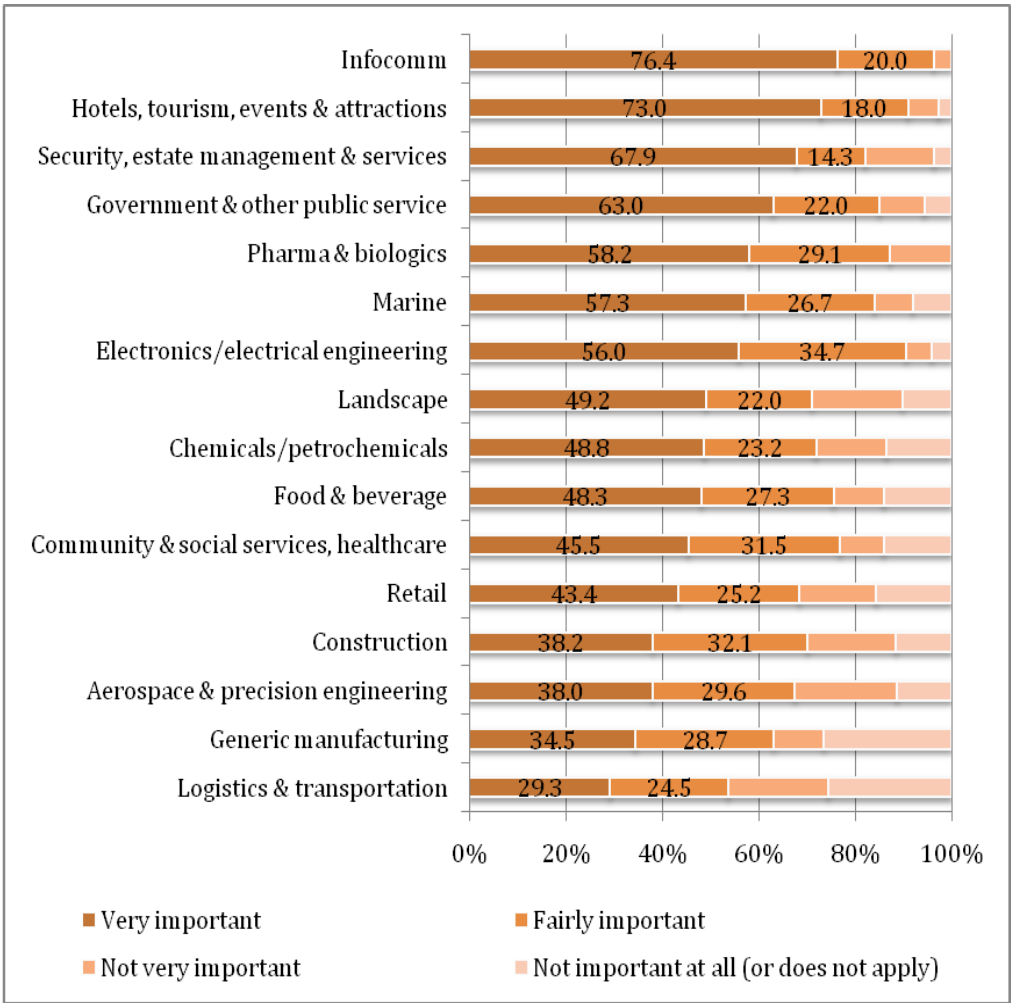
Figures 6.2.3 reports the importance of the internet use by occupation. The general picture is similar to that of computer use, though the level of internet importance is generally lower. Interestingly, compared with computer and computerised equipment use, the importance of internet use for the elementary occupations has 'moved up' to 4th position. Only in two occupations – elementary and plant, machinery operator – is the use of the internet rated as 'important' by less than 50% of their jobs.

Figure 6.2.3. The Importance of the Use of Internet by Occupation



The industry data show a very high level of importance of internet use across all industries. Even in logistics & transportation, ranking the importance of internet use the lowest, 53.8% of the jobs reported the use of the internet as 'very important' or 'fairly important'. Comparing the importance of computer use (Figure 6.2.2) and the importance of Internet use (Figure 6.2.4), there are some interesting differences that largely reflect the job environment of the technology in question. For example, the F&B industry has the least jobs ranking the use of computers and computerised equipment amongst different industries. However, its position on the importance of internet use moves to almost mid-table in Figure 6.2.4. There are also other industries that move around a bit between these two figures. The point is that we cannot assume that the importance of internet use is the same as the importance of computer and computerised equipment use. As such, they demand very different skills.

