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The Demand for Digital and Complementary Skills in Southeast Asia

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Abstract

As the economies of Southeast Asia continue adopting digital technologies, policy makers increasingly ask how to prepare the workforce for emerging labor demands. However, little is known about the skills that workers need to adapt to these changes. Skills profiles in low- and middle-income countries are typically derived from data collected in the United States, which is known to inaccurately reflect their occupational skills. This paper uses online job postings data from Malaysia to identify the digital, cognitive, and socioemotional skills required for digital and non-digital occupations. The skills profiles for each occupation are then merged with labor force survey data from Cambodia, Malaysia, Thailand, and Vietnam to sketch skills profiles of the workforces in these countries. Using descriptive statistics and linear probability model regressions, the paper finds evidence that highly digital occupations require not only digital skills, but also cognitive and socioemotional skills. Similarly, virtually all occupations, regardless of the digital intensity of the job, require some basic or intermediate digital skills. Pairwise correlations and a factor analysis confirm the complementarity between digital skills and different subsets of cognitive and socioemotional skills. The data also confirm that, even with the excitement about the digital revolution, the bulk of employment in Southeast Asia is in low- (around two-thirds) or medium-digital (around one-third) occupations. Only between 1 and 5 percent of jobs are highly digital in the four countries studied. These findings suggest that as education and training systems adapt to teach basic digital skills, they will need to continue to foster cognitive and socioemotional skills.

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The Demand for Digital and Complementary Skills in Southeast Asia*

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The World Bank

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1. Introduction

Digital technology has become common in the workplace. Nearly two-thirds of workers in the European Union reported using a computer or smartphone at work in 2015 (OECD 2019). Computer use at work is less widespread but still prevalent in low- and middle-income countries: 30 percent of respondents in 10 middle-income countries reported using computers at work in 2012-13, ranging from 34 percent in urban Vietnam to 55 percent in Yunnan, China (Saltiel 2020). Ride-hailing and digital payment apps have made smartphones an important tool in even the most elementary occupations, such as motorbike taxis and small shopkeepers, in developing countries around the world.

The COVID-19 pandemic accelerated the adoption of digital technologies in workplaces. In response to the pandemic, firms in low- and middle-income countries, including in Southeast Asia, increased their use of and investments in digital platforms and solutions, such as e-commerce technology and online payment systems (Apedo-Amah et al. 2021; DeStefano and Timmis *forthcoming,* discussed in World Bank 2021). Firms looked for ways to facilitate remote work for workers who could do their jobs from home.

Despite these trends, there is limited evidence on the skills needed to accompany the increasing digitalization at work, especially in low- and middle-income countries. While Southeast Asian countries are anticipating an Industrial Revolution 4.0 driven by the rise of digital technologies, there is little information about how these technologies will change the task content and skills requirements of jobs. Demand for digital skills is almost certain to rise. However, the types of digital skills required, and the extent to which occupations outside of the information and communications technology (ICT) sector will require digital skills, remains unclear. Furthermore, there is limited information on the extent to which other crucial skills, specifically cognitive skills (general knowledge and mental abilities) and socioemotional skills (behaviors and attitudes to manage emotions, relationships and personal goals), are needed to learn and manage digital technologies required in the workplace.

Previous work using data from high-income countries provides evidence of the complementarity among digital, cognitive, and socioemotional skills. Research using the PIAAC surveys of adults in 30 countries (mostly high-income) shows that workers using more digital skills at work also have higher basic cognitive skills (e.g. numeracy) and perform more tasks that require cognitive and socioemotional skills, such as management and communication, accountancy and sales, and negotiation (OECD 2016, 2019). ICT occupations, such as software and application developers and database professionals, require more advanced digital skills (e.g. programming). However, the PIAAC data also show that workers in ICT occupations perform many tasks that require cognitive and socioemotional skills (OECD 2019). Furthermore, workers in more digitally intensive sectors in those same countries earn higher wages when they have higher numeracy and self-organization skills (both cognitive skills) (Grundke et al. 2018). A similar result is found in the United States: using online job postings for professional occupations, Deming and Kahn (2018) find positive pairwise correlations of 0.5 between posted requirements for basic digital skills (computer literacy and office programs) and skills categories related to cognitive and socioemotional skills, as well as positive correlations of around 0.2 between advanced digital skills (programming and specialized software) and cognitive and socioemotional skills categories.[1]

In this paper, we investigate the extent to which digital and non-digital (cognitive and socioemotional) skills are complements in digital and non-digital occupations and how these skills are distributed across the labor market in four Southeast Asian countries. Since detailed data on the skills requirements of occupations is not available for the study countries, we build a data set of skills requirements by occupation using data from more than half a million online job advertisements posted in Malaysia between 2016 and 2018. We classify the skills as digital, cognitive, socioemotional, and others. We use the resulting data set to create skills profiles at the occupation level, which we then match to employment data from nationally representative surveys in Cambodia, Malaysia, Thailand, and Vietnam. We define four levels of the digitalization of an occupation (very-low, low, medium, and high) based on the share of basic, intermediate, and advanced digital skills in each occupational profile. This allows us to answer two questions. First, we explore how digital, cognitive, and socioemotional skills correlate with each other within occupations, focusing on Malaysia where the primary source of data was collected. Second, we estimate the extent to which digital and nondigital skills are used in each country, given the occupational structure of the individual labor markets.

In addition to providing the answers to these questions, the data and methodology add value in two ways. First, this is the first paper to use data from a Southeast Asian country to construct occupational skills profiles that include cognitive, socioemotional, and digital skills. Most studies use the occupational skills profiles reported in the U.S. Occupational Information Network (O*NET).[2] However, O*NET tends to misrepresent the occupational skills in low- and middle-income countries due to differences in job tasks, skills, and production technologies across countries (Caunedo, Keller, and Shin 2021; Lewandowski et al. 2021; Lo Bello, Sanchez-Puerta, and Winkler 2019). The Malaysia

[1] Deming and Kahn (2018) also find that people management (linked to supervision, leadership, non-project management, mentoring, staff), which can be classified as a socioemotional skill, has a much lower correlation with their measures of basic and advanced digital skills: 0.24 and -0.06, respectively (p. 351).
[2] See for example Acemoglu and Autor (2011) for the U.S.; Goos, Manning, and Salomons (2009) for Western Europe; and Apella and Zunino (2018) for Latin American and Eastern and Central Europe countries.

data on occupational skills profiles is likely to proxy the other three Southeast Asian countries in the study more accurately than occupational skills profiles from the U.S. Second, the analysis identifies skills requirements from unstructured data – job postings – rather than from a predefined list of skills or tasks (as done in a firm survey, for example), allowing the data to "speak for itself" when creating skills categories.

The analysis has three conclusions. First, virtually the entire employed population in the four-country sample are in low- and medium-digital occupations. Around two-thirds of the employed population is in low-digital occupations, which means that their tasks require limited use of even the most basic digital technologies. Less than 3 percent work in highly digital occupations, which require frequent use of digital technologies.

Second, highly digital occupations require similar levels and kinds of cognitive and socioemotional skills as do low- and medium- digital occupations. Three exercises confirm this conclusion. Using data from Malaysia and regression analysis, we observe that low-, medium-, and highly digital occupations have different shares of digital skills but roughly the same shares of cognitive and socioemotional skills. The few exceptions are that medium- and high-digital occupations more frequently require thinking skills (one of the three cognitive skills subsets that we explore) and low-digital occupations more frequently require relationship skills (one of the three socioemotional skills subsets in our sample). Furthermore, pairwise correlations and an exploratory factor analysis confirm complementarities between levels of digital skills and subsets of cognitive and socioemotional skills. Similar analysis using occupational data from Cambodia, Thailand, and Vietnam show similar results.

Third, all occupations are digital to some degree. In Malaysia, the share of skills that are digital in very low-, low-, and medium-digital occupations are 5, 9, and 15 percent. At least 1 percent of skills in every occupation in Malaysia is digital, ranging from 1 percent for cooks to 58 percent for software and applications developers and analysts. Results emerging from Cambodia, Thailand, and Vietnam occupational data show similar orders of magnitude.

Overall, our findings show that the education and training sector will need to provide instruction that covers digital, cognitive, and socioemotional skills, regardless of the extent of technological change in the workplace. Since even low-digital occupations will need some level of digital skills, basic digital skills training is necessary for all.

2. Conceptual Framework and Definitions of Skills

There are intuitive reasons why cognitive and socioemotional skills would be complements to digital skills. Cognitive skills linked to analytical and critical thinking help make sense of the information accessed through digital skills, say surfing the internet or analyzing data. Learning and problem solving can help to develop more digital skills and take advantage of complex computer processes. Socioemotional skills may help workers collaborate through digital technologies, use these technologies to produce creative outputs, and adapt as technologies evolve.[3]

As such, we can think of cognitive and socioemotional skills as building blocks of digital skills, which themselves are divided in several levels of complexity. The levels of digital skills may also be pyramidal: tasks requiring more complex digital skills, for example, may not explicitly use less complex ones, but the underlying knowledge and skills encompassed in basic digital skills can be seen as pillars of more complex digital skills.

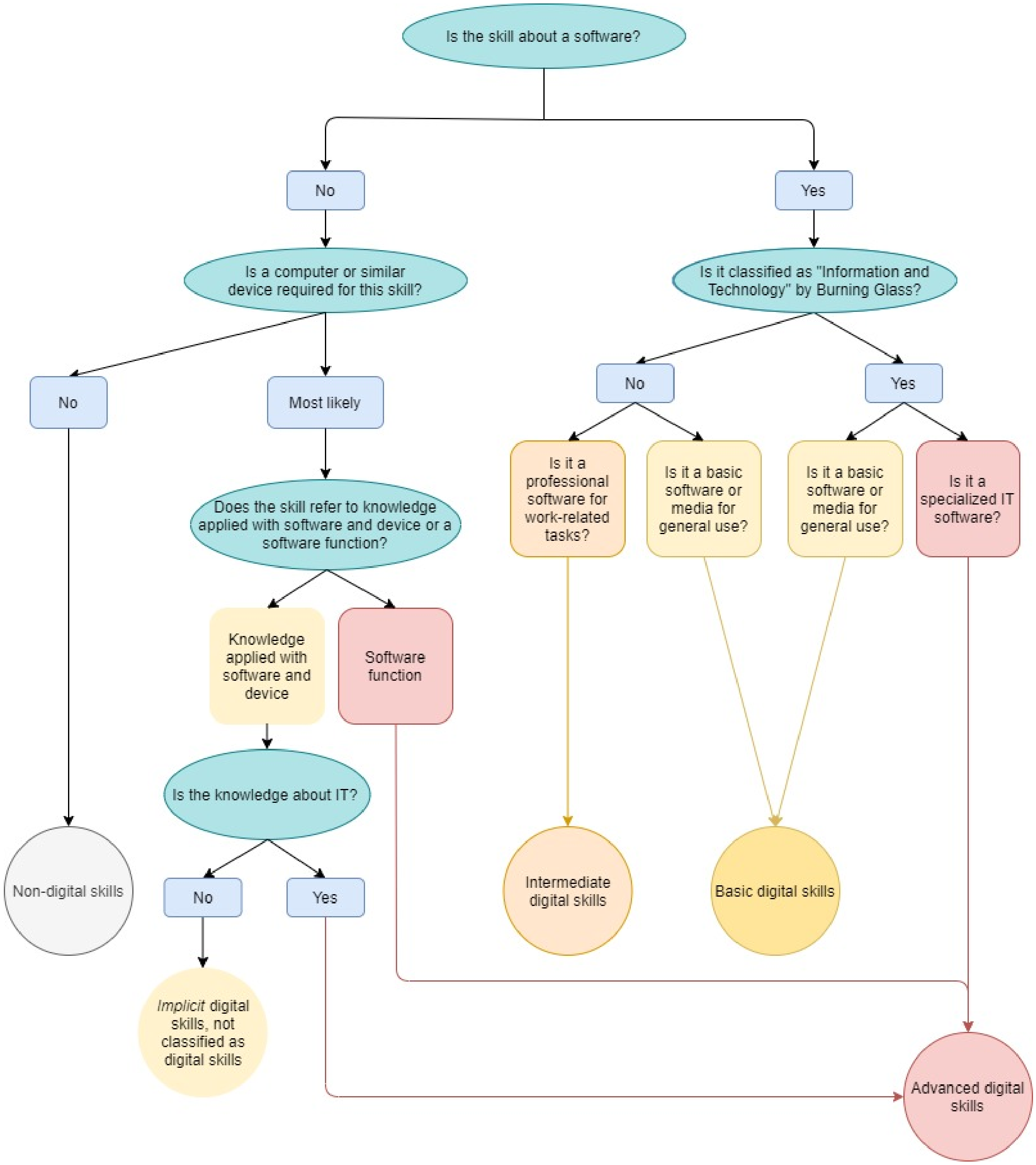
Defining digital, cognitive, and socioemotional skills

We define three main skills categories, each with three subsets of skills. The main categories are digital, cognitive, and socioemotional. Skills that do not fit these categories are defined as other technical and language skills.

Digital skills are the skills that are needed to work with information and communications technology (ICT) software and devices. Digital skills allow people to access and use digital technologies. Digital skills are often mistaken for a narrow set of specialized skills used by ICT workers, such as programming or data science. However, digital skills encompass a wide range of complexity and are increasingly used across many kinds of tasks in a wide range of occupations (UNESCO 2017, IFC 2019, ITU 2020, DE4A 2021). Figure 1 presents the decision tree that we use to identify and classify digital skills.

[3] Cognitive and socioemotional skills are themselves complementary to each other. In the U.S., job requirements for cognitive and social skills are positively correlated with pay and firm performance, and more so when both skills are required (Deming and Kahn 2018). Longitudinal data of adults, also for the U.S., show that wage returns to cognitive and socioemotional skills are increasing (Weinberger 2014, Deming 2017). Online job postings collected in Ukraine show that the shares of postings requiring cognitive and socioemotional skills within an occupation are very similar (Muller and Safir 2019).

Figure 1. Decision tree to identify digital skills and their levels



Source: Own elaboration

Following the framework in UNESCO (2017), we define three subsets of digital skills: basic, intermediate, and advanced (Table 1). At the basic level, workers use technology to perform basic tasks such as using Facebook to advertise products, sending and receiving emails, carrying out online transactions, using mobile apps for driving, and basic word processing. At the intermediate level, workers use existing technologies for analysis, creation, management, and design, for example engineers using modeling software and architects using design software. The advanced level refers to specialized ICT skills such as software design, managing cybersecurity, and data science using big data analytics and artificial intelligence.

Table 1. Definitions of digital skills levels

Level	Definition	Examples of tasks
Basic	Ability to access and use digital technologies to perform basic tasks	1. Functional use of digital devices 2. Online communication via emails 3. Using software for presentations, basic spreadsheet use 4. Finding, managing and storing digital information and content (e.g. social media)
Intermediate	Ability to use professional software for analysis, creation, management, and design	1. Using professional software for analytics, accounting, project management 2. Digital marketing, social media analytics 3. Web design, graphic design
Advanced	Ability to perform specialized ICT tasks	1. Computer programming 2. Cloud computing, network management 3. Artificial intelligence 4. Data science, big data analytics 5. Cyber security 6. Web development, search engine optimization

Source: adapted from UNESCO (2017) and IFC (2019).

Cognitive and socioemotional skills are commonly identified as two fundamental broad skills categories that people use in their work and life. Cognitive skills are our mental abilities to think, learn, and solve problems (Almlund et al. 2011). They range from basic academic knowledge (literacy and numeracy) to more demanding tasks, such as critical thinking, problem-solving, and time management. Socioemotional skills are the attitudes and behaviors upon which we manage personal and social situations (Guerra, Modecki, and Cunningham 2014; Weissberg et al. 2015). Technical skills are commonly identified as a separate skillset, though they may also be thought of as a subset of cognitive and socioemotional skills that are the know-how to carry out one's specific job, which includes digital skills. These three broad categories of skills are used on the job (World Bank 2018).

