# FEATURE ARTICLE

## SKILLS FOR BILLS: UNDERSTANDING THE RETURNS TO SKILLS FOR LOW WAGE WORKERS

# SKILLS FOR BILLS: UNDERSTANDING THE RETURNS TO SKILLS FOR LOW WAGE WORKERS


## EXECUTIVE SUMMARY

- This study examines the returns to various skills for low-wage Singaporean workers.
- Our findings suggest that workers in jobs which require high analytical, creative and service skills enjoyed a wage premium. The wage premium on gross motor skills depended on the gender of the worker, with males receiving higher wages.
- We also find that the wage premiums for analytical, creative, service and gross motor skills tended to diminish with age. By contrast, the premium for management skills increased with age.




## BACKGROUND

Against the backdrop of rising income inequality in Singapore, there have been increasing concerns over how to raise the income of low-wage Singaporean workers. To increase the wages of these individuals in a sustainable manner, a key policy adopted by the government is to encourage training and skills upgrading. Notably, many incentives, such as the Workfare Training Support (WTS) Scheme, have been rolled out for this purpose. A key question that naturally arises in this regard is whether employers value certain skills more and are therefore willing to pay higher wages for them.

By utilising survey data on low-wage Singaporean workers, we address this question by estimating the returns to skills for low-wage workers. Our study involved two main steps. First, we constructed a set of skill dimensions that described the skills required for the jobs in our sample. Second, we incorporated these skill dimensions into a Mincer wage equation to determine the returns to each skill for low-wage workers.

## CONSTRUCTING SKILL DIMENSIONS

In the first part of our analysis, we constructed a comprehensive set of skill dimensions that characterised the skills required in a given job in our sample.[1]

### Matching Jobs to Quantitative Job Descriptors

As Singapore does not have a database that contains information on the skills required for the various jobs in Singapore, we used the O*NET database, which is a database funded by the US Department of Labour, as our source of skills information. The O*NET database is compiled from surveys of US employers, wherein they were asked to score the importance of various job descriptors, such as skill requirements and work activities, for their respective jobs (Exhibit 1).[2] From the 277 job descriptors available in O*NET, we shortlisted 72 for our study based on two conditions. First, the descriptors had to

[1] The jobs are defined at the 5-digit level, which is the most detailed level available from the Department of Statistics' Singapore Standard Occupational Classification 2005.

[2] The O*NET contains 277 standardised, measurable set of variables called "descriptors". These descriptors depict the day-to-day aspects of a job including the skill and knowledge requirements, work activities and the working environment. All the 974 jobs listed in O*NET are scored on a scale of 0 to 100 for each of these descriptors. Note that by utilising O*NET, our assumption is that the skill requirements in the US approximate those in Singapore, conditional on the type of jobs listed in our sample.

depict the skill and ability requirements of a job.[3] Second, the descriptor must have scores for all the jobs in our survey sample.[4] After shortlisting the 72 descriptors, we then assigned the O*NET scores of each descriptor to all the jobs listed in our sample.[5]

**Exhibit 1: Sample Of Jobs and Job Descriptors from O*NET**

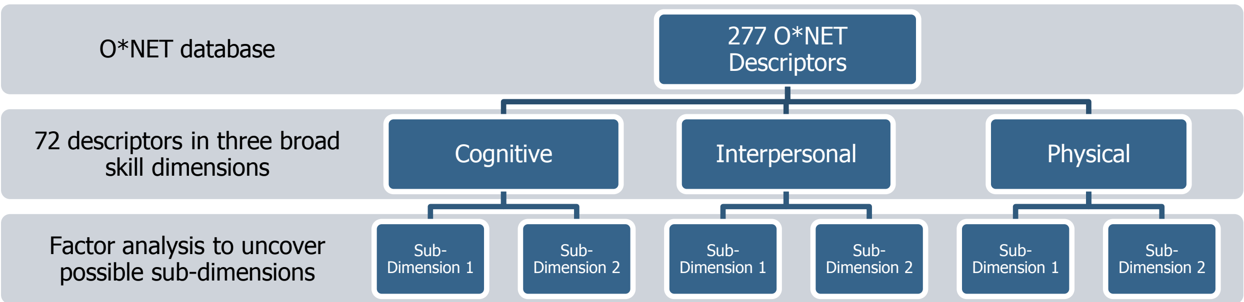
| Jobs | Knowledge | | Skills | | Abilities | | Work Activities | | Work Context | |
|---|---|---|---|---|---|---|---|---|---|---|
| | English | Computers & Electronics | Reading | Systems Analysis | Speech Clarity | Originality | Interacting with Computers | Training Others | Spend Time Sitting | Exposed to Contaminants |
| Librarians | 84 | 75 | 75 | 41 | 69 | 47 | 82 | 61 | 53 | 41 |
| Bakers | 44 | 31 | 50 | 28 | 56 | 41 | 35 | 52 | 3 | 23 |
| Cooks | 47 | 15 | 41 | 28 | 53 | 41 | 23 | 57 | 8 | 56 |