Figure 6.2.4. The Importance of the Use of Internet by Industry (%)



The discussion above provides strong evidence to support the centrality of the use of computers or computerised equipment in most jobs. Both the occupational and industrial data show variability in importance, but also very high levels of important use.

Section 7: Job Environment and Skills Utilisation

In this section, we will examine three important aspects of work places that are likely to affect skills utilisation:

1) Task discretion

2) Workplace involvement

3) Worker commitment

The SU survey primarily collects data that reflect skills and are demanded by jobs. However, the questions of skills utilisation cannot be ascertained unless we also have some information about the job environment. After all, it is not difficult to see that organisations that are high bound by rules and demarcation of job descriptions that may hinder the opportunities to utilise a higher level of skills through discretionary effort. Also, under the current policy attempt to raise productivity at work, many industries in Singapore are looking at their work practices in order to structure their work processes. Some of this effort looks at the role of technology, while others will examine the impact of practices.

In the SU survey, we have included some workplace and worker characteristics questions so that we can examine the wider context of skills utilisation. Many of these questions were informed by research in the last 20 years. Indeed, there is a huge amount of research in the management and work process literature that looks at the consequences of job environment (Godard, 2004, Braverman, 1974, Simmons and Mares, 1983, Osterman, 2000, Barker, 1993, Godard, 2001).

The more recent research, the 'high performance working' strand, tends to examine how work practices may lead to 'high performance' (e.g. productivity) outcomes (Appelbaum et al., 2000, Becker and Huselid, 1998, Ichniowski et al., 1997). Others, for example, the work process researchers, look at the opposite of effects of 'new' work practices (high involvement, team working etc), and argue that performance outcomes are likely to be 'managerial' in nature and serve little to further workers' well-being (Thompson and McHugh, 2002, Batt, 2004, Gallie, 2003). As such, ‘new’ practices may lead to work intensification and work stress. This may also ultimately leads to performance problems to an organisation. Conclusive research evidence on this debate is not yet available.

In the following discussion, we will not venture into the performance-stress debate. However, we will examine if the SU data lends support to the idea that there is a relationship between workplace characteristics and the level of skills utilisation. Again, we know of little research data currently available in this area. We hope to provide further information to enhance the productivity debate and policy efforts to raise productivity in Singapore.

7.1 Task Discretion

The connection between workplace performance and work practices such as high involvement and task discretion is strongly supported by research evidence (Bailey and Merritt, 1992, Ichniowski et al., 1997, Cappelli and Rogovsky, 1998, Kalleberg et al., 2009). However, none of this research addresses the issue of skills utilisation because none of those projects measure skills.

In the UK skills research, results show that task discretion is positively related to the Broad Skills Index (BSI). In other words, in workplaces that are characterised by high level of job autonomy and high trust, workers tend to exercise a higher level of skills (compared with a similar job elsewhere). This result is consistent with much of management research that suggests that there are beneficial effects associated with ‘empowerment’. Thus, in the ‘high performance working’ literature, task discretion is associated with high commitment, mutual gains and innovations (Tamkin, 2005).

In the SU survey, we ask a general question “How much influence do you personally have on how hard you work?” In addition, we include five more detailed questions on the extent to which the worker can influence: what task to do; how to do the task; to what standard/quality of the task; what time to start and finish the task and what resources to be employed.

The first indicator is designed to provide a general picture of workers' autonomy on the job. The survey actually found that the majority (61.2%) of Singaporean workers have a great deal of influence on how hard they work. A further 35.1% reported that they have 'a fair amount' of influence.

However, further analysis shows that the extent of personal influence over how hard one works seems to be related to the skills content of the job. For example, for those jobs which require no qualification, 57.1% have 'a great deal' of influence over how hard they work; 6.1% have 'very little or no' influence at all. For jobs that require a degree or above, the respective figures are 65.2% (have a great deal of influence) and 4.3% (very little or no influence).