We identify three subsets of cognitive skills and three subsets of socioemotional skills. Using lists of skills that employers commonly demand identified in previous work, we select three cognitive subsets: communication, organization, and thinking, which summarize 21 individual skills (Table 2) (Cunningham and Villaseñor 2016; Muller and Safir 2019). We also define three socioemotional subsets: emotions, relationships, and personal growth, which summarize 25 socioemotional skills (Table 3).[4]

Table 2. Subsets of cognitive skills

Subset skill category	Skills
Thinking	1. Analytical Skills 2. Creative Problem Solving 3. Critical Thinking 4. Decision Making 5. Independent Thinking 6. Problem Solving
Communication	7. Communication Skills 8. Oral Communication 9. Presentation Skills 10. Public Speaking 11. Verbal / Oral Communication 12. Written Communication
Organization	13. Goal Setting 14. Meeting Deadlines 15. Multi-Tasking 16. Organizational Skills 17. Planning 18. Prioritizing Tasks 19. Scheduling 20. Strategic Planning 21. Time Management

Table 3. Subsets of socioemotional skills

Subset skill category	Skills
Emotions	1. Coping Strategy 2. Detail-Orientated 3. Due Diligence
Relationships	4. Articulate 5. Building Effective Relationships 6. Conflict Management 7. Cultural Awareness 8. Listening 9. Mentoring 10. Negotiation Skills 11. People Management 12. Persuasion 13. Staff Management 14. Supervisory Skills 15. Teaching 16. Team Building 17. Team Management 18. Teamwork / Collaboration 19. Leadership 20. Thought Leadership
Personal growth	21. Creativity 22. Initiative 23. Positive Disposition 24. Self-Motivation 25. Self-Starter

[4] Although we base our classification on previous work (Cunningham and Villaseñor 2016; Muller and Safir 2019), we acknowledge that alternative categorizations are possible.

3. Data

We build a data set of occupational skills profiles for four Southeast Asian countries that we call the Southeast Asia Digital [SEAD] data set. The SEAD is created from online job postings data collected in Malaysia that we link to employment data from household and labor force surveys in Malaysia, Cambodia, Thailand, and Vietnam. The online job postings data are used to identify the types of skills (digital, cognitive, socioemotional, and others) associated with each occupation in Malaysia. These occupational requirements are then extrapolated to the employed population of Malaysia and the three other countries selected because of similar interests in digital development, potential synergies from being in the same sub-region, and the availability of data.[5] The household and labor force surveys provide information on the distribution of employment by occupation in each country.

3.1. Deriving skills requirements from online job postings data

The World Bank-Burning Glass Online Job Postings data in Malaysia

We begin with a data set of more than half a million online job postings collected by the firm Burning Glass Technologies (Burning Glass hereafter) in Malaysia from May 2016 to December 2018.[6] In collaboration with the World Bank, Burning Glass collected more than 600,000 unique online job postings.[7] More than 95 percent of vacancies listed at least one skill requirement for a total of 8,221 unique skills. The raw data, in the form of job postings, include the job title, a free-text description field that lists required skills, and other job characteristics. Burning Glass parsed the text of each job vacancy, coded keywords and phrases as skills, and categorized the job titles into the 2013 Malaysia Standard Classification of Occupations (MASCO).[8] Burning Glass grouped individual skills into 633 clusters (groups of similar skills commonly learned together or substitutable),[9] which were then further grouped into 28 cluster families that are roughly aligned with sector-occupations (Burning Glass 2019).

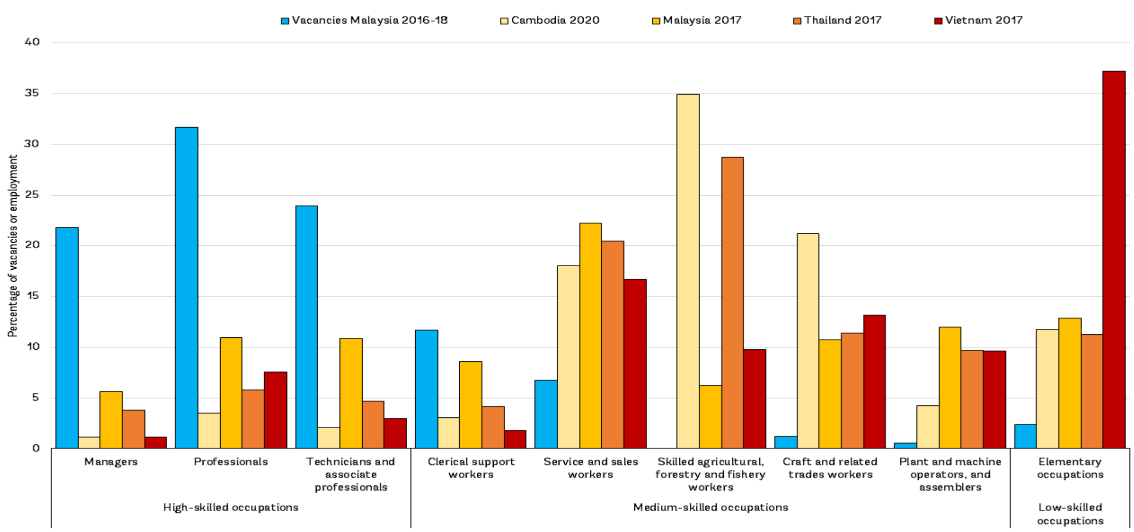
The World Bank-Burning Glass Malaysia Job Postings data is not representative of the distribution of jobs in Malaysia for two main reasons. First, the job postings collected by Burning Glass between 2016 and 2018 are a subset of all job vacancies during this period: they represent one-fifth of the number of

[5] Cambodia and Vietnam are lower-middle income countries and Malaysia and Thailand are upper-middle income countries.
[6] For recent studies using Burning Glass data for the U.S., see Deming and Kahn (2018), Acemoglu et al. (2020), and Deming and Noray (2020). For the U.S. and five other countries (Australia, Canada, New Zealand, Singapore, and the United Kingdom), see Cammeraat and Squicciarini (2021) and Squicciarini and Nachtigall (2021).
[7] See appendix 6 of CSC (2019, pp. 126–134) for details on the online job postings data collected by Burning Glass in Malaysia. The data we use in this paper uses one additional month of vacancies (December 2018). The preliminary version of this data set was used to identify demand for occupations in Malaysia (CSC 2019).
[8] Only 1.8 percent of postings could not be mapped to occupation codes and are thus excluded from the sample from which we draw skills requirements for occupations.
[9] Similar skills commonly learned together include, for example, Microsoft Word and Excel in a course on Microsoft Office.

vacancies reported by a public online job board and in an employer survey in Malaysia (CSC 2019).[10] Second, as in other countries, the job postings are biased towards higher-skilled occupations. Three-quarters of the job postings are for high-skilled occupations (managers, professionals, and technicians corresponding to ISCO-08 1-digit codes 1 to 3). In contrast, in the four countries we study between 7 percent (Cambodia) and 27 percent (Malaysia) of the employed population are in these occupations (Figure 2). In fact, 27 occupations in the labor force surveys of the four countries do not appear at all in the Burning Glass Malaysia job postings data.[11]

Figure 2. Distribution of job postings and employment across occupations

Share of job postings in the Burning Glass Malaysia data set and employment across 1-digit occupations in Cambodia, Malaysia, Thailand, and Vietnam



Sources: World Bank-Burning Glass data set of online job postings in Malaysia (2016-18), Cambodia 2020 Socioeconomic Survey, and 2017 employment surveys of Malaysia, Thailand, and Vietnam.
Notes: Occupations are classified with the ISCO-08 (ILO 2012), here at the 1-digit level. The category "skilled agriculture, forestry and fishery workers" includes subsistence and other low-skilled workers and can basically be grouped with the "elementary occupations" category.

The discrepancies between the occupational distributions of job postings and current employment are expected for a few reasons. First, job postings represent employers' search for new hires, which do not necessarily align with the level of current employment in an occupation since some occupations may

[10] This is typical of online job postings data. For example, CareerBuilder.com, one of the largest job search sites in the United States, was found to capture 35 percent of all vacancies in January 2011 (Marinescu and Wolthoff 2020).
[11] The discrepancy between the occupational distributions of job postings as compared to employment for the Burning Glass Malaysia data is similar to that found in six other countries (Cammeraat and Squicciarini 2021) and Ukraine (Muller and Safir 2019). However, this discrepancy is not always observed, as Marinescu and Wolthoff (2020) find similar distributions of employment in the U.S. and of job postings in of the main job website in the U.S.

have higher turnover (and thus vacancies) than others. Second, online job postings mostly target more skilled occupations, often published by formal firms looking for skilled workers who are comfortable using online sites for job search. Third, low-skilled work in South-East Asia frequently consists of self-employed jobs that would not appear on online job search websites (Cunningham 2018).

The selectivity of vacancies is not an issue for the purpose of our study as long as there are a sufficient number of vacancies for a given occupation to construct a skills profile. Since we are not analyzing dynamics of vacancies but only using them to define skills requirements, the relative magnitude of the number of vacancies by occupation is irrelevant. Instead, we only need enough information to capture a representative picture of the skills profile for each occupation.[12]

Building skills categories

We categorize the 8,221 skills in the World Bank-Burning Glass Malaysia data set into our three main skills categories of interest (digital, cognitive, and socioemotional) and nine subsets of the skills categories. Skills that do not fit these three categories are defined as "other technical and language skills." We categorize the skills manually by assigning the 633 skills clusters to each skills category. When all skills within a cluster belong to one category, that cluster is assigned to the respective category. If the individual skills within a skill cluster cannot be assigned to one category, we assign each skill within the cluster to the appropriate category.[13] Skill clusters that are left unclassified by Burning Glass, as is the case for about a third of skills (2,592), are assigned manually, facilitated by a maximum likelihood method to estimate most likely skills clusters and cluster family.[14]

About a third of the total skills in the Burning Glass Malaysia data are digital, cognitive, or socioemotional according to our classification. The 20 most frequently cited skills are a mix of cognitive (6), socioemotional (4), and other (7) skills, as well as three basic digital skills (computer literacy, Microsoft Office, and Excel) (Figure 3). We identify 2,622 unique digital skills: 24 are basic digital skills, 794 are intermediate digital skills, and 1,804 are advanced digital skills. Among the nondigital skills, 24 are cognitive and 29 are socioemotional. The remaining two-thirds of skills are

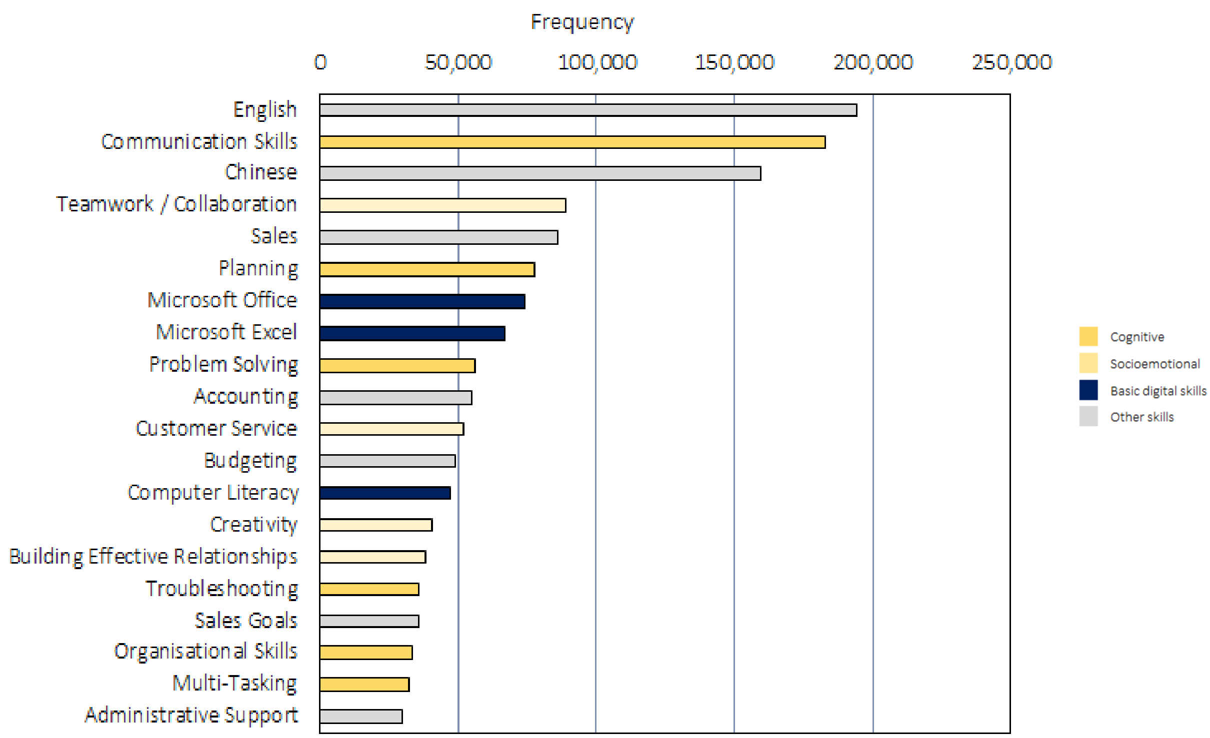
[12] We acknowledge that the skills listed in vacancies may diverge from those actually employed by workers in firms; indeed, enterprise surveys from the region show large gaps between employers' notional skills demands and workers' supply of skills – digital and otherwise – in local labor markets (Cirera et al. 2021).

[13] To assist with the categorization of digital skills, we also use the O*NET-based methodology for calculating digital occupation scores in Muro et al. (2017). However, we only use this measure as an initial categorization, followed by a manual review the categorization of every skill.

[14] To infer the cluster and cluster family for the 2,592 skills that were not assigned to a cluster by Burning Glass, we implemented a nearest neighbor search of similar skills with available information to the skills with missing information. For each skill with missing information, we assign the most common cluster and cluster family of the top 30 skills similar to it. Similarity is defined as the cosine similarity of the vectors representing the skills. The skills are assigned a 100-dimensional vector by training a Word2Vec model where we represent the job postings as "documents" and the skills as the "words" within the document. The Word2Vec model learns semantic relationships between skills as they co-occur across job posts and embed this information into their respective vectors.

other technical skills and languages. Cognitive and socioemotional skills have a higher frequency in the database than digital skills, and basic digital skills appear more frequently than advanced digital skills. Figure 4 shows the frequencies of the top 20 skills in each category.