Note: Employers were asked to score from 0 to 100 based on the importance of each descriptor. Our study focused on the skill and ability requirements of a job.

### Condensing 72 Job Descriptors into 6 Skill Dimensions

To make the analysis more manageable, we next condensed the 72 shortlisted descriptors into a smaller group of skill dimensions. We first grouped the descriptors into three broad skill dimensions in line with the empirical literature: Cognitive, Interpersonal and Physical skills (Ingram & Neumann, 2006; Yamaguchi, 2011). We then used a statistical method, known as Factor Analysis, to pare down the descriptors in each broad skill dimension and to group them into sub-dimensions based on the direction and strength of the correlations between the descriptors across various jobs (e.g., if two descriptors are highly correlated in terms of whether they are important to a particular job, and this is true across all jobs, they will be grouped into a sub-dimension) (Exhibit 2). Please refer to Annex A for more details on Factor Analysis.[6]

**Exhibit 2: Condensing Descriptors into Skill Dimensions**




[3] O*NET contains several categories of descriptors, some of which are irrelevant to our study as our focus is on skills. These include descriptors on the work context (e.g. how much of this job requires standing) and work activities (e.g. how often do you have to use electronic mail in this job).

[4] As some of the O*NET surveys are ongoing, a number of skill and ability descriptors did not yet have scores for all the jobs in our sample at the time of study.

[5] The jobs from O*NET and our sample were matched manually due to differences in the occupational classification. Most of the matching was done via exact and related job title matches.

[6] Ex-ante, it was difficult to know what these sub-dimensions were. While it was possible to make reference to existing literature, a better approach would be to allow the data to guide the construction of these sub-dimensions.

Based on Factor Analysis, we derived two sub-dimensions for each of the three broad skill dimensions. They were: Analytical and Creative skills (from Cognitive skills), Management and Service skills (from Interpersonal skills), as well as Gross and Fine motor skills (from Physical skills). Of the 72 descriptors, a total of 28 descriptors were eventually categorised under the six skill sub-dimensions (Exhibit 3). Factor Analysis also allowed us to assign normalised scores to each sub-dimension for all the jobs in our sample, based on the weighted scores of the descriptors covered in the sub-dimension. The normalised scores give an indication of the importance of each sub-dimension to a job relative to the job that had the average score within our sample. With the skill sub-dimensions and their scores for each of the jobs in our sample, we were then able to run a Mincer regression to determine the returns to the six skills.

**Exhibit 3: Six Skill Sub-Dimensions and their Respective Skill Descriptors**

| Cognitive Skills | | Interpersonal Skills | | Physical Skills | |
|---|---|---|---|---|---|
| Analytical | Creative | Management | Service | Gross Motor | Fine Motor |
| • Reading Comprehension<br>• Writing<br>• Written Expression<br>• Number Facility<br>• Memorisation | • Design<br>• Thinking Creatively<br>• Visualisation | • Developing and Building Teams<br>• Coordinating the Work and Activities of Others<br>• Coaching and Developing Others<br>• Training and Teaching others<br>• Monitoring and Controlling Resources<br>• Provide Consultation and Advice to Others | • Communicating with Supervisors, Peers, or Subordinates<br>• Interpreting the Meaning of Information for Others<br>• Service Orientation<br>• Assisting and Caring for Others<br>• Establishing and Maintaining Interpersonal Relationships | • Dynamic Strength<br>• Speed of Limb Movement<br>• Gross Body Coordination<br>• Gross Body Equilibrium | • Control Precision<br>• Finger Dexterity<br>• Rate Control<br>• Reaction Time<br>• Response Orientation |

## SUMMARY STATISTICS

Before presenting the results of the Mincer wage regression, we describe in this section the key summary statistics of the jobs in our sample and the characteristics of the workers holding the various jobs.