By combining all six autonomy questions together, we form a Task Discretion Index (TDI) (Cronbach's α = 0.818). This index therefore provides an overall measure of task discretion from different perspectives around the job. We then correlate TDI with BSI to see if these two measures are related. The result shows that in Singapore, the TDI is significantly and positively correlated with BSI ($r = 0.119$, $n = 2065$, $p = .000$) confirming that if a Singapore workplace which has high levels of task discretion, the skills utilisation of that workplace is expected to be higher than those places with low task discretion for their jobs.

The implication is that skills utilisation in Singapore can be addressed at two levels. At the job level, the result suggests that job design (in particular that concerns task discretion) can augment skills utilisation. Job design is already on the radar of workforce policy in Singapore. The question is whether various job design initiatives are also addressing the fundamental aspects of task discretion which may require the support of high involvement practices and high skills training.

At the organisational level, the result suggests that wider work processes within the workplace can support higher skills utilisation if training, coaching, teamwork, communication are constructed to enable effective task discretion.

In spite of the above results, research on 'high performance work practices' reminds us that task discretion alone is not the only path to high skills utilisation, workplace involvement and workers' involvement and commitment may also have an important effect (Boxall, 2009).

7.2 Workplace Involvement

High involvement work practices have attracted a lot of attention in recent times because of their potential benefits to productivity, though the effect of high involvement is often mediated via other factors, e.g. task discretion, at work. One of the most revealing studies is research carried out by (MacDuffie, 1995) on automotive manufacturing which identifies a significant and positive relationship between high involvement practices and skill levels of workers. MacDuffie's detailed study demonstrates that when a workplace switches over to flexible production (as part of the response by U.S. manufacturers to the productivity lead of the Japanese), there is the need to deal with contingencies arising from the production/service processes. This gives rise to a further need to developing the workforce's capacity for learning in order that flexible production can be effectively carried out.

In the Singapore context, we do not have a full picture regarding the extent to which workplaces are engaging in flexible production. However, the SU data does enable us to have an estimate of the extent of high involvement and where this is located.

Table 7.2.1 shows that aspects of consultation vary quite substantially across workplaces[11]. The most common form of consultation concerns health and safety. Just over 51% of the jobs in the sample are consulted on health and safety. Around 40% of the jobs are consulted on matters such as planned changes in work practices and what is generally happening in the organisation, while 37% of the jobs are consulted on changes in products or services. However, it is important to note that workers' views about the operation of business (29.7%) and important decisions such as finance or strategy are the least consulted matters amongst workers (27.2%).

[11] We did not include the middle response 'Workers are sometimes consulted' for clarity and contrast.

Table 7.2.1. Extent of Consultation at Your Workplace (%)

	Workers Are Always Consulted	Workers Are Not Consulted
Health and safety issues	51.4	21.7
Training plans	45.7	22.5
Planned changes in work practices	41.8	23.1
What is happening in organisation	40.7	19.8
Planned changes in products and services	37.3	28.9
Your views about the operation	29.7	31.2
Important decisions (e.g. finance or strategic matters)	27.2	40.7

We also combine the various consultation measures together to form an involvement index (Cronbach's $\alpha = 0.824$). This index provides a general measure of how much the worker is consulted within his/her work environment. Figure 7.2.1 examines how the index is distributed across occupations. Relative to the whole sample, PMET, plant, machine operators, and the elementary job categories have involvement above the sample average. Whereas clerical, service, shop, sales, production, craftsmen and related jobs are below sample average, jobs in the plant, machine and assembly have the highest involvement index at work in terms of its median. PMET jobs, however, have the highest 75th percentile involvement index.

Clerical workers occupy the opposite of the scale. The median, 25th and 75th percentiles of this group are all below the sample average and other groups' values, perhaps reflecting their general working environment. This is consistent with our earlier findings that some generic skills of clerical and related jobs are well below average use, e.g. leadership, problem solving, planning and influencing skills. The 25th percentile of this group is also the lowest. The involvement index for the elementary jobs is generally higher than expected and is difficult to explain.