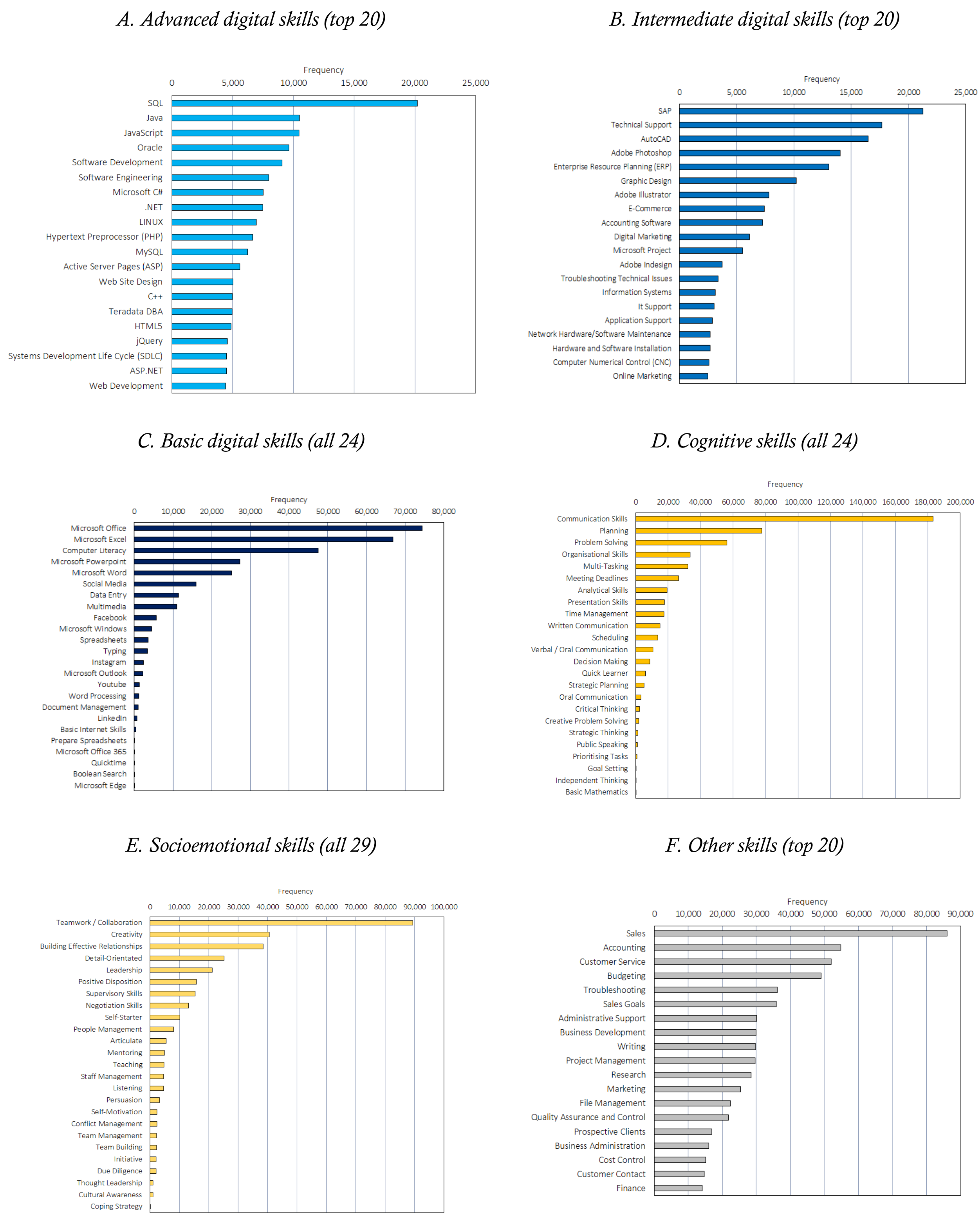
Figure 3. Top 20 skills in the Malaysia's job postings data set



Source: Authors' calculations based on World Bank-Burning Glass online job postings data in Malaysia (2016-18).

Figure 4. Top skills across skills categories in Malaysia's job postings data

Number of postings for each skill



Source: Authors' calculations based on WB-Burning Glass online job postings data in Malaysia (2016-18).

Measuring skills requirements by occupation

We calculate two measures of skills requirements. The first measure is the skills count, that is the average number of times a skill from a given skill category appears in job postings mapped to a given occupation. We use this measure to explore complementarities among the nine subsets of skills categories (advanced, intermediate, and basic digital skills; three subsets each of cognitive and socioemotional skills and their subsets) within occupations.

Our second skills measure is the average relative frequency with which a skill category appears in an occupation. The measure is calculated by averaging for each occupation the number of times a skill category appears in the job posting mapped to that occupation divided by the total count of skills in the job postings for that particular occupation (that is, expressed as a share of total skills rather than the raw skill count).

3.2. Creating occupational skills profiles and digital occupation levels

Using the online job postings data to create occupational skills profiles

We take two additional steps to create our final data set. First, we map each job posting classified with the 2013 Malaysia Standard Classification of Occupations (MASCO) and its related skills profile to the 2008 International Standard Classification of Occupations (ISCO-08; see ILO 2012), the international occupational classification system.[15] This gives us occupational skill profiles for the occupational codes in the employment data from other countries.

Second, we impute the occupational skills profiles of 27 occupations. Among the 127 3-digit ISCO-08 occupations, the online job postings data did not include job postings for 16 occupations — primarily agricultural workers and street vendors — and 11 did not have sufficient job vacancy postings to generate a skills profile for that occupation.[16] These 27 occupations roughly represent between 20 and 40 percent of employment in the four countries studied.[17] Omitting them would distort the distribution of digital skills in a country. Instead, we impute their skills profiles by identifying similar

[15] Job vacancies are mapped to ISCO codes at the 4-digit level.
[16] We defined a threshold of at least 45 job postings per occupation.
[17] The imputed occupations with employment shares exceeding 1 percent in any of the four countries (and the ISCO code) in the sample are: street and market salesperson (521), market gardeners and crop growers (611), animal producers (612), fisheries workers/hunters/trappers (622), subsistence crop farmers (631), subsistence livestock farmers (632), subsistence fishers/hunters/trappers/gatherers (634), street vendors (excluding food) (952). The full list of imputed occupations, and the occupations used to impute their skills profiles, are provided in Annex 1.

occupations in the job postings data and use the skills profiles of those occupations as a proxy for the skills profile of missing occupations.[18]

Description of the occupational skills profiles

The average number of, and types of, skills listed in (or imputed from) the job vacancy data differs by occupation. Occupations require an average of 6 skills, ranging from 2.2 to 12 skills (Table 4). Heavy truck and bus drivers require the fewest skills (2.2) while software and applications developers and analysts are at the other end of the distribution requiring 12 defined skills. On average, occupations require one digital skill, less than one cognitive and socioemotional skill each, and more than three other skills, which include languages and other technical skills, highlighting the high degree of job-specific skills.

Table 4. Count and share of requirements for skills categories and their subsets across the 127 occupations

	Variable	Mean	Std dev	Minimum	Maximum
Average number of skills (count)	**Total**	5.6	1.8	2.2	12.0
	Digital	1.0	1.1	0.0	7.6
	Advanced	0.3	0.8	0.0	6.4
	Intermediate	0.3	0.4	0.0	2.5
	Basic	0.4	0.2	0.0	1.9
	Cognitive	0.7	0.3	0.2	1.3
	Thinking	0.1	0.1	0.0	0.3
	Communication	0.3	0.1	0.1	0.6
	Organization	0.3	0.1	0.1	0.6
	Socioemotional	0.5	0.2	0.1	1.2
	Emotions	0.0	0.0	0.0	0.2
	Relationships	0.3	0.2	0.1	1.0
	Personal growth	0.1	0.1	0.0	0.6
	Others	3.4	0.9	1.5	6.5
Average share among total skills	**Digital**	12.7	10.6	1.0	58.1
	Advanced	3.2	6.4	0.0	47.5
	Intermediate	3.9	4.8	0.0	28.5
	Basic	5.6	5.2	0.3	51.0
	Cognitive	10.9	2.9	3.6	18.5
	Thinking	1.2	0.7	0.1	3.9
	Communication	5.3	1.9	1.0	10.3
	Organization	4.2	1.5	1.2	9.2
	Socioemotional	8.3	5.0	2.1	42.2
	Emotions	0.5	0.5	0.0	4.3
	Relationships	5.8	4.5	1.3	38.2
	Personal growth	2.0	1.5	0.3	8.6
	Others	68.2	10.6	28.6	84.3

[18] We use two sources to define similar occupations. ILO (2012) lists related occupations in ISCO-08. The O*NET Career Changers Matrix lists occupations in the US that have similar skills and experience and that workers could transfer between with minimal additional preparation (O*NET 2021). We only use these two sources to identify potential similar occupations. Once identified, the imputed occupations take the average share of skills requirements for each skills category of their similar occupations in the Malaysia data (or the skill profile of the similar occupation when the similar occupation is only one).

Source: Authors' calculations based on World Bank-Burning Glass online Malaysia job postings data (2016-18). The means and ranges for the main skills categories (e.g. digital or cognitive) are higher than the statistics for the subsets (e.g. advanced or basic) since an occupation may require skills from more than one subset within a main skills category.

The average relative frequency of digital, cognitive, and socioemotional skills is in the range of 8-13 percent. The relative frequency of digital, cognitive, and socioemotional skills is similar (8-13 percent) while nearly three quarters of skills are classified other skills. Basic digital skills have a higher relative frequency than intermediate or advanced digital skills, though occupations requiring intermediate or advanced digital skills will implicitly require basic digital skills, as well.

When ranking occupations by their digital skill level, the ordering is similar to a ranking of these occupations based on the O*NET digital skill level, but with significant variance. In other words, our measure of the demand for digital skills in occupations generally tracks, but differs from, the O*NET measures. Thus, our estimates of the digital intensity of occupations may return results that are closer to the Malaysian – and perhaps the Southeast Asian – reality than the O*Net would have allowed.[19]

Defining occupation digital levels

We use cluster analysis to assign each occupation to a digital occupation level. The cluster analysis allows the data to endogenously sort the occupations into groups with similar digital skills profiles. Since cluster analysis is an unsupervised machine learning technique, informed selection of the variables must be done to increase the likelihood of the clustering model to generate meaningful groups. We use the 13 variables as input to the model.

Five "raw" variables are included. The values for the "share of advanced, intermediate, and basic digital skills" (1) are the fundamental characteristics that encode an occupation's digital level. The sum of these three, i.e., the "total share of digital skills" (2), provides a summary of how much digital skills is required by an occupation across levels of digital skills complexity. We also include three variables that represent the share of combinations of digital skills levels: advanced and intermediate digital skills share (3), advanced and basic digital skills share (4), and intermediate and basic digital skills share (5). Notably, all 127 occupations have at least 1 percent of their skills that are digital skills.

Several derived variables are included to increase the complexity of the model.[20] In particular, the ratio of a level of the digital skill share (i.e., the ratio of advanced digital skills to the total share of digital skills) intuitively provides a quantitative measure of the intensity of the digital skill (e.g., advanced)

[19] It was not possible to directly compare the digital scores and occupational ranking by digital scores using the Malaysia data to that used by O*Net due to differences in methodology for generating digital scores between the two data sets.

[20] The complexity of the model, in this context, pertains to the additional information that is used to fit the model. For example, a regression model with 100 variables is more complex than another regression model that uses only 10 variables.

compared with the other digital skills (e.g., intermediate and basic). These variables will inherently discriminate between occupations having the same total share of digital skills, but their respective digital skill components are different.[21] We include six variables, each a ratio of advanced, intermediate, basic or a combination thereof.[22]

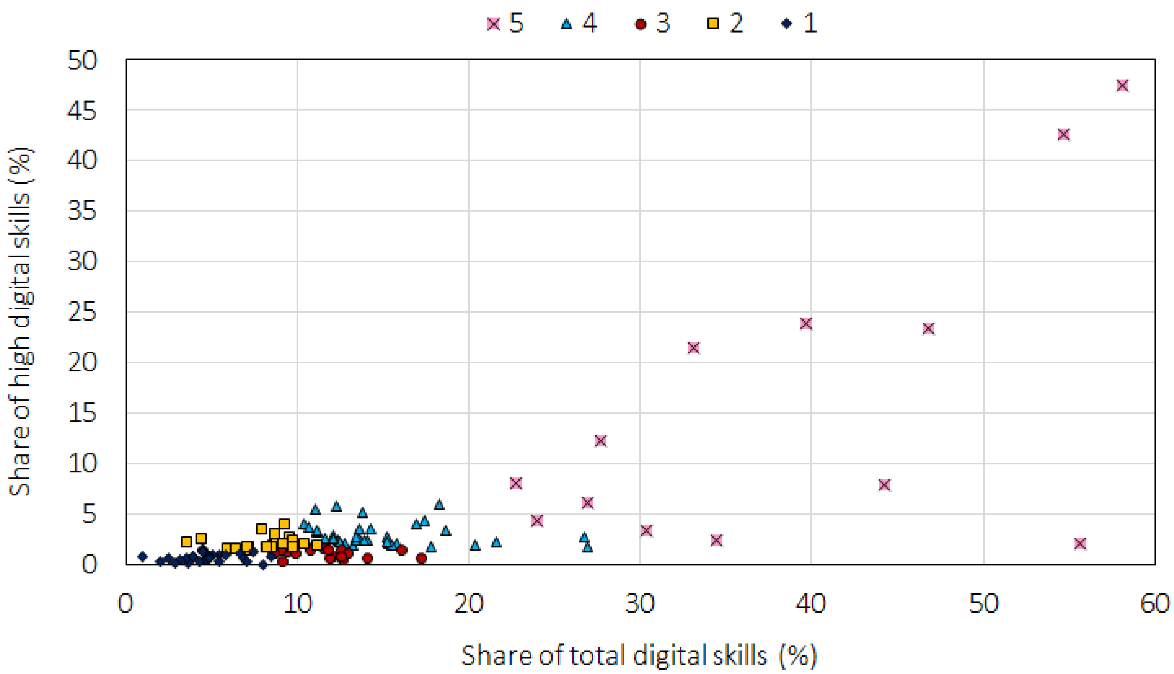
The final two variables are rank variables. We expect that adding the variables corresponding to the "rank of the occupations with respect to the share of advanced digital skills" further reinforces the signal that we want the model to learn. Using the rank variables discourages the model from grouping together occupations that belong in opposing regimes of the share of advanced digital skills. This rationale holds true for the second variable, namely the "rank of the occupations with respect to the total share of digital skills."

We apply K-means clustering using the above 13 variables. The resulting five clusters of occupations can be ranked in their degree of digitalization by averaging the values of the "share of total digital skills" and "share of advanced digital skills" (Figure 5.A). We then analyze the resulting clusters to assess the quality of the groupings. Our analysis suggests that two of the five clusters generally share similar characteristics. To simplify the presentation and given the similarity of their digital skills, we combine the second and third clusters (numbers 2 and 3 in Figure 5.A) into a single cluster, resulting in four digital skills levels (Figure 5.B).[23] The full list of occupations assigned to each of the four levels, and the share of skills in each occupation that are advanced, intermediate, and basic digital skills, is provided in Annex 2.

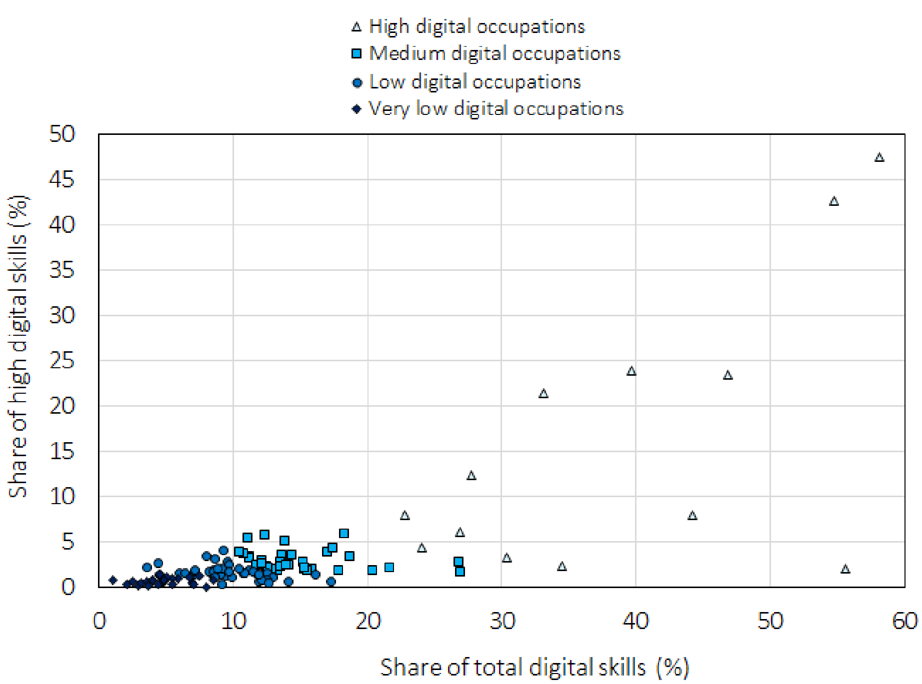
[21] For example, two occupations both have 50% total share of digital skills but the first has (40% Advanced, 5% Intermediate, 5% Basic) digital skills while the other has (5% Advanced, 5% Intermediate, 40% Basic) digital skills.
[22] The variables are: (1) ratio of Advanced digital skills to the total share of digital skills, (2) ratio of Intermediate digital skills to the total share of digital skills, (3) ratio of Basic digital skills to the total share of digital skills, (4) ratio of the sum Advanced and Intermediate digital skills share to the total digital skills share, (5) ratio of the sum Advanced and Basic digital skills share to the total digital skills share, and (6) ratio of the sum Intermediate and Basic digital skills share to the total digital skills share.
[23] The empirical results when using the four-cluster classification are similar to those when using the five-cluster classifications (Annex 7).