**Profiling the Skill Dimensions for Different Jobs**

In total, there are 212 unique jobs in our sample. The four most common jobs in our dataset are cleaners, office clerks, shop sales assistants and food & beverage (F&B) stall assistants. Their skill scores are presented in Exhibit 4, whereby positive (negative) values denote skill requirements that are more (less) than the sample average. For example, cleaners, with a score of -1.4 for analytical skills, required less analytical skills than low-income jobs on average. On the other hand, they had a score of 0.67 for gross motor skills, suggesting that their job required more than average gross motor skills.[7] This is in contrast to office clerks, who required more than average analytical skills and less than average gross motor skills. It is important to note that our sample compromises mainly of individuals holding low-wage jobs, so although F&B stall assistants had a high score for analytical skills (e.g., numeracy skills), this was relative to the other jobs in our sample.

[7] The magnitude of the scores equals the number of standard deviations from the mean under a standard normal distribution. For instance, a score of -1 on analytical skill means that the job requires more analytical skill than 15.8 per cent of the jobs in our sample (this corresponds to 1 standard deviation under a standard normal distribution).

**Exhibit 4: Common Jobs and their Scores across the Six Skill Sub-Dimensions**

| Job | Analytical | Creative | Service | Management | Gross Motor | Fine Motor |
|---|---|---|---|---|---|---|
| Cleaner | -1.43 | -0.58 | -0.48 | -0.79 | 0.67 | -0.24 |
| Office Clerk | 1.02 | -0.55 | 1.11 | -0.99 | -2.08 | -0.49 |
| Shop Sales Assistant | 0.50 | 0.71 | 0.86 | 0.16 | 0.52 | -1.16 |
| F&B Stall Assistant | 0.68 | -0.66 | -0.62 | -0.48 | -0.73 | -0.43 |

To illustrate the types of skills and jobs in our dataset, we compiled the common jobs with high and low scores on each of the skill sub-dimensions (Exhibit 5). While we may usually associate a high score in management skills to CEOs and managing directors, these jobs do not exist in our sample. Instead, pre-primary education teachers and premises & facilities maintenance managers have high scores in management skills, relative to the other occupations in our sample.

**Exhibit 5: Common Jobs that had High or Low Scores in Various Skill Dimensions**

| | Low Score | High Score |
|---|---|---|
| Analytical | • Road making machine operator<br>• Butcher | • Real estate agent<br>• Customer service clerk |
| Creative | • Telemarketer<br>• Filing and copying clerk | • Cook<br>• Beautician |
| Service | • Building painter<br>• Hotel cleaner | • Bus driver<br>• Hair dresser |
| Management | • Motorcycle delivery man<br>• Sales demonstrator | • Pre-primary education teacher<br>• Premises and facilities maintenance manager |
| Gross Motor | • Optician<br>• Data entry clerk | • Security guard<br>• Sports coach |
| Fine Motor | • Sales rep<br>• Tour guide | • Motor vehicle mechanic<br>• Musical instrument repairer |

**Profiling Worker Attributes by Skill**

Finally, we examined the demographic attributes of Singaporean workers in the various jobs. We did this by running the following regression, with the score of each skill sub-dimension as the dependent variable[8]:

$$\text{Skill score}_i = \alpha + \beta_1 \text{Male}_i + \beta_2 \text{Age}_i + \beta_3 \text{Years of Education}_i + \gamma' X_i + \varepsilon_i$$

where $X_i$ is a set of controls

A positive (negative) $\beta_i$ coefficient means that workers with attributes associated with the coefficient held jobs that required more (less) of the skill reflected in the dependent variable. For instance, if the dependent variable is the score on analytical skills and $\beta_2$ is positive, this means that, controlling for all other attributes, older workers held jobs that required more analytical skills than younger ones. We summarise the signs of the $\beta_i$ coefficients below (Exhibit 6).

[8] In total, we ran six regressions, one for each of the six skill sub-dimensions.