Figure 7.2 1. High Involvement Index by Occupation

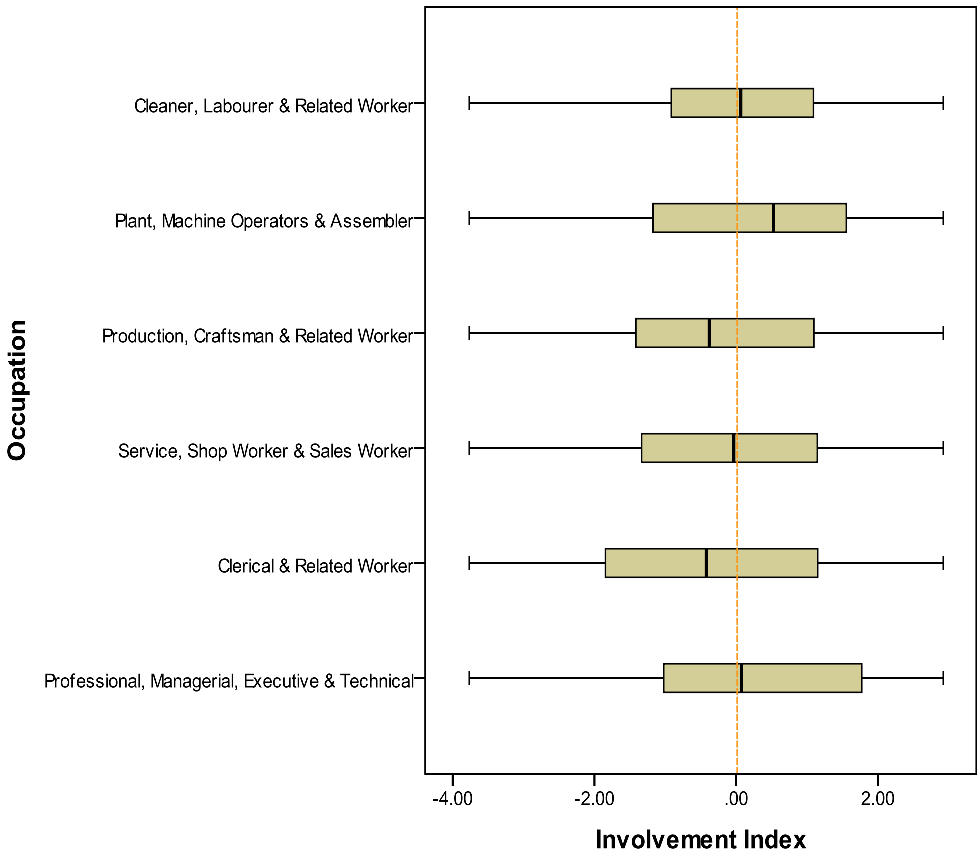
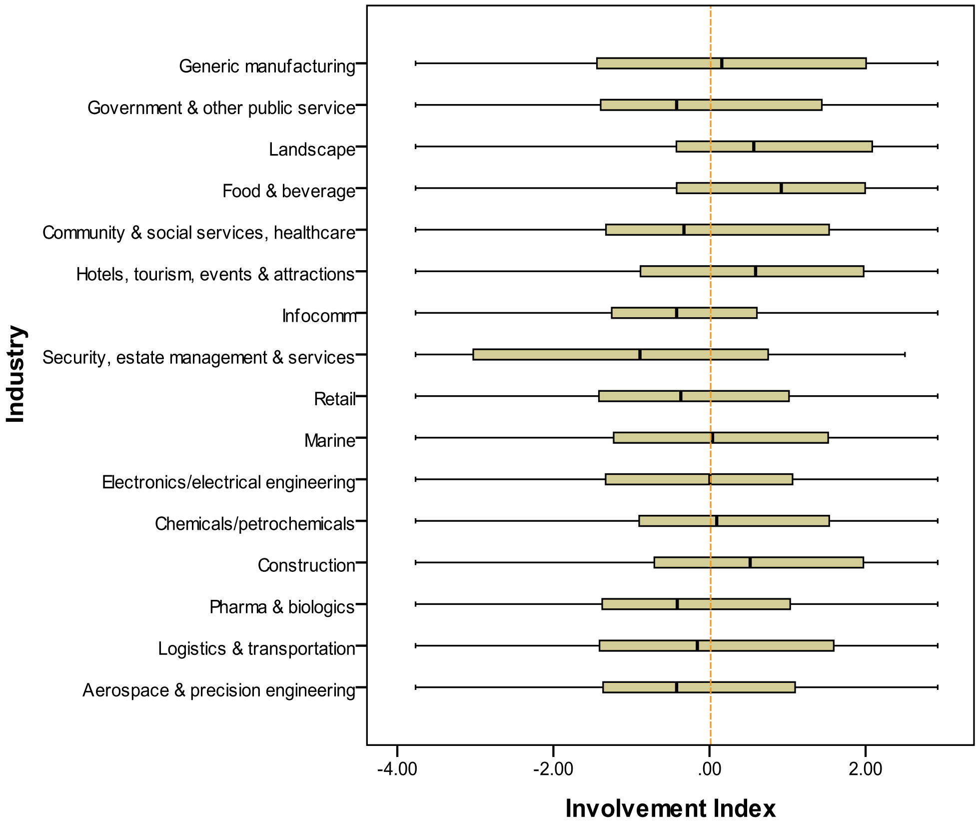