Figure 5. Occupations' clusters and digital levels according to their total and high digital skills

A. Share of total and advanced digital skills of occupations by the original five clusters



B. Share of total digital and high digital skills of occupations by their digital level (final four clusters)



Source: Authors' calculations based on World Bank-Burning Glass online Malaysia job postings data (2016-18).

The "high digital" occupational cluster includes 13 occupations (Table 5). All require all levels of digital skills. All also have a high share of digital skills among total skills, ranging from 28 to 58 percent. The high-digital cluster includes, for example, software developers, a high-skilled occupation, and keyboard operators, a medium-skilled occupation. Both have a similar share of their skills that is digital (56-58 percent) but software developers mostly require advanced digital skills while keyboard operators mostly require basic digital skills. The bulk of these 13 occupations are consistent with the ISCO taxonomy of information technology occupations and most of these 13 occupations also have high scores on an index of digitalization created for occupations in the United States based on O*NET data (Muro et al. 2017). [24,25]

Table 5. Digital skill and number of occupations of digital levels based on clusters

Cluster number	Digital level	Average share of digital skills (%)				Number of occupations
		Total	Advanced	Intermediate	Basic	
0	Very Low	4.8	0.8	1.0	2.9	38
1	Low	8.1	2.1	1.7	4.2	20
2	Low	11.5	1.1	3.5	7.0	21
3	Medium	15.0	3.0	5.0	7.1	35
4	High	38.3	15.8	13.3	9.3	13

Source: Authors' calculations based on World Bank-Burning Glass online Malaysia job postings data (2016-18).
Notes: Darker red colors show higher percentage.

Thirty-five occupations map to the "medium digital" occupation cluster. These occupations have low requirements for advanced digital skills, but a moderate demand for intermediate- and basic-digital skills. This category includes machine operators, technical education teachers, and office clerks, who regularly use specialized software to carry out their jobs.

Most occupations can be classified as low digital. To provide some nuance to this group, we maintain the two clusters that emerged from the exercise and name them "low digital" and "very low digital" occupations. The exercise maps 41 occupations to the low-digital occupation category. These occupations require a moderate use of basic-digital skills. A broad range of occupations are in this category, including transport specialists (like Grab drivers who use digital phone apps to identify their next transport gig job), chief executives who may use MS Office for daily work, or salespeople who operate cash registers and inventory control software. The very low digital jobs include 38

[24] Eight of the thirteen occupations are information technology occupations as defined by the ISCO occupation classification (ILO 2012, pp. 25-26). The two occupations we define as high digital that are not ICT occupations are mathematicians, actuaries, and statisticians (ISCO code 212) and engineering professionals (excluding electrotechnology) (ISCO code 214).
[25] The occupation digital score is based on occupations' three digitalization aspects as measured by O*Net for occupations in the US —computer & electronics, programming, and interacting with computer— following the methodology by Muro et al. (2017).

occupations. These occupations require few digital skills, and the digital skills that they do require are mostly basic digital skills. Cooks, who might use computers or smartphone for purchasing or inventory management, and Early Child Development teachers, who may use digital technologies to access or provide lessons, are examples of occupations in the very low digital occupations category.[26]

3.3. Matching the occupational skills profiles with country employment data: The Southeast Asia Digital (SEAD) data set

To analyze the skills profile of the employed population in the four countries we study, we create the Southeast Asia Digital (SEAD) data set that matches the occupation skills profiles to country employment data. We use the occupation variable to do the match with data from four Southeast Asian countries: the 2020 Cambodia Socioeconomic Survey and the 2017 labor force surveys in Malaysia, Thailand, and Vietnam. Each country data set is representative of the population at the national level, allowing us to quantify the number of people working in an occupation. As such, we have a data set of occupation skills profiles for 127 occupations and weights representing the occupations' employment share in the four countries.

4. Methodology

To explore the complementarity of digital and other skills and the levels of occupation digitalization, we use descriptive statistics, pairwise correlations, a factor analysis, and linear probability model (LPM) regressions.

Similarity of skills required in very low-, low-, medium-, and highly digital occupations

After an inspection of summary statistics, we apply an LPM to estimate the probability that a skill i in occupation o is found in a particular digital occupation group g. We use an LPM to estimate marginal effects of binary outcomes following Friedman (2012) and Bellemare (2015, 2018). The LPM is as follows:

$$y_{og} = \alpha_g + \sum_i \beta_{oig} D_{oi} + \epsilon_g \tag{1}$$

where y_{og} is a binary variable representing occupation o dependent on the (digital occupation level) groups g of interest (e.g. medium- vs. low-digital occupations, high- vs. low-digital occupations, etc.). D_{oi} is a dummy variable for skill i of occupation o taking the value of one if the skills count of a skills category of an occupation is above the mean. β_{oig} is the coefficient for the groupings g quantifying the

[26] An alternative methodology that uses a smaller set of variables to assign occupations to high, medium, and low digital categories resulted in a similar mapping. Results are available from the authors.

effect of the dummy variable for skill i in occupation o. α is a constant, and ε is the error term. The dummy variable for a given skill i of occupation o is derived as follows:

$$D_{oi} = \begin{cases} 1, & x_{oi} \geq \overline{x_i} \\ 0, & x_{oi} < \overline{x_i} \end{cases} \tag{2}$$

where x_{oi} represents the average count of skill i in occupation o and $\overline{x_i}$ is the mean of x_{oi} over all occupations, where i is a vector of six skills subsets. Three of the skills subsets are cognitive skills: thinking, communication, and organization. The other three are socioemotional skills: emotions, relationships, and personal growth. The dummy variable is used for easier interpretation of the LPM's coefficients than the raw skills count variables would allow. This transformation, in the context of LPM, allows us to interpret the coefficients as percentage point increase (or decrease) towards the probability of being a given occupation digital level if the raw skills count for the variable is above (or below) the mean of the skills count over all occupations.[27]

We run the above analysis to be representative of the employed population of Malaysia (around 14 million of workers). Since we are interested in understanding the skills required by employers in a country-specific job market, we use the Malaysia subsample of the SEAD, with each occupation being weighted by the percentage of the employed population in it.[28] We carry out two additional analyses using different subsamples. First, we run the LPM with an unweighted sample to understand the correlation between skills within occupation, irrespective of the occupational composition of the workforce. Second, we carry out a similar analysis using the Cambodia, Thailand, and Vietnam subsamples. The results are similar to those from the Malaysia subsample so, in the interest of parsimoniousness, mostly present the results from the Malaysia subsample.[29] Results for the occupation skills profile (unweighted by the distribution of occupations in a particular country) and replications for other countries are presented in Annex 3.

[27] Since the outcome is binary and we are using a probability linear model, we can interpret the coefficient of a dummy variable to be a percentage point contribution towards the probability of the outcome. For illustration, assume a PLM model with a constant value of zero. If we analyze one non-zero dummy variable and let all the other variables take a value of zero, then the coefficient of the non-zero dummy variable will equate to the probability of the outcome. Adding another non-zero dummy variable will linearly increase or decrease the probability according to the value of the coefficient. A regression using the raw skills count is available from the authors.

[28] Studies on job skills demand and technological similarly combine data on job tasks at the occupational level from the O*NET database and individual-level employment survey that weight each occupation by the percentage of the employed population in each occupation (Autor, Levy, and Murnane 2003; Hardy, Keister, and Lewandowski 2018; Caunedo, Keller, and Shin 2021).

[29] By construction, the variation between the results with occupational skills profile and those for the employed populations are only due to differences in the distribution of the employed population across occupations.

Complementarities between digital and non-digital (cognitive, and socioemotional) skills

Next, we investigate complementarities between digital, cognitive, and socioemotional skills in Malaysia's jobs.[30] We first examine pairwise correlations. The pairwise correlations show the magnitude of relationships between two subsets of skills. We use Pearson correlations and test the significance of the correlation through t-test.

We then carry out a factor analysis using the skills count of the nine digital, cognitive, and socioemotional skills subsets (three each) detailed in section 2. The exploratory factor analysis allows us to model the relationships among skills subsets by reducing them to fewer variables thus highlighting stronger links between several skills subsets. We use a standard exploratory factor analysis that finds a number q of factors that linearly reconstruct our nine original variables according to the following relationship:

$$y_{ij} = z_i b_{1j} + z_i b_{2j} + \cdots + z_i b_{qj} + e_{ij} \tag{3}$$

where y_{ij} is the value of the *i*th observation on the *j*th variable, z_{ik} is the *i*th observation on the *k*th common factor, b_{jk} is the set of linear coefficients called the factor loadings, and e_{ij} is similar to a residual but is known as the *j*th variable's unique factor (StataCorps 2019). We use varimax rotation to produce orthogonal factors,[31] to get maximized factor loadings. Again, we use the SEAD data for Malaysia, weighted by the distribution of employment across occupations, to study those relationships within the existing job structure. Occupation-level results (unweighted by the distribution of occupations in a particular country) and replications for other countries are also estimated and presented in Annex 4.

Occupation digitalization and skills requirements in Cambodia, Malaysia, Thailand, and Vietnam

Finally, we use descriptive statistics to calculate the levels of occupation digitalization and skills requirements across the four countries we study. We use the SEAD data set to understand the distribution of skills across the four countries of interest. We also generate occupation-weighted data sets over several years for Malaysia, Thailand, and Vietnam to understand how the distribution of skills across each country evolves over a 4-6 year period.[32]

[30] We repeat this analysis for unweighted occupations, and weighting for the Cambodian, Thai, and Vietnamese occupational distributions. Again, results are similar to those when using the Malaysia-weighted data.
[31] By definition, orthogonal factors are not correlated with each other.
[32] We were unable to access multiple years of the Cambodian SES.

5. The Skills Profile of Very Low-, Low-, Medium-, and High Digital Occupations: The Case of Malaysia

The level of the digital occupation is positively correlated with the share of digital skills required by employers in Malaysia.[33] Using simple summary statistics, we find that one-third of the skills required in Malaysia's highly digital occupations are digital skills, while 16 percent of the skills required in Malaysia's medium-digital occupations can be classified as digital skills (Figure 6, panel A). An even lower share of digital skills is required in low- and very-low-digital occupations (9 and 5 percent, respectively) in Malaysia. These trends are observed in the other three sample countries, with slight differences in point estimates (Annex Table A.3.1). First, Thailand's highly digital occupations require a higher share of digital skills (37.1) than Malaysian highly digital occupations (33.3 percent). Second, Malaysia's low digital occupations require the fewest digital skills among the four countries (9.4 percent) compared to 9.7 percent (Vietnam), 9.8 percent (Cambodia), and 10.1 percent (Malaysia). Highly digital occupations require the most digital skills across the three skill levels. The relative importance of advanced digital skills in Malaysia is much higher for highly digital occupations: 13 percent of their required skills are advanced digital as compared to 1-3 percent for very-low, low, and medium digital occupations (Figure 6, panel A). A similar trend and point estimates are observed in the other countries, suggesting robust proportionality in advanced digital skills across digital occupation categories.

However, highly digital occupations also require a larger share of intermediate digital skills than medium digital occupations require (14 vs. 3.8 percent).[34] That might be because medium-digital occupations, while requiring some digital skills, mostly require skills in a job specialty (e.g. finance or marketing). This trend emerges in the other countries (Annex Table A.3.1). Similarly, the share of basic digital skills is less demanded for very-low and low-digital occupations than medium digital occupations in Malaysia (Figure 6, panel A).[35] This reflects that while basic digital skills are a required in those occupations, they mostly require other skills.

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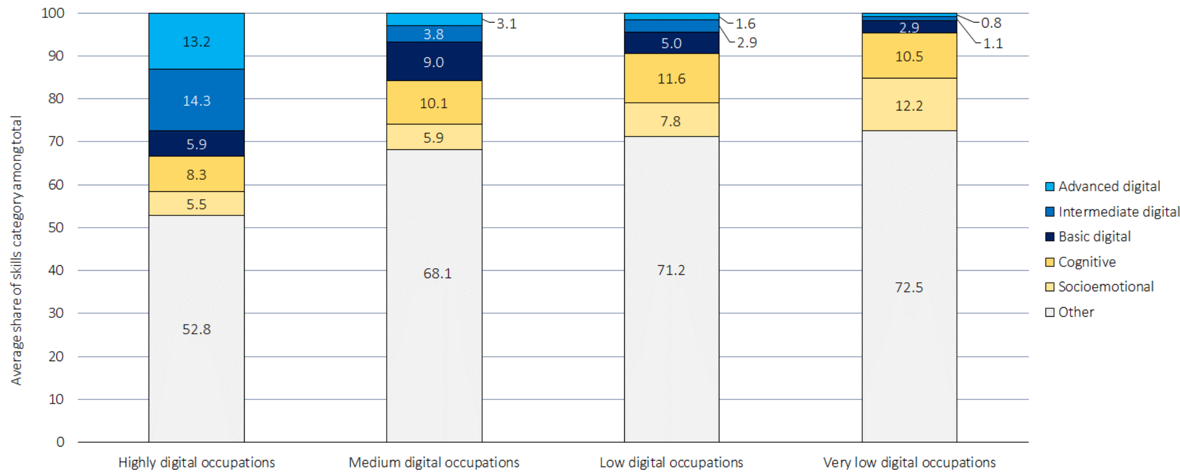
[33] These results deviate from those in Table 5, which presents the average share of digital skills – total and by level – for each of the four digital occupation levels, due to the weighting of occupations by country. Table 5 assigns an equal weight to each occupation with the country-specific estimates use country weights. Thus, occupations with certain skills mixes, even within digital occupation level, may play a more prominent role in the country averages than in the unweighted average.

[34] Cambodia is the only country where intermediate digital skills play a larger role than advanced digital skills in highly digital jobs. Annex Table A.3.1 shows that 17.5 percent of skills in Cambodia's highly digital occupations are classified as intermediate digital skills, as compared to 5.2 percent in medium occupations. At the same time, only 8 percent of advanced digital skills are required in Cambodian highly digital occupations. Thus, Cambodia's 13 highly digital occupations require more intermediate, rather than advanced, digital skills.

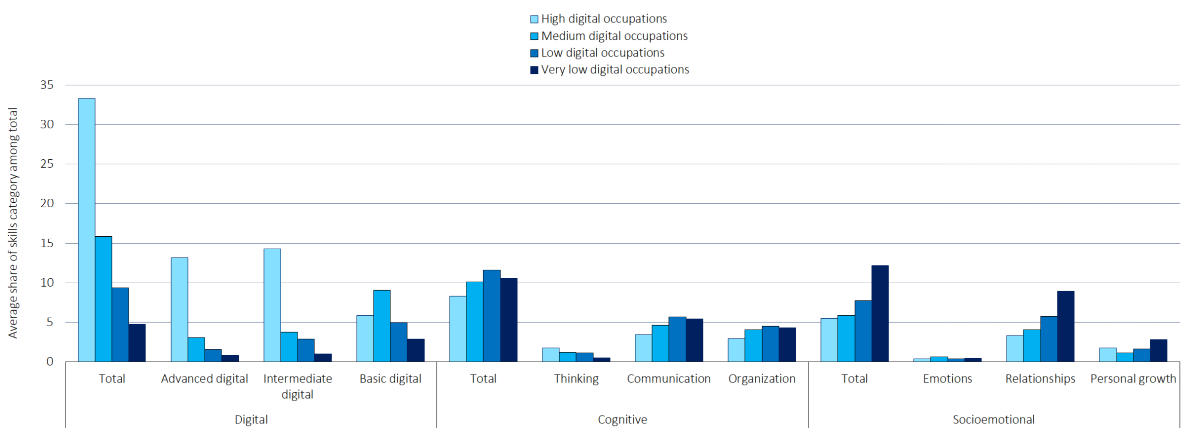
[35] Basic digital skills are also more demanded in highly digital occupations in Cambodia, Vietnam, and especially Thailand (8.8 percent).