On average, we find that males tended to hold jobs which required more creative, management, gross and fine motor skills. Conversely, women were more likely to be in jobs which required more service skills. Also, less educated and older workers tended to be in jobs which required more gross motor skills.[9]

**Exhibit 6: Signs of $\beta$ Coefficients from Regression**

| | Analytical | Creative | Service | Management | Gross Motor | Fine Motor |
|---|---|---|---|---|---|---|
| Males (Relative to Females) | | + | - | + | + | + |
| Older Workers | - | - | - | - | + | - |
| Years Of Education | + | + | + | + | - | - |

Note: Boxes without any sign indicate that the coefficient from the regression was statistically insignificant.

## THE RETURNS TO SKILLS: REGRESSION RESULTS

To quantify the monetary returns to various skills among low-wage Singaporean workers, we estimated a Mincer wage equation:

$$\log(monthly\ wage)_i = \alpha + \beta_1 \text{Analytical Skills}_i + \beta_2 \text{Creative Skills}_i + \beta_3 \text{Service Skills}_i + \beta_4 \text{Management Skills}_i + \beta_5 \text{Gross Motor Skills}_i + \beta_6 \text{Fine Motor Skills}_i + \gamma' X_i + \varepsilon_i$$

Where $X_i$ is a comprehensive set of controls (see Annex B for more details) and the $\beta_i$ coefficients indicate the wage premium that employers were willing to pay for the different skills. Our key results are in Exhibit 7. The salient points are as follow:

1. Different returns associated with different skills. Jobs that required creative skills yielded a 6.4 per cent wage premium, the highest among the six skill sub-dimensions. Analytical and service skills also yielded positive returns of 4.3 per cent and 1.9 per cent respectively. [10]

2. Returns to gross motor skills differed by gender. While females suffered a 5.6 per cent wage penalty in jobs which required gross motor skills, males had a 1.2 per cent wage premium.

3. No statistically significant returns to management and fine motor skills. This could be due to the nature of our sample, which does not include jobs that required high management and fine motor skills (such as CEOs, operations managers, musicians and watch makers, etc).

[9] This is after controlling for education, which indicates this could be a cohort effect. In other words, regardless of education, workers from the older generation, compared to those from the later generations, tend to work in physical jobs. This could be because (i) they started their careers in physical type jobs, developed the necessary skills and stayed on, or (ii) they do not have the skills (e.g. computer skills) to remain in cognitive and interpersonal types of jobs.

[10] This may partly be due to a relative scarcity of low-wage workers with analytical, creative and service skills. Over time, if the supply of workers with such skills increases and demand remains constant, the associated wage premiums may fall.

**Exhibit 7: Returns to Different Skills**

| | Monthly Wage Premium for a One Standard Deviation Increase in Skill Requirement |
|---|---|
| Analytical | 4.3%*** |
| Creative | 6.4%*** |
| Service | 1.9%* |
| Management | -0.9% |
| Gross Motor (Females) | -5.6%*** |
| Gross Motor (Males) | 1.2%*** |
| Fine Motor | 0.4% |
| Observations | 4,236 |
| R-squared | 0.444 |
| *** p<0.01, ** p<0.05, * p<0.1 | |

We also interacted the skill variables with individuals' age to examine if the wage premiums of different skills changed with age. Our main findings are in Exhibit 8. The key observations are:

1. Wage premiums in general declined with age. The wage premium for analytical, creative, service and gross motor skills decreased with age. This could either be because workers' skills actually diminished with age[11], or because employers' perception was that workers' skills diminished with age.

2. Conversely, the wage premium for management skills increased with age. Workers aged 60 and above were found to have a 1 per cent wage premium for management skills. There are two possible reasons for this. First, it could be due to employers' perception that management skills improved with experience on the job. Second, it could be due to selection effect, i.e., workers above 60 who were still in jobs that required high management skills could have higher abilities, thereby justifying higher wages.

**Exhibit 8: Returns to Skills across Different Age Groups**

| | Monthly Wage Premium for a One Standard Deviation Increase in Skill Requirement | |
|---|---|---|
| | 30-39 Years Old | 50-59 Years Old |
| Analytical | 11.7%*** | 2.8%*** |
| Creative | 11.6%*** | 4.9%** |
| Service | 8.3%** | 1.4%* |
| Management | -4.6%** | -0.9% |
| Gross Motor (Females) | -2.1% | -7.1%*** |
| Gross Motor (Males) | 6.2%*** | 1.2%*** |
| Fine Motor | 3.7% | 1.2% |
| Observations | 4,236 | |
| R-squared | 0.450 | |
| *** p<0.01, ** p<0.05, * p<0.1 | | |

[11] For instance, Feyrer (2007) and Werding (2007) found that there tends to be a hump-shaped labour productivity (value-added (VA) per worker) profile across ages, with productivity peaking when workers are in their forties, and declining thereafter.