Figure 7.2.2 examines the involvement index by industry. Clearly, the industry differences are diverse. We will single out a few interesting cases to discuss here. In terms of the median score of the Involvement index, landscape, F&B, hotels & tourism and construction industries are all above the sample average involvement at work. A few industries: generic manufacturing, marine and chemicals/ petrochemicals are around the sample average. The rest are all below the sample average involvement.

However, the median scores do not tell the full picture. For example, despite the average median involvement, generic manufacturing has one of the highest 75th percentile scores. Likewise, the 75th percentile scores of the landscape, F&B, construction and hotels industries are some of the highest involvement, reflecting that the majority of these jobs are better involved than those in other industries. The security, estates management & services industry has the lowest involvement index and its 25th percentile is also the lowest by far in comparison with other industries.

Figure 7.2.2. High Involvement Index by Industry



Some may argue that task discretion may be linked to pay. Thus, in terms of job income, the SU data result shows that there is a significant, positive but modest correlation between the Involvement index and pay, reflecting the fact that generally the higher the job income, the higher is the involvement index ($r = .100$, $n = 2090$, $p = 0.000$). And not surprisingly, in terms of contract type, the self-employed group has the highest above average Involvement index score with fixed-term and permanent contract workers having around average involvement index. Temporary and part-time contract workers are well below the sample average involvement index.

For a general pattern between skills utilisation and job involvement, we correlate the Involvement index with the BSI. The result confirms studies elsewhere that, like task discretion, high involvement in the job is linked to high skills utilisation ($r = 0.119$, $n = 1996$, $p = 0.000$).

7.3 Worker Commitment

Worker commitment has been one of the cornerstones of human resource management (HRM) research (Wood and Albanese, 1995). Much of this research tries to establish the link between workers' value and that of the organisation. Often, mutual gains and reward practices are the major tools to achieving high commitment (Guest, 1987, Tamkin, 2005). In the high performance working literature, employee commitment works in a synergetic manner with other practices such as high involvement and skills training (Ashton and Sung, 2002). These three elements are linked and form a particular job environment for high skills utilisation and discretionary effort. It is in this regard that we will look at the SU survey and see if there is any evidence of high commitment workplaces that are linked to high skills utilisation.

The basic SU data focuses on the job and not the jobholder. However, there is one set of questions that poll the workers' attitudes towards the job/workplace that they are associated with. These questions include the following:

> "I have enough opportunity to use the knowledge and skills that I have"
>
> "My values and the organisation's are very similar"
>
> "This organisation inspires me to perform well"
>
> "I am proud to be part of this organisation"
>
> "I would take almost any job to stay in this organisation"
>
> "I would turn down another job with higher pay to stay in this organisation"
>
> "I am willing to work harder to help my organisation succeed"

These questions may have one of the four responses ranging from strongly disagree to strongly agree (with no neutral position). We then form a Worker Commitment Index with these questions. These seven measures prove to be highly consistent (Cronbach's α = .841).