Figure 6. Relative importance of skills categories across digital occupation levels in Malaysia

A. Composition of skills categories across occupation digital levels



B. Composition of skills categories and subsets across occupation digital levels



Source: Authors' calculations based on SEAD data.
Notes: The share of skills splits between digital, cognitive, and socioemotional, and other skills. Digital skills levels and cognitive and socioemotional skills subsets are subcategories counted in the total.

All four digital occupation levels in Malaysia require cognitive and socioemotional skills that are relatively similar in share and type. About 8-12 percent of skills required in all four digital occupation levels are classified as cognitive skills, though Malaysia's highly digital occupations are those that rely less on cognitive skills as compared to other occupations in the category. There is slightly more variance in the share of skills defined as socioemotional: while 6 percent of skills defined in highly digital occupations are socioemotional, 12 percent of skills required by very-low-digital occupations are socioemotional (Figure 6, panel A and B), as compared to 5-8 percent of skills for the other digital occupation levels. Breaking down by skills subsets suggests some small differences within categories. For example, relationship skills (a socioemotional skill) are a few percentage points more expected in very-low-digital occupations than in highly digital occupations (Figure 6, panel B). These trends also emerge for the other three sample countries with a few exceptions (Annex Table A.3.1).[36]

The similar requirement for cognitive and socioemotional skills across digital occupation levels in Malaysia is confirmed when controlling for potential correlations between variables. The regression analysis finds that the required subsets of cognitive and socioemotional skills are quite similar across very-low, low-, medium-, and highly digital occupations.[37] The most notable exception is that, on average, occupations that require more thinking skills (a subset of cognitive skills) are 209 percentage points more likely to be a highly digital occupation relative to a very low-digital occupation (Table 6). This correlation was strongly identified for the other three countries, as well. A weak positive correlation is also found between thinking skills and low (versus very low) and high (versus low) digital occupations in all countries except Thailand (Annex Table A.3.2). While more emotional skills (a subset of socioemotional skills) are expected from medium-digital occupations compared to low digital occupations in Malaysia, the size and imprecision of the estimates for the other occupation types do not reveal more general patterns. However, this relationship emerged with more precise estimates for the other three countries. Relationship skills are weakly negatively correlated with low (versus very low) and high (versus low) digital occupations, though correlations are stronger for Cambodia. A few other weak correlations emerge, but most subsets are not statistically different across occupation levels at the 5 percent significance level or below, meaning that there is no discernable difference in demand for those skills across digital occupation levels.[38]

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[36] Namely, relationship skills are less important for very low digital occupations in the other three countries, as compared to Malaysia, while personal growth is more prevalent among highly digital occupations.

[37] These associations should not be interpreted as causal but rather as conditional correlations for at least two reasons. First, there are factors beyond cognitive and socioemotional skills that could influence the digital occupation level. Second, subsets of cognitive and socioemotional skills may be correlated with each other to some degrees, especially those in the cognitive subsets, and thus may bias the conditional correlations with digital occupation levels (see Table 7).

[38] Similar results emerge from LPM estimates using the unweighted occupational skills profile sample and the country-specific weighted occupations for Vietnam and Thailand. The communications, relationships, and personal growth variables play a greater explanatory role in the Cambodia -and, to some extent, the Vietnam - estimates, with the coefficient signs and magnitudes were similar to the Malaysia-weighted sample (Annex Table A.3.2).

Table 6. Conditional correlations between digital occupation level and cognitive and socioemotional skills requirements in Malaysia

LPM regressions of digital occupation levels on dummies taking the value of one if the skills count of a skills category of an occupation is above the mean

		Occupation digital level				
		Low vs. Very low	Medium vs. Low	High vs. Medium	High vs. Low	High vs. Very low
		(1)	(2)	(3)	(4)	(5)
Cognitive	Thinking	**0.36***	0.22	0.01	**0.53***	**2.09*****
		(0.17)	(0.13)	(0.15)	(0.23)	(0.40)
	Communication	**0.47***	-0.19	0.01	-0.17	-0.09
		(0.21)	(0.14)	(0.33)	(0.24)	(0.16)
	Organization	0.00	-0.16	0.12	-0.13	-0.60
		(0.16)	(0.15)	(0.10)	(0.14)	(0.41)
Socioemotional	Emotions	-0.00	**0.48****	-0.30	0.12	0.81
		(0.15)	(0.15)	(0.21)	(0.19)	(0.41)
	Relationships	**-0.30***	-0.35	0.08	**-0.58***	-0.67
		(0.14)	(0.18)	(0.38)	(0.24)	(0.43)
	Personal growth	-0.16	-0.03	**0.36***	0.34	-0.55
		(0.16)	(0.17)	(0.18)	(0.20)	(0.41)
	Constant	0.44**	1.47***	2.22***	1.39***	0.74
		(0.14)	(0.14)	(0.22)	(0.33)	(0.54)
	N	79	75	47	54	51
	R-sq	0.36	0.36	0.13	0.15	0.44

Source: Authors' calculations based SEAD data.
Note: The regressors for the outcome are dummy variables taking the value of one if the skills count of a skills category of an occupation is above the mean. The 2017 Malaysian labor force survey does not report any workers in one of the 127 occupations from our occupational skills profile (paramedical practitioners, ISCO code 224).
*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

6. Complementarities among Digital, Cognitive, and Socioemotional Skills: The Case of Malaysia

Cognitive and socioemotional skills correlate more strongly with basic digital skills than with intermediate and advanced digital skills in Malaysia. Basic digital skills correlate highly with all three subsets of cognitive skills and with one socioemotional skill in Malaysia. The correlation coefficient between basic digital skills and thinking, communication, organization (cognitive), and emotions (socioemotional) is around 0.5 (Table 7). Basic digital skills are not correlated with relationships or personal growth in Malaysia. In contrast, intermediate digital skills correlate with thinking and personal growth, around 0.4, and to a lesser extent with organization and emotions, around 0.3.[39] By contrast, advanced digital skills only meaningfully correlate with thinking skills (0.5) in Malaysia. In other words, thinking skills strongly correlate with all levels of digital skills while complementarities with other socioemotional and cognitive skills are particular to the level of digital skills. The correlation between advanced digital skills and other cognitive skills is positive, but weak, while the correlation is close to zero for most socioemotional skills in Malaysia. The findings are robust across the other country samples and the unweighted occupational sample, though the correlation point estimates are higher in these other country samples than in Malaysia (Annex Table A.4.1).

Table 7. Correlations between skills in Malaysia

Pairwise correlations based on the number of skills counts of skills categories

		Digital			Cognitive			Socioemotional		
		Advanced	Intermediate	Basic	Thinking	Communication	Organization	Emotions	Relationships	Personal growth
Digital	Intermediate	0.46***								
	Basic	0.07	0.28**							
Cognitive	Thinking	0.46***	0.42***	0.45***						
	Communication	0.17	0.15	0.51***	0.67***					
	Organization	0.11	0.30***	0.53***	0.69***	0.64***				
Socioemotional	Emotions	0.15	0.28**	0.55***	0.57***	0.45***	0.50***			
	Relationships	-0.01	-0.08	0.01	0.28**	0.49***	0.29***	0.16		
	Personal growth	0.06	0.39***	-0.09	0.00	0.09	0.18*	0.04	0.26**	
Others		0.06	0.23**	0.50***	0.65***	0.78***	0.61***	0.34***	0.23*	0.03

Source: Authors' calculations based SEAD data.
Notes: Darker red and blue colors show higher and lower magnitudes, respectively.

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

The Malaysia findings are consistent with evidence from online job postings for professional occupations in the U.S. Deming and Kahn (2018) find that basic digital skills correlate more highly with cognitive and socioemotional skills than do advanced digital skills. Basic digital skills (computer literacy and office programs) have a correlation with skills categories related to cognitive and socioemotional skills of 0.5 while advanced digital skills (programming and specialized software) have also positive but lower correlations around 0.2.

While cognitive skills subsets highly correlate among themselves in Malaysia, this is less the case for digital skills subsets, and almost nonexistent among socioemotional skills subsets. The three cognitive subsets have high correlation coefficients of around 0.7 for Malaysia, which is consistent with theories and empirical work showing that different specific cognitive skills tend to be highly correlated

[39] In Cambodia, organization and emotions are more strongly correlated with intermediate digital skills than thinking and personal growth (Annex Table A.4.4).

(Almlund et al. 2011) (Table 7). The three socioemotional skills, by contrast, correlate little between each other in Malaysia, except for personal growth and relationship skills that correlate around 0.3, reflecting that they mostly capture different facets of socioemotional skills. The correlations between the digital skills subsets are modest for Malaysia but significant between basic and intermediate (0.3), much higher between intermediate and advanced (0.5). The correlation is close to zero between basic and advanced digital skills in Malaysia.[40] This may be due to employers who wish to hire workers with advanced digital skills assume that the potential hires already have basic digital skills, so they do not mention the basic skills in the job postings. The last correlation is lower than estimated for professional occupations in the U.S. that have a correlation of 0.2 between their basic and advanced digital skills (Deming and Kahn 2018).

An alternative methodology to consider not only pairwise relationships between skills subsets but possible systematic association between more subsets shows stronger complementarities.[41] Exploratory factor analysis finds that three groups of skills break out across the 9 digital, cognitive, and socioemotional subsets for Malaysia. The first factor is a mix of the three cognitive skills subsets, relationship skills (socioemotional) and basic digital skills (Table 8). It appears to be a factor of less digital skills for a broad range of occupations in Malaysia. The occupations with more of this skills mix are low- and medium digital occupations, such as government professionals and plant and machine operators (Annex Table A.5.1). The second factor is based on intermediate and advanced digital skills and to a lesser extent thinking skills (cognitive) and personal growth (socioemotional).[42] The typical occupations in Malaysia requiring a high weight on these kinds of skills are highly digital occupations, such as software developers and network professionals. The third factor heavily loads on the socioemotional skills subsets of emotions and personal growth.[43] Typical Malaysian occupations using this skill set include occupations from all three levels of occupation digitalization, such as architects and primary school teachers. Similar factors emerge for the other three countries.[44]

[40] The other three countries and the unweighted occupation profile data find similar results (Annex Table A.4.1).
[41] Very similar results are found when not rotating factors and using oblique rotations (i.e. allowing for correlations across factors) (results available upon request).
[42] The socioemotional skills that weighed most heavily in this factor in Vietnam was organization and in Thailand was relationship skills (Annex Table A.4.2).
[43] The third factor is the least stable across the alternative subsamples. For example, in Cambodia, it only weighs heavily on advanced digital skills. In Thailand, the highest factor loadings are on personal growth and a lower loading on intermediate digital skills, though very low basic skills, as in the Malaysia-weighted sample. The Vietnam-weighted sample also weighs very heavily on personal growth and very low on all other skills (Annex Table A.4.2).
[44] A notable exception is that an "advanced digital" factor emerges for Cambodia. No other skills weight positively heavily in this factor while socioemotional skills are particularly negative (Annex Table A.4.2).

Table 8. Exploratory factor analysis of skills in Malaysia

Exploratory factor analysis based on skills counts of skills categories

A. Factor loadings and uniqueness

	Skills category	Skill subset	Factors 1	Factors 2	Factors 3	Uniqueness
1	Digital	Advanced	0.15	0.74	-0.07	0.43
2	Digital	Intermediate	0.20	0.87	0.07	0.20
3	Digital	Basic	0.76	0.09	-0.26	0.34
4	Cognitive	Thinking	0.80	0.36	0.07	0.22
5	Cognitive	Communication	0.82	-0.02	0.32	0.23
6	Cognitive	Organization	0.80	0.14	0.23	0.29
7	Socioemotional	Relationships	0.74	0.16	-0.06	0.42
8	Socioemotional	Emotions	0.34	-0.25	0.78	0.22
9	Socioemotional	Personal growth	-0.12	0.43	0.75	0.24

B. Factors with heavy loadings on specific skills

Factor	Skills subset	Skill category
Factor 1	Communication	Cognitive
	Organization	Cognitive
	Thinking	Cognitive
	Basic	Digital
	Relationships	Socioemotional
Factor 2	Intermediate	Digital
	Advanced	Digital
Factor 3	Emotions	Socioemotional
	Personal growth	Socioemotional

Sources: Authors' calculations based on SEAD data.
Note: The factor analysis is based on varimax rotation for orthogonal factors. Darker red and blue colors show higher and lower magnitudes, respectively.

The factor analysis thus confirms that in Malaysia, cognitive and socioemotional skills tend to associate more with basic digital skills than with intermediate and advanced digital skills, with some differences in the pairwise correlations. Both approaches confirm that basic digital skills are strongly associated with cognitive and socioemotional skills subsets. However, the two methods find different results in the kinds of socioemotional skills that associate with basic digital skills. For example, basic digital skills load highly in a factor with high relationship skills factor loadings, while their pairwise correlation is modest. Similarly, in Malaysia, basic digital skills have a low loading in factors where emotional skills load high, while both strongly correlate.[45] Some disconnects are observed in cognitive skills, as well. For example, thinking skills (cognitive) load lightly in the factor of intermediate and advanced digital skills but they are strongly correlated and highly significant Pearson correlations.

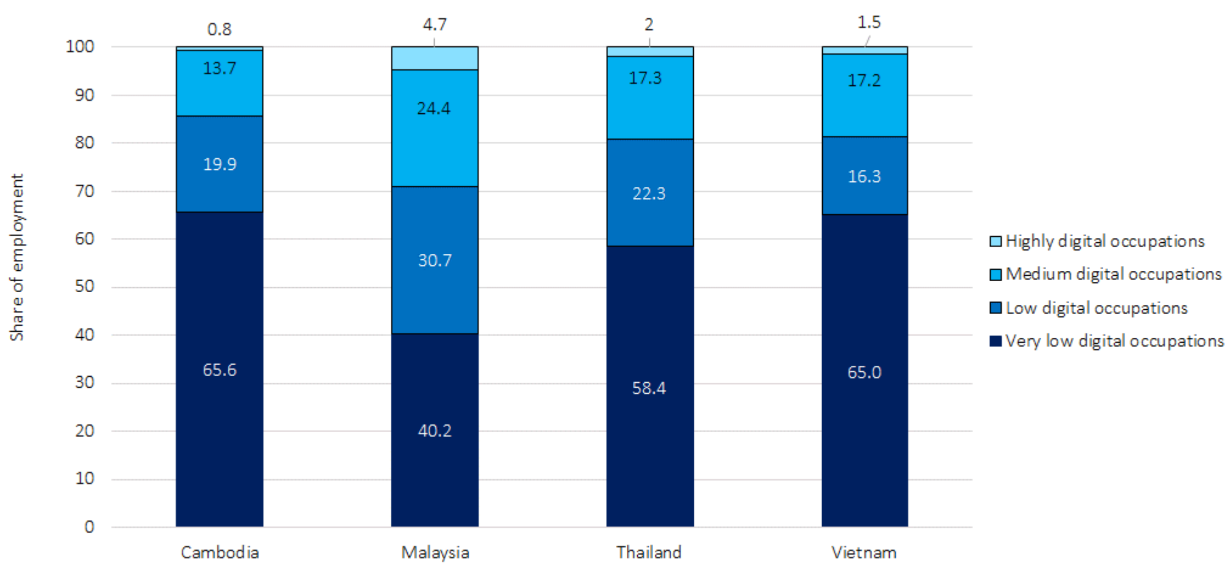
The lower association between cognitive and socioemotional skills, on one hand, and intermediate and advanced digital skills, on the other hand, may be due to the lower prevalence of the latter in Malaysia (and the other sample countries). Indeed, since basic digital skills are widespread, they associate with cognitive and socioemotional skills, which are also widespread. This is illustrated by the fact that, when only considering the occupation skills profile, i.e. not projected to Malaysia's employed population, advanced digital skills load highly with thinking skills and intermediate digital skills with personal growth (Annex Table A.4.2).

[45] Emotions and basic digital skills load highly in the same factors in the other three countries (Annex Table A.4.2).