## CONCLUSION

Our findings suggest that, among Singaporean low-wage workers, employers pay significant wage premiums for creative, analytical and service skills. Policy makers and employers should hence consider helping low-wage workers to acquire these skills. Anecdotally, we would expect that education and training play an important role in the acquisition of such skills. In fact, our descriptive statistics revealed a positive correlation between a worker's educational attainment and the level of creative, analytical and service skill that was required of the worker in his/her job.

Of potential concern is our finding that the wage premium for most skills tends to decline with age. If this is due to workers' skills actually declining with age, efforts to promote an elderly-friendly environment at the workplace, as well as training programmes to keep the elderly abreast of new technologies, ideas and methods might be necessary. If this is due to employers' perception that workers' skills diminish with age, and such perceptions are prevalent, employment and workplace norms will have to be changed.

A possible extension to our study involves estimating the impact of current training schemes in helping workers, including older workers, to improve their skills and hence the returns to training. Better wages could come about if training raises the workers' productivity in their current jobs, or if it enables them to move into better paying jobs.

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# ANNEX A: FACTOR ANALYSIS

In this section, we illustrate how Factor Analysis is used to construct our skill sub-dimensions by using Cognitive skills as our working example. In all, there were three steps.

**Step 1: Determining the Number of Sub-Dimensions**

The first step required us to determine the number of sub-dimensions that can be decomposed from each broad skill dimension. Based on the initial set of 25 descriptors listed under Cognitive skills, Factor Analysis assumed the following linear relationship between each descriptor $(Y_i)$ and sub-dimension $(F_n)$. Note that because we do not know the number of underlying sub-dimensions ex-ante, we do not place restrictions on the number of $F_n$ included in the model.[12]

$$
\begin{gathered}
Y_1 = \beta_{10} + \beta_{11}F_1 + \cdots + \beta_{1n}F_n + e_1 \\
\vdots \\
Y_{25} = \beta_{25,0} + \beta_{25,1}F_1 + \cdots + \beta_{25,n}F_n + e_{25}
\end{gathered}
$$

Here, $\beta_{in}$ is defined as a factor loading. Given that $Y_i$ is normalised, $\beta_{in}$ ranges from -1 to 1 and can be interpreted in the same manner as the correlation coefficient r (i.e. $\beta_{in}$ describes the strength and direction of the relationship between a descriptor $Y_i$ and a sub-dimension $F_n$).

By assuming the linear structural form as seen above, we were able to establish both the theoretical as well as the observed variance-covariance matrices (Exhibits A-1 & A-2):

**Exhibit A-1: Theoretical Variance-Covariance Matrix**

| Descriptor | $Y_1$ | $Y_2$ | ............... | $Y_{25}$ |
|---|---|---|---|---|
| $Y_1$ | $\beta_{11}^2 + \cdots + \beta_{1n}^2 + \sigma_1^2$ | $\beta_{21}\beta_{11} + \cdots + \beta_{2n}\beta_{1n}$ | ............... | $\beta_{25,1}\beta_{11} + \cdots + \beta_{25,n}\beta_{1n}$ |
| $Y_2$ | $\beta_{11}\beta_{21} + \cdots + \beta_{1n}\beta_{2n}$ | $\beta_{21}^2 + \cdots + \beta_{2n}^2 + \sigma_2^2$ | ............... | $\beta_{25,1}\beta_{21} + \cdots + \beta_{25,n}\beta_{2n}$ |
| . | . | . | | . |
| . | . | . | | . |
| . | . | . | | . |
| $Y_{25}$ | $\beta_{11}\beta_{25,1} + \cdots + \beta_{1n}\beta_{25,n}$ | $\beta_{21}\beta_{25,1} + \cdots + \beta_{2n}\beta_{25,n}$ | ............... | $\beta_{25,1}^2 + \cdots + \beta_{25,n}^2 + \sigma_{25}^2$ |