Table 7.3.1 shows the correlation results amongst the different indices. All of the pair-wise correlations are significant at the 0.01 level, except for the correlation between the high commitment index and BSI. There is no evidence to suggest that high commitments are linked to high skilled jobs, though results do support the close relationships between high involvement and high commitment, and between high commitment and task discretion. Instead, high skilled jobs are positively linked to task discretion and high involvement, suggesting that job autonomy and employee involvement in decision-making are good for skills utilisation. Perhaps this is where job re-design can help.

Table 7.3.1. Correlation Analysis of Job Environment and BSI

	BSI	High commitment index	High involvement index	Task discretion index
BSI	1	.029	.119(**)	.119(**)
N		2026	1996	2065
High commitment index	.029	1	.281(**)	.312(**)
N	2026		2081	2154
High involvement index	.119(**)	.281(**)	1	.181(**)
N	1996	2081		2123
Task discretion index	.119(**)	.321(**)	.181(**)	1
N	2065	2154	2123	

** Correlation is significant at the 0.01 level (2-tailed)

Section 8: Conclusion and Policy Implications

As the first exercise of its kind in Singapore, what has the SU survey achieved? From the workforce development and WDA perspective, there are a number of significant contributions.

First, with the broad skills measure, which examines the minimum qualification required, initial and continuous training time involved, we can map out the skills content of various jobs in terms of their skills demand. This result is new and is only possible because we have been able to measure skills the way that we designed. The measure shows that when training time is considered, technical industries tend to score more highly than service oriented industries. Although this does not come as a surprise, as the service industries tend to have relatively shorter initial and continuous training requirements, compared with the technical industries, the results highlight the significant difference between skills measures that focus on qualifications only and those that include training and learning content.

Most interestingly, when we decompose the BSI into its various components, we obtain greater insights into how the BSI varies across industries and occupations. For example, we can see that the major reason for the relatively low BSI score for retail comes from the relatively low level of training, but not qualifications. Jobs in retail require a fairly high level of minimum qualification compared with other service jobs. However, it is in the areas of initial and continuous training that retail jobs lose ground to other service jobs, though it has been argued that there is a lot of training that is embedded within the daily working activities. These activities may not be seen as training. On the other hand, discussion with the retail industry also suggests that in many segments of the retail industry, e.g. the smaller retail firms, there is very low level of product knowledge development, which leads to very little continuous learning. At the same time, the nature of 'selling' requires relatively little initial training in most cases. All of these factors contribute to a generally low BSI score.

Information like that gives us a sense of perspective for the first time when we examine the skills content of jobs. Should there be the need for policy intervention, the analysis here would provide insights into the sources of the skills deficit. Thus, the results suggest that if skills deepening were to take place in retail, it would be in the area of greater initial training and also greater continuous learning on the job.

The components of BSI also show that there is still a continuing reliance on secondary education as the basic qualification around which jobs are designed. This was identified by earlier research in the 1990s and early 2000s. Thus, the current result does not make comfortable reading that many of the jobs have not been up-skilled when arguably the workers have done so via the CET system over the years.

Second, repeated large scale research under the human capital approach shows that there is a link between low pay and low skills (via the measure of education attainment as a proxy for skills). The SU survey measures skills demanded by the job directly. The results show that in Singapore, low pay jobs are indeed linked to low skilled job content. To escape this low pay 'trap', the results would suggest that the low-wage worker would have to move into jobs with a substantial increase in minimum required qualification or training content. Alternatively, there is the need to redesign the current jobs to increase the skills content.

Skills information such as the BSI also enables us to ask important policy questions. For example, if job income were associated with skills of the job, would low skills be the source of low productivity? Also, from the result of sectors such as hotel, restaurants and F&B, there seems to be a link.

Third, through the SU study, we are getting a much better picture about the skills of PMET jobs. Previously, we had information about PMET jobs through other means, e.g. the WDA definition of PMET which defines workers who have a diploma or above qualifications. This is largely an administrative definition which facilitates public funding decisions for training. This is also a definition for the workers involved and not necessarily for the jobs. The drawback of this administrative definition is that it says very little about the skills that PMET jobs may require other than what qualifications PMET workers may already have. Another shortcoming is that the WDA definition is relatively static which defines who are already in PMET jobs. It does not tell us the existence of other jobs that can be counted as PMET jobs, as they are excluded because the job holder does not have a diploma or above qualification.