7. Levels of Occupation Digitalization and Skills Requirements in Cambodia, Malaysia, Thailand, and Vietnam

In the four countries studied, between 40 and 66 percent of the employed population are in very low digital occupations, 20-31 percent in low digital occupation, 13-24 percent in medium-digital occupations, and 1-5 percent in highly digital occupations (Figure 7).[46] Malaysia, the country with the highest GDP per capita of the four countries, also has the highest share of employment in medium- and highly digital occupations (24 and 5 percent, respectively) (Figures 7 and 8). Thailand and Vietnam are relatively similar in their distribution of employment across digital occupation groups. Cambodia, the country with lowest GDP per capita of the four countries, has only 0.8 percent of its employed population in highly digital occupations. While methodologies for classifying the digitization of occupations differ across studies, Muro et al. (2017) also find a low proportion of employed people in highly digital occupations in the US in 2002: 56 percent in low-digital occupations, 40 percent in medium-digital, and 5 percent in high digital. By 2016, the distribution in the US became 30 – 48 – 23 percent, in low-, medium-, and highly digital occupations, respectively.

Figure 7. Employment across digital occupation level, by country

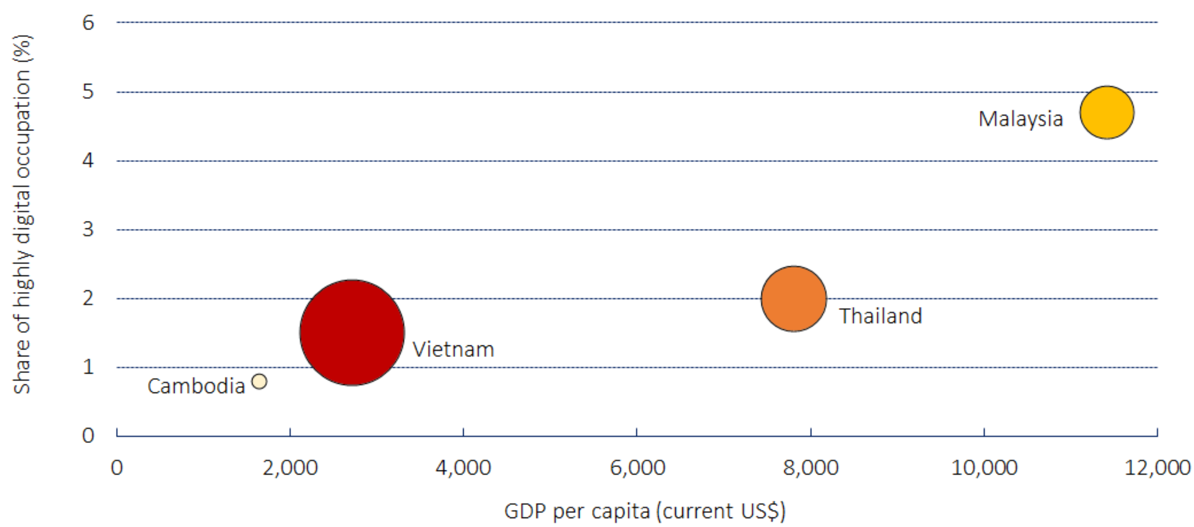


Source: Authors' calculations based SEAD data.

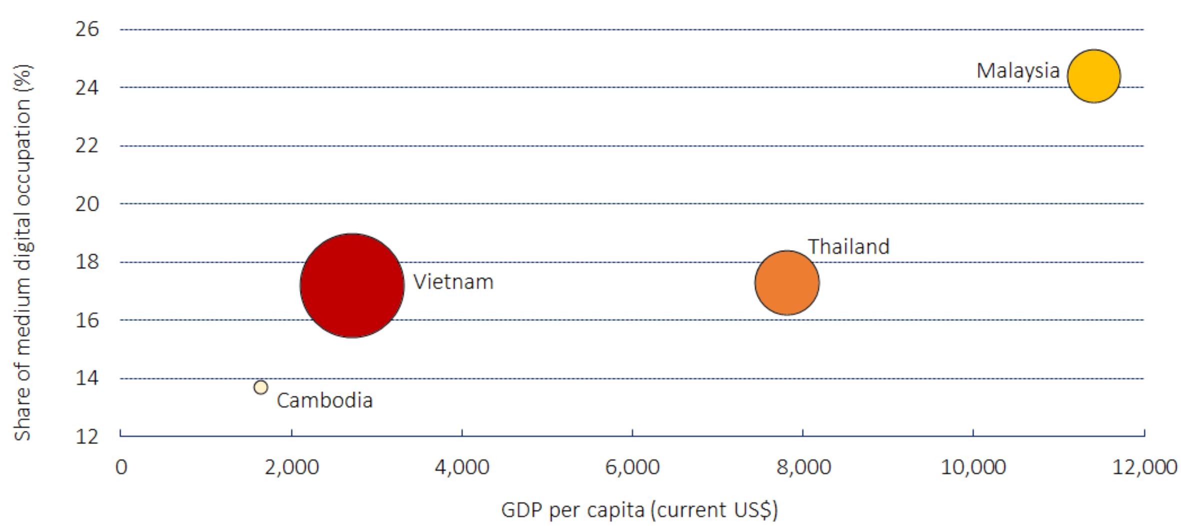
[46] Annex Table A.6.1. shows the employment share of the occupation in each country and its digital level.

Figure 8. Share of intermediate and highly digital occupations by country's GDP per capita

A. Share of high digital occupations and GDP per capita



B. Share of medium digital occupations and GDP per capita



Source: Authors' calculations based SEAD data and World Bank's World Development Indicators.
Note: the size of the bubbles represents the employed population in millions: 9.3 for Cambodia, 14.0 for Malaysia, 36.6 for Thailand, and 52.4 for Vietnam.

Digital, cognitive, and socioemotional skills, as aggregate categories[47] have roughly the same relative importance, around 8-10 percent of skills (Figure 9), however the average share of digital skills differs slightly across countries. Malaysia has a higher average share of digital skills; ten percent of Malaysian workers' skills are digital while eight percent are digital in the other three countries. This suggests that

[47] Namely, all skills types and not disaggregating by digital occupation level to allow for cross-country comparison.

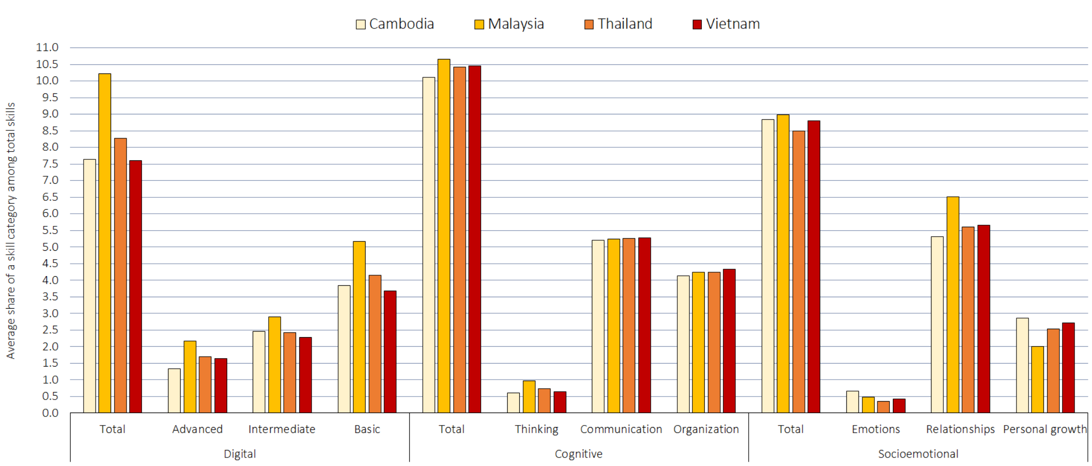
a higher share of Malaysia's workforce is engaged in occupations that require at least some digital skills. In all four countries, the share of jobs requiring basic digital skills is greater than the share requiring intermediate digital skills, which, in turn, is greater than the share requiring advanced digital skills. Given that digital skills are likely cumulative, the share of jobs requiring basic digital skills is likely better represented by the "total digital skills" category than the "basic digital skills" category.

The demand for cognitive skills is very similar across countries. The bulk of jobs require the subsets communication (oral and verbal communication) and organization (planning, multitasking, time management, etc.) (4-5 percent). The third cognitive skill — thinking skills (problem solving, critical thinking, decision making, etc.) — is required by less than 1 percent of jobs in each country.

Socioemotional skills, though a little less demanded, still show a strong presence. The most requested subset of socioemotional skills is relationship skills (teamwork, management, leadership, etc.) around 5-7 percent, twice the showing of personal growth skills (creativity, initiative, self-motivation, etc.), and well above emotional skills (coping strategy, detail-orientation, diligence, etc.). The average share of socioemotional skills and their subsets also shows minor differences across countries. The fact that the shares of cognitive and socioemotional skills look so similar across countries despite differences in their employment distribution across occupations may reflect that both cognitive and socioemotional skills are required in most types of jobs.

Figure 9. Relative importance of skills categories across countries

Average share of a skill category among total skills, by country

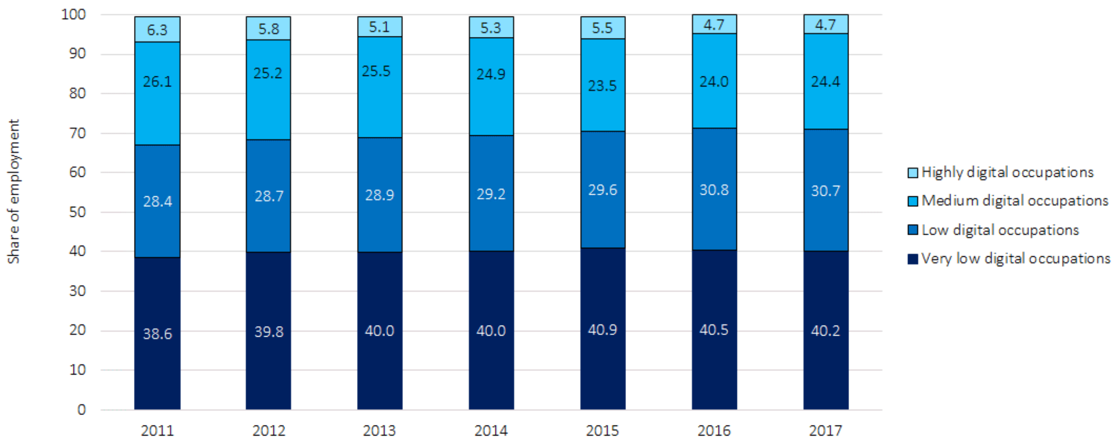


Source: Authors' calculations based SEAD data.
Note: Since occupational skills profiles are derived from the same source (World Bank-Burning Glass data set of job postings), cross-country differences are due to the distribution of employment across occupations of each country. The distribution can be seen at 1-digit level in figure 2 and at 3-digit level in Annex Table A.6.1.

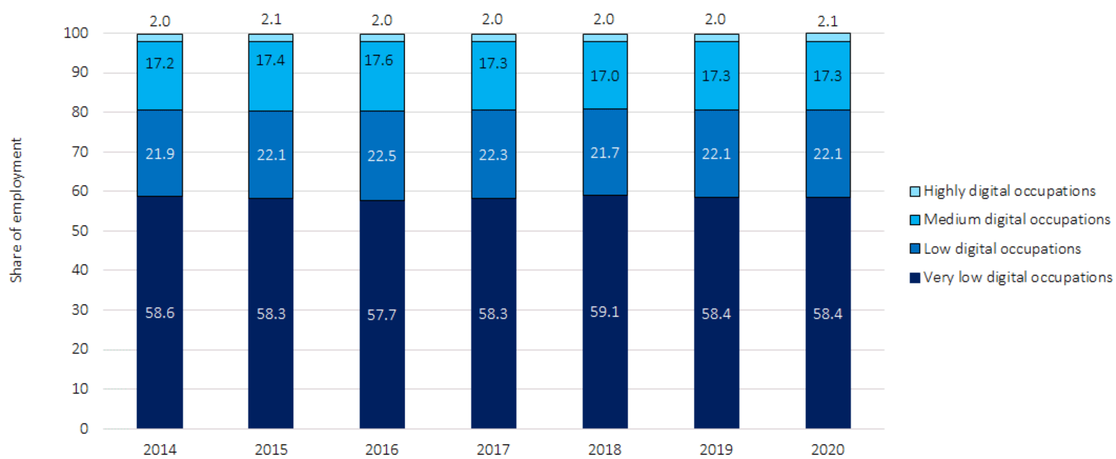
A short time series finds a slow transition to digital occupations in Southeast Asia, with only Vietnam showing a trend toward greater digitalization. When expanding the sample to annual labor force surveys in Malaysia (2011-17), Thailand (2014-20), and Vietnam (2014-15, 2017-18), we find that any changes in the occupational structure of labor markets in Malaysia and Thailand did not affect the distribution of the workforce across digital skills levels (Figure 10). In contrast, the data from Vietnam finds a decline in very low digital occupations (from 70 percent to 64 percent over the five-year period) and a 3-percentage point increase in low- and medium digital occupations. The micro-data explain these changes, where the share of workers in occupations related to subsistence agriculture — very low digital occupations — declined significantly over the period with slow increases in craft occupations (assemblers, construction, machine operators) and services (shop salespeople) which are classified as low or medium digital occupations.

Figure 10. Employment across digital occupation level, by year and country, in Malaysia, Thailand, and Vietnam

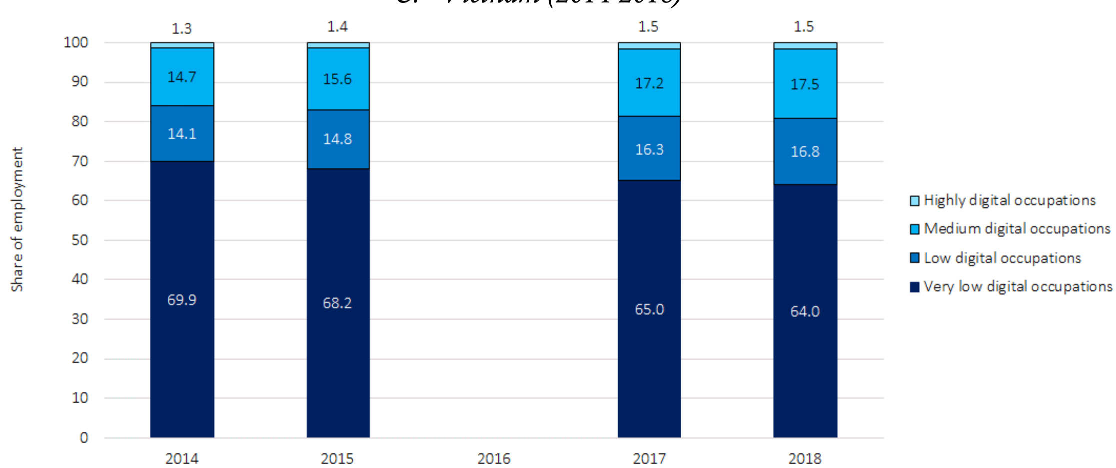
A. Malaysia (2011-17)



B. Thailand (2014-20)



C. Vietnam (2014-2018)



Source: Authors' calculations based SEAD data matched with and employment surveys of Malaysia, Thailand, and Vietnam for corresponding years.

8. Conclusion

Our study confirms that digital skills are common in Southeast Asia. The job postings data from Malaysia in 2016-18 reveals that all occupations require at least some digital skills. Highly digital occupations, however, still represent a very small share of employment in the four countries studied: 5 percent in Malaysia, around 2 percent in Thailand and Vietnam, and 1 percent in Cambodia. Instead, the bulk of employment is in very-low-digital occupations (from 40 percent in Malaysia to 66 percent in Cambodia) and low-digital occupations (from 16 percent in Vietnam to 31 percent in Malaysia). These shares are changing very slowly over time, with the exception of Vietnam's somewhat rapid shedding of very low digital occupations in favor of low and medium digital occupations

We find that occupations from all four digital occupations levels need cognitive and socioemotional skills. While the share of intermediate and advanced digital skills differs across digital occupation levels in Malaysia, all four levels of occupations require roughly the same share of basic digital skills (5-9 percent), cognitive skills (8-12 percent), and socioemotional skills (6-12 percent). Cognitive and socioemotional skills are even more important than digital skills for very-low, low-, and medium-digital occupations (nearly the entire employed population). The share of cognitive and socioemotional skills combined is greater than digital skills: 23 versus 5 percent for very-low digital occupations, respectively, 20 versus 9 percent for low-digital occupations, respectively, and 16 versus 15 percent for medium-digital occupations, respectively. Conditional correlations estimated through regressions show that medium- and highly digital occupations require more thinking skills (cognitive) than very low digital occupations but require similar levels of the other cognitive and socioemotional subsets as do occupations that are less digitally intensive. Similar patterns emerge for Vietnam, Cambodia, Thailand.