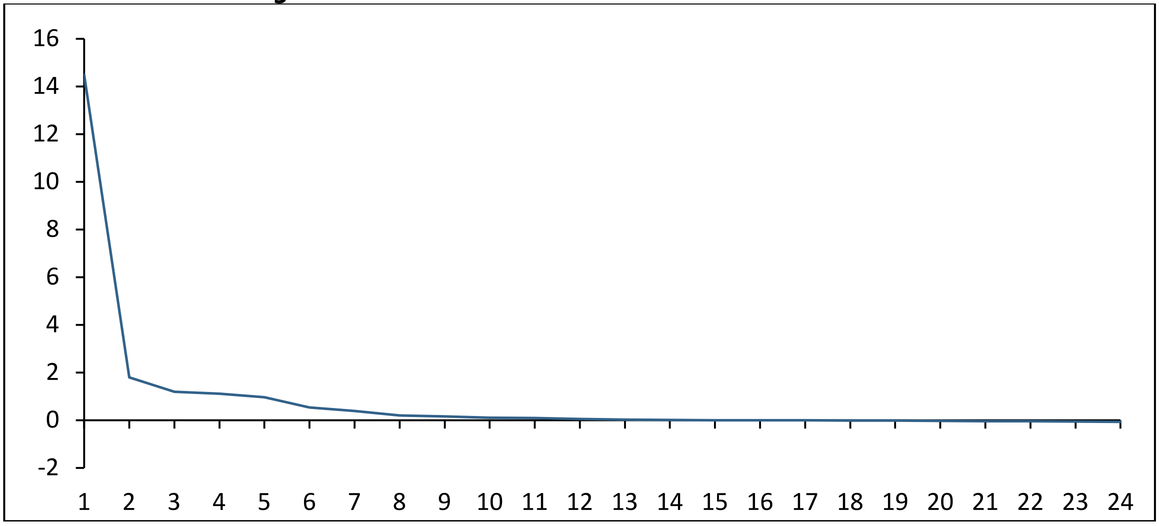
**Exhibit A-2: Observed Variance-Covariance Matrix**

| Descriptor | $Y_1$ | $Y_2$ | ............... | $Y_{25}$ |
|---|---|---|---|---|
| $Y_1$ | $S_1^2$ | $Cov(Y_2, Y_1)$ | ............... | $Cov(Y_{25}, Y_1)$ |
| $Y_2$ | $Cov(Y_1, Y_2)$ | $S_2^2$ | ............... | $Cov(Y_{25}, Y_2)$ |
| . | . | . | | . |
| . | . | . | | . |
| . | . | . | | . |
| $Y_{25}$ | $Cov(Y_1, Y_{25})$ | $Cov(Y_2, Y_{25})$ | ............... | $S_{25}^2$ |

Essentially, Factor Analysis derives a set of factor loadings that yields theoretical variances and covariances that fit the observed ones as closely as possible. After estimating the theoretical variance and covariance matrix, we plot the respective eigenvalues generated from each of the n sub-dimensions assumed. The optimal number of sub-dimensions is determined by the number of points that occur before the bend in the plot (Exhibit A-3). In our example, we note that Cognitive skills can be decomposed into two sub-dimensions.

[12] Note that while we did not explicitly place restrictions on the number of sub-dimensions, STATA imputes results for up to n = 24.