The SU survey results show that the demand for skills in PMET jobs tends to be very high. The normalised BSI scores show that the skills demand in PMET jobs is on average almost 50% higher than the rank and file workers (calculation not shown). Compared with other occupations, PMET jobs generally require greater formal qualifications, more initial learning time and a much higher level of continuous learning.

Fourth, the use of generic skills is not uniform across industries and occupations. The biggest surprise of all the skills indicators is that generic skills are far less generic than people would think. Not only are generic skills accorded different levels of importance generally (e.g. ‘managing own feelings’ is very important for 57.2% of the jobs while literacy skills for ‘writing long documents’ is very important only for 16.3% of the jobs), generic skills are utilised to a very different extent across industries and occupations.

Information on generic skills utilisation differences across industries is very useful for the current debate on greater contextualisation of the ES system. For example, if a particular generic skill is not widely used in certain jobs, the need for contextualisation is relatively inconsequential. Thus, the need to contextualise ‘planning skills’ in the Food & Beverage industry is probably less important than contextualising all other generic skills because ‘planning skills’ appears to be far less utilised in the F&B industry (Table 5.2.2).

Occupationally, PMET jobs need to go through the ‘T-shape’ transformation (broadening and deepening skills) under the current national strategic plan. One generic skill that appears to be underutilised by PMET in the current SU survey, but is increasingly becoming important, is ‘emotional labour’ or EQ (Table 5.2.1). As well as upskilling PMET in this area, we ought to examine why EQ is underutilised in the first place. Thus, the SU data provides rare information and insights into policy areas that previously had to work on very little information, if at all.

The generic skills analysis also shows that new skills such as ‘influencing skills’ are very ‘new’ such that most jobs do not utilise them in the current SU results.

However, if the UK results are anything to go by, the importance of influencing skills is expected to grow. In the UK influencing skills started with a very low base in 1997. By 2006, it became the fastest growing generic skill.

Fifth, the use of skills is significantly influenced by job environment. One of the most important findings is the positive impact of task discretion and high involvement on high levels of skills utilisation. Not only are these two indicators significantly correlated with our broad skill content measure (BSI), they also correlate with generic skills utilisation. In other words, a high skill workplace does not rely on the transmission of skills alone, task discretion and high involvement may form important foundations on which skills utilisation can flourish. The policy implication here is that for PMET training, it may be very important to increase the level of appreciation of job context and its impact on skills utilisation, as PMET would be the gatekeepers to facilitate positive change and greater skills utilisation in the workplace through new practices or new processes. Within the existing WSQ frameworks, other than Service Excellence Training especially at the managerial level, there is still insufficient emphasis on the need for improvement in the job environment in order to bring about greater skills utilisation.

Sixth, we have been aware of the importance of computer or IT skills for some time. Indeed, it is quite clear from the SU data that the use of computers and computerised equipment is already forming a central part of most jobs in Singapore. However, our previous knowledge on the use of computers at work was fairly 'broad-stroke'. Often, when we consider computer training for employees, we are providing training according to the technical complexity of the computer, e.g. introductory, intermediate and advanced. But this set of skills can be very different from what is needed to perform a range of tasks in a job.

With the two notable exceptions – the infocomm and pharmaceuticals & biologics industries – computers and computerised equipment have been used mostly for automising routine manual tasks (e.g. invoicing, reporting, record-keeping etc.), many industries have not utilised IT in the advanced areas such as using computers in analytical activities. In the current effort to improving productivity, it would seem useful to examine the role of computers in tackling routine cognitive and nonroutine cognitive activities. All of these will have implications for skills and CET qualifications in delivering IT skills to industry.

In summary, this study has provided the first ever skills analysis from the work perspective. It raises many issues that we need to look at if we are to increase the level of skills utilisation in Singapore workplaces. The results of this study clearly suggests that until we pay attention to skills that are actually used at work, providing ever greater amounts of training alone is unlikely to impact issues such as productivity and low wage. And because of that, we believe that skill utilisation studies, such as the one we conducted here, will form a crucial link in the effectiveness of future skills strategies of Singapore.

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