When disaggregating cognitive and socioemotional skills, subsets of these skills categories are found to associate more closely with certain levels of digital skills. Using an exploratory factor analysis for Malaysia, we find three clusters of skills from nine digital, cognitive, and socioemotional subsets of skills. Two of these factors are a mix of digital skills and subsets of cognitive and socioemotional skills: 1) basic digital skills with the three subsets of cognitive skills (thinking, communication, and organization), and socioemotional skills related to relationships; and 2) intermediate and advanced digital skills with (to a lesser extent) thinking skills and personal growth. The third cluster does not include digital skills, instead being limited to socioemotional skills, namely with emotions and personal growth. This shows that basic digital skills can be considered a generic skill as much as cognitive and socioemotional and that digital skills are associated to some degree with cognitive and socioemotional skills. Pairwise correlations among those subsets confirm those patterns. Similar patterns emerge for Vietnam, Cambodia, and Thailand.

Our estimations have three main limitations. First, we proxy a skills profile for 20 percent of occupations that are not sufficiently listed in the job postings data set used to create a skills profile. These occupations represent a sizeable share of employment in the four studied countries: from 14 percent in Malaysia to 43 percent in Cambodia. We address this shortcoming by imputing skills profiles for these occupations based on similar occupations. Second, we derive skills use from requirements in job postings, which may omit skills that employers implicitly require rather than explicitly request. Employers do not specify the level of skills proficiency or use, so we equally weight all skills listed in the job posting. As a result, our skills profiles may not be complete, particularly omitting lower-level skills or under- (or over-) weighting the importance of certain skills. Third, we may be over-estimating the degree of digital-ness of the 127 occupations. Since we draw our skills data from on-line jobs vacancy postings, the jobs within each of the 127 occupations that are listed on the internet – and used to construct a skills profile that is a proxy for all jobs within an occupation – may be those that are more inclined to use digital technologies.

Overall, our findings show that all occupations require digital, cognitive, and socioemotional skills, suggesting that policy makers may need to reform the "basic package" provided by education systems in response to digital technologies in the workplace. Education system still need to teach technical and language skills, since those are in very high demand by employers. However, they may also want to rethink the "basic package" of education, namely, to continue teaching cognitive skills, increasing emphasis on socioemotional skills, and adding basic digital skills to the general curriculum. Learning to learn will become increasingly important as new technologies enter the workplace and workers need to adapt to them.

Finally, while advanced digital skills are increasingly emphasized in policy circles, they are only needed for a very small subset of jobs. The growth in demand for these jobs is growing very slowly in Southeast Asia, as comparison to the US. Even as economies grow into the next level of development, advanced skills will still be a minority of the skillset employers value. So, while advanced digital training may be a goal, the reality of the evolving landscape of jobs and technologies is more modest with a continued demand for the traditional cognitive, the increasingly explicit socioemotional, and the newest basic and intermediate digital skills.

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Annex 1. Imputations of skills requirements for occupations unrepresented by job postings data

Table A.1.1. Employment share of the 27 imputed occupations

#	Occupation name	Occupation code	Employment share (%)			
			Cambodia	Malaysia	Thailand	Vietnam
1	Legislators and senior officials	111	0.5	0.1	0.7	0.4
2	Traditional and complementary medicine professionals	223	0.0	0.0	0.0	0.0
3	Traditional and complementary medicine associate professionals	323	0.0	0.1	0.0	0.0
4	Veterinary technicians and assistants	324	0.0	0.0	0.0	0.0
5	Secretaries (general)	412	0.0	0.1	0.0	0.0
6	Street and market salespersons	521	4.8	4.2	3.5	7.1
7	Market gardeners and crop growers	611	9.6	5.1	21.7	4.8
8	Animal producers	612	6.8	0.2	2.5	1.8
9	Mixed crop and animal producers	613	0.0	0.0	0.2	0.0
10	Forestry and related workers	621	0.4	0.0	0.2	0.0
11	Fishery workers, hunters and trappers	622	1.3	0.7	0.8	1.8
12	Subsistence crop farmers	631	12.2	0.0	3.1	1.1
13	Subsistence livestock farmers	632	3.5	0.0	0.0	0.1
14	Subsistence mixed crop and livestock farmers	633	0.0	0.0	0.0	0.1
15	Subsistence fishers, hunters, trappers and gatherers	634	1.1	0.2	0.2	0.0
16	Wood treaters, cabinet-makers and related trades workers	752	0.9	0.5	0.3	0.8
17	Other craft and related workers	754	0.0	0.1	0.5	0.5
18	Metal processing and finishing plant operators	812	0.0	0.2	0.3	0.2
19	Rubber, plastic and paper products machine operators	814	0.1	0.6	0.6	0.3
20	Food and related products machine operators	816	0.3	0.3	0.5	0.2
21	Wood processing and papermaking plant operators	817	0.0	0.5	0.1	0.2
22	Locomotive engine drivers and related workers	831	0.0	0.0	0.0	0.0
23	Ships' deck crews and related workers	835	0.0	0.1	0.1	0.2
24	Vehicle, window, laundry and other hand cleaning workers	912	0.7	0.2	0.4	0.1
25	Street and related service workers	951	0.0	0.0	0.0	0.1
26	Street vendors (excluding food)	952	0.4	0.3	1.1	0.2
27	Refuse workers	961	0.4	0.5	0.3	0.3
		Total	43.0	14.0	37.1	20.3

Sources: Employment shares are from Cambodia 2020 Socioeconomic Survey, and 2017 employment surveys of Malaysia, Thailand, and Vietnam.

Table A.1.2. Similar occupations used for imputations

#	Occupation name	Code	Code of occupations used for imputations
1	Legislators and senior officials	111	112, 121, 122, 134, 141, 142, 143, 232, 242, 243, 261, 331, 332, 333, 335, 422, 522, 541
2	Traditional, and, complementary, medicine, professionals	223	222, 224, 225, 226
3	Traditional, and, complementary, medicine, associate, professionals	323	321, 322, 325
4	Veterinary, technicians, and, assistants	324	321, 324, 325, 516, 532
5	Secretaries, (general)	412	334, 421, 422, 441
6	Street, and, market, salespersons	521	512, 522, 524, 911, 941, 962
7	Street, and, related, service, workers	951	
8	Street, vendors, (excluding, food)	952	
9	Market, gardeners, and, crop, growers	611	921
10	Animal, producers	612	
11	Mixed, crop, and, animal, producers	613	
12	Forestry, and, related, workers	621	
13	Fishery, workers,, hunters, and, trappers	622	
14	Subsistence, crop, farmers	631	
15	Subsistence, livestock, farmers	632	
16	Subsistence, mixed, crop, and, livestock, farmers	633	
17	Subsistence, fishers,, hunters,, trappers, and, gatherers	634	
18	Wood, treaters,, cabinet-makers, and, related, trades, workers	752	313, 711, 722, 723, 731, 732, 751, 752, 811, 815, 818, 821, 921, 932
19	Other, craft, and, related, workers	754	311, 312, 313, 315, 325, 421, 422, 441, 512, 513, 522, 524, 621, 711, 721, 722, 723, 732, 741, 742, 753, 813, 818, 821, 833, 932
20	Metal, processing, and, finishing, plant, operators	812	313, 512, 711, 722, 723, 732, 751, 811, 813, 815, 818, 932
21	Rubber,, plastic, and, paper, products, machine, operators	814	265, 313, 512, 711, 712, 721, 722, 723, 731, 732, 751, 753, 811, 813, 815, 818, 821, 932
22	Food, and, related, products, machine, operators	816	313, 722, 732, 751, 811, 813, 818, 821, 932
23	Wood, processing, and, papermaking, plant, operators	817	512, 722, 732, 815, 818, 821, 932
24	Locomotive, engine, drivers, and, related, workers	831	511, 711, 811, 832, 833, 931
25	Ships', deck, crews, and, related, workers	835	313, 711, 742, 751, 811, 813, 833, 834, 931
26	Vehicle,, window,, laundry, and, other, hand, cleaning, workers	912	815
27	Refuse, workers	961	441, 711, 712, 832, 834, 921

Sources: Own elaboration based on ILO (2012) and O*NET (2021).

Notes: ILO (2012) lists some related occupations to a given one. O*NET (2021) lists occupations in the United States that have similar skills and experience and which workers could transfer between with minimal additional preparation.

Table A.1.3. Name of occupations used for imputations

Code	Occupation name
112	Managing directors and chief executives
121	Business services and administration managers
122	Sales, marketing and development managers
134	Professional services managers
141	Hotel and restaurant managers
142	Retail and wholesale trade managers
143	Other services managers
222	Nursing and midwifery professionals
224	Paramedical practitioners
225	Veterinarians
226	Other health professionals
232	Vocational education teachers
242	Administration professionals
243	Sales, marketing and public relations professionals
261	Legal professionals
265	Creative and performing artists
311	Physical and engineering science technicians
312	Mining, manufacturing and construction supervisors
313	Process control technicians
315	Ship and aircraft controllers and technicians
321	Medical and pharmaceutical technicians
322	Nursing and midwifery associate professionals
324	Veterinary technicians and assistants
325	Other health associate professionals
331	Financial and mathematical associate professionals
332	Sales and purchasing agents and brokers
333	Business services agents
334	Administrative and specialised secretaries
335	Regulatory government associate professionals
421	Tellers, money collectors and related clerks
422	Client information workers
441	Other clerical support workers
511	Travel attendants, conductors and guides
512	Cooks
513	Waiters and bartenders
516	Other personal services workers
522	Shop salespersons
524	Other sales workers
532	Personal care workers in health services
541	Protective services workers
621	Forestry and related workers
711	Building frame and related trades workers
712	Building finishers and related trades workers
721	Sheet and structural metal workers, moulders and welders, and related workers
722	Blacksmiths, toolmakers and related trades workers
723	Machinery mechanics and repairers
731	Handicraft workers
732	Printing trades workers
741	Electrical equipment installers and repairers
742	Electronics and telecommunications installers and repairers
751	Food processing and related trades workers
752	Wood treaters, cabinet-makers and related trades workers
753	Garment and related trades workers
811	Mining and mineral processing plant operators
813	Chemical and photographic products plant and machine operators
815	Textile, fur and leather products machine operators
818	Other stationary plant and machine operators
821	Assemblers
832	Car, van and motorcycle drivers
833	Heavy truck and bus drivers
834	Mobile plant operators
911	Domestic, hotel and office cleaners and helpers
921	Agricultural, forestry and fishery labourers
931	Mining and construction labourers
932	Manufacturing labourers
941	Food preparation assistants
962	Other elementary workers

Sources: ILO (2012).

Annex 2. Occupations classified by digital levels, and share of levels of digital skills in each

Table A.2.1 Highly digital occupations

#	Occupation name	Code	Share of digital skills: Total	Advanced	Intermediate	Basic	O*NET digital score
1	Software and applications developers and analysts	251	58.1	47.5	8.0	2.6	78
2	Database and network professionals	252	54.7	42.6	8.3	3.9	76
3	ICT service managers	133	39.7	23.9	11.7	4.1	59
4	ICT operations and user support technicians	351	46.8	23.3	18.6	4.8	68
5	Electrotechnology engineers	215	33.1	21.4	8.7	3.0	68
6	Electronics and telecommunications installers and repairers	742	27.7	12.3	10.3	5.1	55
7	Mathematicians, actuaries and statisticians	212	22.7	8.0	6.6	8.2	61
8	Architects, planners, surveyors and designers	216	44.2	7.9	28.5	7.9	54
9	Telecommunications and broadcasting technicians	352	26.9	6.1	12.8	8.0	52
10	Physical and engineering science technicians	311	24.0	4.3	14.0	5.6	47
11	Printing trades workers	732	30.4	3.3	17.5	9.6	48
12	Creative and performing artists	265	34.4	2.3	25.1	7.0	45
13	Keyboard operators	413	55.6	2.0	2.6	51.0	46

Table A.2.2. Medium digital occupations

#	Occupation name	Code	Share of digital skills: Total	Advanced	Intermediate	Basic	O*NET digital score
1	Blacksmiths, toolmakers and related trades workers	722	26.9	1.6	23.2	2.0	48
2	Other clerical support workers	441	26.7	2.7	2.4	21.7	45
3	General office clerks	411	21.6	2.2	2.4	17.1	47
4	Numerical clerks	431	20.4	1.8	3.7	14.9	45
5	Chemical and photographic products plant and machine op.	813	18.7	3.4	4.2	11.1	47
6	Engineering professionals (excluding electrotechnology)	214	18.3	6.0	7.4	4.9	57
7	Financial and mathematical associate professionals	331	17.8	1.8	4.5	11.5	42
8	Administration professionals	242	17.4	4.3	4.4	8.7	45
9	Vocational education teachers	232	16.9	3.9	8.0	5.1	45
10	Sales, marketing and public relations professionals	243	15.8	2.0	6.3	7.5	49
11	Building frame and related trades workers	711	15.5	1.8	7.5	6.2	32
12	Authors, journalists and linguists	264	15.3	2.0	5.8	7.5	46
13	Secretaries (general)	412	15.3	2.1	2.1	11.0	46
14	Food and related products machine operators	816	15.2	2.7	7.0	5.5	40
15	Librarians, archivists and curators	262	14.3	3.5	4.6	6.2	62
16	Wood processing and papermaking plant operators	817	14.1	2.4	7.4	4.3	39
17	Regulatory government associate professionals	335	13.9	2.4	2.5	9.0	47
18	Protective services workers	541	13.8	5.1	1.3	7.4	36
19	Administrative and specialised secretaries	334	13.6	2.5	2.7	8.4	47
20	Paramedical practitioners	224	13.6	3.5	3.6	6.4	40
21	Rubber, plastic and paper products machine operators	814	13.5	2.3	6.7	4.5	37
22	Other craft and related workers	754	13.4	2.7	5.1	5.7	40
23	Ship and aircraft controllers and technicians	315	13.3	1.9	2.9	8.6	41
24	Metal processing and finishing plant operators	812	12.8	2.0	6.1	4.8	38
25	Manufacturing labourers	932	12.5	2.1	4.9	5.5	33
26	Wood treaters, cabinet-makers and related trades workers	752	12.4	2.3	6.0	4.1	36
27	Assemblers	821	12.3	5.8	2.7	3.8	37
28	Other health associate professionals	325	12.2	2.5	2.2	7.4	38
29	Ships' deck crews and related workers	835	12.1	2.9	4.3	4.9	37
30	Other stationary plant and machine operators	818	11.7	2.5	2.8	6.4	43
31	Process control technicians	313	11.2	3.2	4.7	3.3	42
32	Physical and earth science professionals	211	11.2	3.4	4.0	3.8	54
33	Sheet and structural metal workers, moulders and welders (…)	721	11.0	5.4	3.4	2.3	37
34	Painters, building structure cleaners and related trades w(…)	713	10.7	3.6	2.9	4.2	35
35	Handicraft workers	731	10.4	3.9	4.9	1.6	35