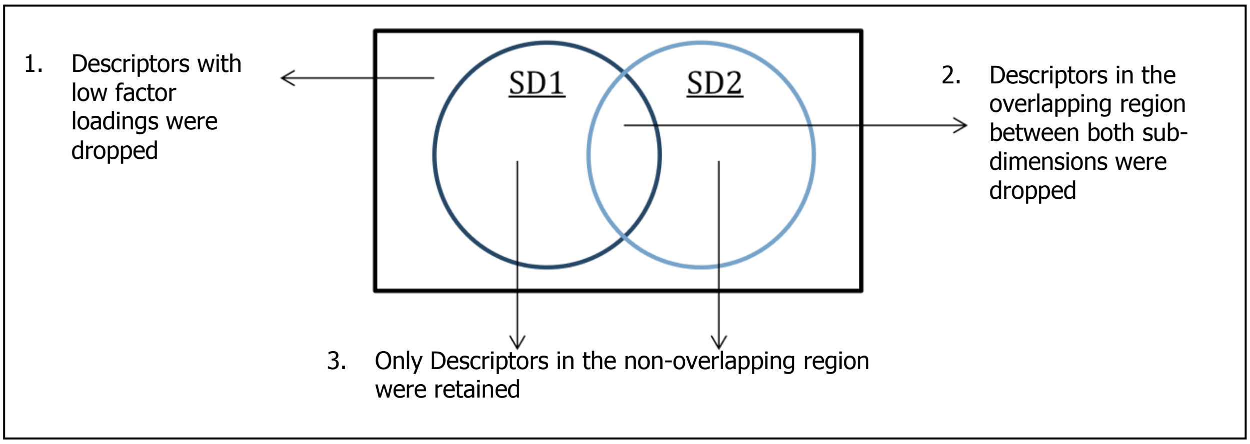
**Exhibit A-3: Plot of Eigenvalues**




**Step 2: Allocating Descriptors Across Sub-Dimensions**

In the second step, we categorised the 25 skill descriptors into the two sub-dimensions. This was done based on their factor loadings. As noted in the Venn diagram below, the descriptors could be placed into 3 possible locations (Exhibit A-4).

**Exhibit A-4: Methodology for Allocating Descriptors Across Sub-dimensions**




First, a descriptor could be placed outside both sub-dimensions. According to the literature, these were descriptors with a factor loading of less than 0.5 for both sub-dimensions. As these descriptors had weak pair-wise correlations with most other descriptors, they could be considered to be sufficiently distinct and hence could not be categorised into any sub-dimension.

Second, a descriptor could be placed in the overlapping region between both sub-dimensions. These were descriptors with factor loadings of at least 0.5 on one sub-dimension and at least 0.32 on the other sub-dimension. As these descriptors shared commonalities with other descriptors across both sub-dimensions, they could not be clearly categorised into a specific sub-dimension.

Third, a descriptor could be placed in a non-overlapping region. For this to occur, the descriptor had a high factor loading on one sub-dimension (higher than 0.5) but a low factor loading on the other (lower than 0.32).

To facilitate the identification of our two sub-dimensions, the literature states that the descriptors in the first two instances had to be dropped (i.e., only descriptors in the non-overlapping region were retained). In all, we retained 28 out of the 72 descriptors shortlisted earlier. In the case of Cognitive skills, only 8 out of the initial 25 descriptors were retained (Exhibit A-5). Based on the factor loadings, Reading

Comprehension, Writing, Written Expression, Memorisation and Number Facility could be clearly categorised under the first sub-dimension, while Design, Thinking Creatively and Visualization could be categorised under the second sub-dimension. Based on the common traits displayed by these two sets of descriptors, we were able to identify our two sub-dimensions as Analytical and Creative skills.

**Exhibit A-5: Finalised Set Skill Descriptors under Analytical and Creative Skills**

| Skill Descriptors | Analytical Skills | Creative Skills |
|---|---|---|
| Reading Comprehension | 0.8677 | 0.3113 |
| Writing | 0.9336 | 0.2923 |
| Written Expression | 0.9129 | 0.3208 |
| Memorization | 0.8564 | 0.1344 |
| Number Facility | 0.7746 | 0.3127 |
| Design | 0.1179 | 0.5584 |
| Thinking Creatively | 0.3092 | 0.6527 |
| Visualization | 0.1850 | 0.6203 |

### Step 3: Calculating the Scores for Each Sub-Dimension

In the final step, we calculated the normalised scores for each sub-dimension across the jobs in our sample. Using the example of Analytical skills, the scores were calculated based on a weighted average of the standardised factor loadings (Exhibit A-6) and the normalised score of each descriptor for a given job, j:

**Exhibit A-6: Standardised Factor Loadings for Analytical and Creative Skills**

| Skill Descriptors | Analytical Skills | Creative Skills |
|---|---|---|
| Reading Comprehension | 0.0270 | 0.0595 |
| Writing | 0.5207 | -0.2291 |
| Written Expression | 0.3459 | 0.1157 |
| Memorization | 0.1914 | -0.2883 |
| Number Facility | 0.0206 | 0.2880 |
| Design | -0.0641 | 0.2606 |
| Thinking Creatively | -0.1419 | 0.3753 |
| Visualization | -0.0887 | 0.2987 |

$$
\begin{aligned}
&Analytical\ skills_j \\
&\quad = 0.027 \times Reading\ Comprehension_j + 0.52 \times Writing_j + 0.35 \times Written\ Expression_j \\
&\quad + 0.19 \times Memorization_j + 0.02 \times Number\ Facility_j - 0.06 \times Design_j - 0.14 \\
&\quad \times Thinking\ Creatively_j - 0.09 \times Visualization_j
\end{aligned}
$$

# ANNEX B: REGRESSION RESULTS

In this section, we detail the variables used in our regression and the regression results:

**Exhibit B-1: Variables included in Regression**

| Category | Variables | Definition |
|---|---|---|
| Skill Dimensions | Analytical Skills | Factor score for analytical skills |
| | Creative Skills | Factor score for creative skills |
| | Service Skills | Factor score for service skills |
| | Gross Motor Skills | Factor score for gross motor skills |
| | Fine Motor Skills | Factor score for fine motor skills |
| | Male-Gross Motor Skills | Interaction term between the respondent's gender and gross motor skills |
| Employment Related Variables | Tenure | Number of years the respondent has been at the job |
| | Employee | Whether the respondent is an employee |
| | Perm | Whether the respondent is a permanent employee |
| | Union | Whether the respondent is in a union |
| | Days worked per week | Number of days worked per week |
| Personal and Household Related Characteristics | Male | Whether the respondent is male |
| | Age | Respondent's age: 35 to 39, 40 to 49, 50 to 59 or above 60 |
| | Married | Whether the respondent is married |
| | Education | Respondent's education level is: Primary, Secondary, College/ITE, Polytechnic, University or others |
| | High spender | Whether the respondent spends more than his income |
| | WIS cash | Whether the respondent received WIS in cash |
| | WIS Medisave | Whether the respondent received WIS in Medisave |
| | Sole bread winner | Whether the respondent is the sole breadwinner of the household |

**Exhibit B-2: Base Regression Model**

| | Base Model |
|---|---|
| | ln (Monthly Wage) |
| Analytical Skills | 0.0427***<br>(0.0111) |
| Creative Skills | 0.0637***<br>(0.0102) |
| Service Skills | 0.0185*<br>(0.0112) |
| Management Skills | -0.0086<br>(0.0083) |
| Gross Motor Skills | -0.0555***<br>(0.0106) |
| Fine Motor Skills | 0.0042<br>(0.0091) |
| Gross Motor Skills - Male | 0.0677***<br>(0.0160) |
| Control Variables | Yes |
| Observations | 4,236 |
| R-squared | 0.444 |
| Robust standard errors in parentheses<br>*** p<0.01, ** p<0.05, * p<0.1 | |

**Exhibit B-3: Regression Model with Age Interactions**

| | Skills Age Interaction | | | | | |
|---|---|---|---|---|---|---|
| | Analytical Skills | Creative Skills | Service Skills | Management Skills | Gross Motor Skills | Fine Motor Skills |
| | Ln (Monthly Wage) | | | | | |
| Analytical Skills | 0.1169***<br>(0.0289) | | | | | |
| Creative Skills | | 0.1155***<br>(0.0245) | | | | |
| Service Skills | | | 0.0831**<br>(0.0360) | | | |
| Management Skills | | | | -0.0458*<br>(0.0253) | | |
| Gross Motor Skills | | | | | -0.0214<br>(0.0199) | |
| Fine Motor Skills | | | | | | 0.0373<br>(0.0228) |
| Gross Motor Skills - Male | | | | | 0.0616***<br>(0.0169) | |
| Age 40 to 49 – Skill Dimensions | -0.0549<br>(0.0348) | -0.0350<br>(0.0296) | -0.0806*<br>(0.0413) | 0.0285<br>(0.0284) | -0.0445**<br>(0.0224) | -0.0410<br>(0.0274) |
| Age 50 to 59 – Skill Dimensions | -0.0891***<br>(0.0339) | -0.0662**<br>(0.0299) | -0.0688*<br>(0.0397) | 0.0369<br>(0.0287) | -0.0492**<br>(0.0234) | -0.0258<br>(0.0262) |
| Age above 60 – Skill Dimensions | -0.0899**<br>(0.0379) | -0.0915**<br>(0.0369) | -0.0765*<br>(0.0441) | 0.0557*<br>(0.0323) | 0.0049<br>(0.0332) | -0.0369<br>(0.0313) |
| Control variables | Yes | | | | | |
| Observations | 4,236 | | | | | |
| R-squared | 0.450 | | | | | |
| Robust standard errors in parentheses<br>*** p<0.01, ** p<0.05, * p<0.1 | | | | | | |