Table A.2.3. Low digital occupations

#	Occupation name	Code	Share of digital skills: Total	Advanced	Intermediate	Basic	O*NET digital score
1	Artistic, cultural and culinary associate professionals	343	17.3	0.6	11.3	5.5	40
2	Material-recording and transport clerks	432	16.1	1.3	3.3	11.5	43
3	Legal, social and religious associate professionals	341	14.1	0.6	0.6	12.8	47
4	Mining, manufacturing and construction supervisors	312	13.0	1.0	5.4	6.5	44
5	Transport and storage labourers	933	12.7	0.5	3.0	9.2	25
6	Manufacturing, mining, construction, and distribution managers	132	12.6	1.5	4.7	6.4	50
7	Building finishers and related trades workers	712	12.6	0.8	6.3	5.5	36
8	Mining and construction labourers	931	12.1	0.7	6.7	4.7	42
9	Business services agents	333	11.9	0.6	2.7	8.5	45
10	Client information workers	422	11.9	1.4	2.0	8.5	47
11	Refuse workers	961	11.8	1.4	3.3	7.1	33
12	Professional services managers	134	11.5	1.6	2.6	7.3	43
13	Legislators and senior officials	111	11.1	1.9	2.9	6.4	44
14	Finance professionals	241	10.8	1.6	3.6	5.6	47
15	Business services and administration managers	121	10.8	1.4	3.0	6.3	45
16	Personal care workers in health services	532	10.4	2.0	0.8	7.6	36
17	Life science technicians and related associate professionals	314	9.9	1.0	2.4	6.5	41
18	Mining and mineral processing plant operators	811	9.7	1.7	2.4	5.7	25
19	Life science professionals	213	9.7	2.4	3.1	4.2	49
20	Managing directors and chief executives	112	9.5	2.7	2.9	3.9	45
21	Sales, marketing and development managers	122	9.5	1.2	3.2	5.0	45
22	University and higher education teachers	231	9.3	4.0	2.4	2.9	49
23	Traditional and complementary medicine associate professionals	323	9.2	2.0	1.6	5.6	42
24	Travel attendants, conductors and guides	511	9.1	0.2	0.6	8.3	33
25	Locomotive engine drivers and related workers	831	9.1	1.3	3.1	4.6	32
26	Tellers, money collectors and related clerks	421	8.8	2.0	1.3	5.5	46
27	Shop salespersons	522	8.7	1.0	2.0	5.7	43
28	Electrical equipment installers and repairers	741	8.7	3.0	2.7	2.9	37
29	Production managers in agriculture, forestry and fisheries	131	8.7	1.1	2.3	5.2	33
30	Social and religious professionals	263	8.6	1.2	1.5	5.8	43
31	Machinery mechanics and repairers	723	8.6	1.9	3.8	2.9	39
32	Veterinary technicians and assistants	324	8.5	1.7	1.3	5.5	39
33	Medical and pharmaceutical technicians	321	8.2	1.7	1.6	4.8	46
34	Sports and fitness workers	342	8.0	3.4	0.9	3.7	41
35	Nursing and midwifery associate professionals	322	7.2	1.7	0.9	4.6	43
36	Cashiers and ticket clerks	523	7.1	1.8	0.8	4.6	35
37	Other teaching professionals	235	7.0	1.4	1.2	4.4	45
38	Traditional and complementary medicine professionals	223	6.5	1.5	1.5	3.4	44
39	Other services managers	143	6.0	1.5	1.5	3.0	46
40	Medical doctors	221	4.4	2.5	0.3	1.6	47
41	Heavy truck and bus drivers	833	3.6	2.2	0.4	1.0	29

Table A.2.4. Very low digital occupations

#	Occupation name	Code	Share of digital skills				O*NET digital score
			Total	Advanced	Intermediate	Basic	
1	Sales and purchasing agents and brokers	332	8.5	0.7	1.7	6.2	42
2	Garment and related trades workers	753	8.0	0.0	4.5	3.5	23
3	Legal professionals	261	7.4	1.2	1.4	4.8	43
4	Mobile plant operators	834	7.1	0.3	1.5	5.3	29
5	Other health professionals	226	6.9	0.5	2.2	4.2	45
6	Child care workers and teachers' aides	531	6.7	1.0	1.5	4.2	29
7	Hairdressers, beauticians and related workers	514	5.9	0.9	0.1	4.8	33
8	Other elementary workers	962	5.4	0.3	0.9	4.3	36
9	Other sales workers	524	5.4	0.9	1.3	3.2	41
10	Food preparation assistants	941	5.1	1.0	0.7	3.4	32
11	Street vendors (excluding food)	952	4.9	0.7	1.0	3.2	35
12	Street and market salespersons	521	4.9	0.7	1.0	3.2	35
13	Street and related service workers	951	4.9	0.7	1.0	3.2	35
14	Veterinarians	225	4.8	0.5	1.3	3.0	49
15	Hotel and restaurant managers	141	4.7	0.5	1.0	3.2	37
16	Retail and wholesale trade managers	142	4.6	0.4	0.8	3.4	42
17	Waiters and bartenders	513	4.5	1.2	0.4	2.9	35
18	Mixed crop and animal producers	613	4.5	1.4	1.0	2.2	27
19	Subsistence mixed crop and livestock farmers	633	4.5	1.4	1.0	2.2	27
20	Animal producers	612	4.5	1.4	1.0	2.2	27
21	Forestry and related workers	621	4.5	1.4	1.0	2.2	27
22	Fishery workers, hunters and trappers	622	4.5	1.4	1.0	2.2	27
23	Agricultural, forestry and fishery labourers	921	4.5	1.4	1.0	2.2	27
24	Subsistence crop farmers	631	4.5	1.4	1.0	2.2	27
25	Market gardeners and crop growers	611	4.5	1.4	1.0	2.2	27
26	Subsistence livestock farmers	632	4.5	1.4	1.0	2.2	27
27	Subsistence fishers, hunters, trappers and gatherers	634	4.5	1.4	1.0	2.2	27
28	Car, van and motorcycle drivers	832	4.5	1.3	1.1	2.1	30
29	Building and housekeeping supervisors	515	4.4	0.2	0.4	3.7	43
30	Textile, fur and leather products machine operators	815	4.0	0.7	1.0	2.3	29
31	Vehicle, window, laundry and other hand cleaning workers	912	4.0	0.7	1.0	2.3	29
32	Domestic, hotel and office cleaners and helpers	911	3.6	0.1	1.4	2.2	23
33	Food processing and related trades workers	751	3.6	0.6	1.1	1.9	33
34	Other personal services workers	516	3.2	0.4	0.6	2.2	35
35	Secondary education teachers	233	2.9	0.1	0.5	2.4	45
36	Nursing and midwifery professionals	222	2.5	0.6	0.2	1.7	41
37	Primary school and early childhood teachers	234	2.1	0.3	0.2	1.6	41
38	Cooks	512	1.0	0.7	0.0	0.3	33

Source: Authors' calculations based on World Bank-Burning Glass Malaysia online job postings data (2016-18).
Notes: Darker red colors show higher magnitudes within the "share of digital skills" or "O*Net digital score" column while darker blue colors show lower magnitudes within each set of columns. O*NET digital score, used as a benchmark here, is based on occupations' three digitalization aspects in measured by O*NET for occupations in the U.S. —computer & electronics, programming, and interacting with computer— following the methodology by Muro et al. (2017).

Annex 3. Replications of Malaysia-focused analyses about the similarity of skills required in very-low, low, medium, and highly digital occupations for the occupational skills profile, Cambodia, Thailand, and Vietnam

Table A.3.1. Share of skills categories across digital occupation levels in the occupational skills profile, Cambodia, Malaysia, Thailand, and Vietnam (replication of data behind figure 6)

	Occupational skills profile				Cambodia				Malaysia				Thailand				Vietnam			
	Digital occupation levels				Digital occupation levels				Digital occupation levels				Digital occupation levels				Digital occupation levels			
Skills	**VL**	**L**	**M**	**H**	**VL**	**L**	**M**	**H**	**VL**	**L**	**M**	**H**	**VL**	**L**	**M**	**H**	**VL**	**L**	**M**	**H**
Digital	4.8	9.9	15.0	38.3	5.0	9.8	15.5	32.7	4.8	9.4	15.9	33.3	4.5	10.1	15.3	37.1	4.6	9.7	14.8	34.4
Advanced digital	0.8	1.6	3.0	15.8	1.0	1.2	2.7	8.7	0.8	1.6	3.1	13.2	1.1	1.3	3.1	12.6	1.1	1.3	3.0	14.5
Intermediate digital	1.0	2.6	5.0	13.3	1.5	3.2	5.2	17.5	1.1	2.9	3.8	14.3	1.0	3.1	4.8	15.8	1.1	3.0	5.1	13.6
Basic digital	2.9	5.6	7.1	9.3	2.5	5.5	7.6	6.5	2.9	5.0	9.0	5.9	2.4	5.7	7.4	8.8	2.4	5.4	6.7	6.2
Cognitive	10.9	11.9	10.3	9.4	9.9	10.7	10.1	8.6	10.5	11.6	10.1	8.3	10.5	11.0	9.5	8.8	10.3	11.3	10.2	8.9
Thinking	0.6	1.3	1.3	2.0	0.4	1.0	1.0	1.6	0.6	1.2	1.2	1.8	0.4	1.1	1.2	1.8	0.4	1.1	1.2	2.0
Communication	5.6	6.0	4.7	3.9	5.2	5.6	4.8	3.5	5.5	5.7	4.6	3.4	5.5	5.4	4.4	3.6	5.3	5.6	4.8	3.7
Organization	4.4	4.5	4.0	3.4	4.2	3.9	4.2	3.4	4.3	4.5	4.1	3.0	4.4	4.2	3.7	3.2	4.4	4.3	4.1	3.1
Socioemotional	11.0	7.9	6.4	6.7	10.0	7.1	5.8	7.6	12.2	7.8	5.9	5.5	9.9	7.1	5.8	6.8	9.9	7.2	6.2	6.1
Emotions	0.5	0.5	0.6	0.7	0.7	0.3	0.8	0.5	0.4	0.4	0.6	0.4	0.3	0.4	0.6	0.6	0.3	0.4	0.7	0.4
Relationships	7.9	5.7	4.3	3.6	5.6	5.4	3.8	3.4	8.9	5.7	4.1	3.3	6.3	5.3	4.0	3.4	6.2	5.4	4.2	3.5
Personal growth	2.6	1.7	1.5	2.4	3.7	1.4	1.2	3.7	2.8	1.6	1.2	1.8	3.3	1.4	1.2	2.8	3.4	1.4	1.2	2.2
Other	73.4	70.4	68.3	45.6	75.0	72.4	68.6	51.2	72.5	71.2	68.1	52.8	75.1	71.8	69.4	47.3	75.2	71.8	68.8	50.6
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Authors' calculations based on SEAD data.

Notes: "VL", "L", "M", and "H" respectively stands for "Very low", "Low", "Medium", and "High". The share of skills splits between digital, cognitive, and socioemotional, and other skills. Digital skills levels and cognitive and socioemotional skills subsets are subcategories counted in the total.

Table A.3.2. Conditional correlations between digital occupation level and cognitive and socioemotional skills requirements (replication of Table 6)

Ordinary Least Square (OLS) regressions of digital occupation levels on dummies taking the value of one if the skills count of a skills category of an occupation is above the mean

A. Occupational skills profile

		Occupation digital level				
		Low vs. Very low	Medium vs. Low	High vs. Medium	High vs. Low	High vs. Very low
		(1)	(2)	(3)	(4)	(5)
Cognitive	Thinking	0.24	0.19	0.23	**0.65***	**2.26*****
		(0.15)	(0.13)	(0.13)	(0.26)	(0.38)
	Communication	**0.28***	-0.19	0.15	-0.13	-0.33
		(0.13)	(0.14)	(0.24)	(0.24)	(0.25)
	Organization	0.24	-0.05	0.05	0.06	-0.45
		(0.13)	(0.13)	(0.17)	(0.27)	(0.61)
Socioemotional	Emotions	-0.01	**0.28***	0.06	0.40	0.91
		(0.13)	(0.13)	(0.18)	(0.27)	(0.54)
	Relationships	**-0.28****	-0.26	-0.25	**-0.58***	-0.45
		(0.10)	(0.18)	(0.28)	(0.28)	(0.27)
	Personal growth	**-0.20***	0.02	0.18	0.13	-0.21
		(0.09)	(0.17)	(0.18)	(0.28)	(0.26)
	Constant	0.45***	1.46***	2.05***	1.22***	0.32
		(0.09)	(0.09)	(0.09)	(0.17)	(0.29)
	N	79	76	48	54	51
	R-sq	0.30	0.15	0.13	0.24	0.61

B. Cambodia and Malaysia

		Cambodia					Malaysia				
		Occupation digital level					Occupation digital level				
		Low vs. Very low	Medium vs. Low	High vs. Medium	High vs. Low	High vs. Very low	Low vs. Very low	Mediu m vs. Low	High vs. Medium	High vs. Low	High vs. Very low
		(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Cognitive	Thinking	0.25	-0.04	0.20	**0.49***	**2.28*****	**0.36***	0.22	0.01	**0.53***	**2.09*****
		(0.16)	(0.13)	(0.11)	(0.21)	(0.46)	(0.17)	(0.13)	(0.15)	(0.23)	(0.40)
	Communication	**0.79*****	**-0.24***	**0.60****	0.04	-0.28	**0.47***	-0.19	0.01	-0.17	-0.09
		(0.15)	(0.09)	(0.21)	(0.16)	(0.24)	(0.21)	(0.14)	(0.33)	(0.24)	(0.16)
	Organization	0.07	**-0.24***	0.01	-0.22	-0.06	0.00	-0.16	0.12	-0.13	-0.60
		(0.12)	(0.10)	(0.05)	(0.15)	(0.10)	(0.16)	(0.15)	(0.10)	(0.14)	(0.41)
Socioemotional	Emotions	-0.06	**0.71*****	-0.03	0.25	0.10	-0.00	**0.48****	-0.30	0.12	0.81
		(0.10)	(0.10)	(0.08)	(0.21)	(0.09)	(0.15)	(0.15)	(0.21)	(0.19)	(0.41)
	Relationships	-0.05	-0.16	**-0.86*****	**-0.75****	-0.09	**-0.30***	-0.35	0.08	**-0.58***	-0.67
		(0.10)	(0.15)	(0.21)	(0.24)	(0.08)	(0.14)	(0.18)	(0.38)	(0.24)	(0.43)
	Personal growth	-0.14	-0.08	**0.46****	**0.60****	-0.07	-0.16	-0.03	**0.36***	0.34	-0.55
		(0.12)	(0.18)	(0.15)	(0.19)	(0.08)	(0.16)	(0.17)	(0.18)	(0.20)	(0.41)
	Constant	0.20	1.46***	2.03***	1.12***	0.08	0.44**	1.47***	2.22***	1.39***	0.74
		(0.12)	(0.14)	(0.07)	(0.10)	(0.08)	(0.14)	(0.14)	(0.22)	(0.33)	(0.54)
	N	79	75	45	52	49	79	75	47	54	51
	R-sq	0.65	0.66	0.49	0.39	0.59	0.36	0.36	0.13	0.15	0.44

C. Thailand and Vietnam

		Thailand					Vietnam				
		Occupation digital level					Occupation digital level				
		Low vs. Very low	Medium vs. Low	High vs. Medium	High vs. Low	High vs. Very low	Low vs. Very low	Medium vs. Low	High vs. Medium	High vs. Low	High vs. Very low
		(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
Cognitive	Thinking	0.26	0.21	0.08	0.46	**2.11*** **	0.24	**0.25***	0.08	**0.65***	**2.59*** **
		(0.18)	(0.13)	(0.09)	(0.25)	(0.40)	(0.14)	(0.12)	(0.08)	(0.25)	(0.28)
	Communication	**0.60***	**-0.26***	0.35	-0.03	-0.15	**0.77*** **	-0.25	0.38	0.24	-0.19
		(0.23)	(0.12)	(0.29)	(0.20)	(0.14)	(0.17)	(0.16)	(0.29)	(0.25)	(0.15)
	Organization	0.10	-0.22	0.06	-0.19	-0.45	0.11	**-0.28***	-0.03	-0.42	-0.01
		(0.12)	(0.12)	(0.09)	(0.20)	(0.37)	(0.11)	(0.13)	(0.08)	(0.21)	(0.12)
Socioemotional	Emotions	-0.08	**0.51*** **	-0.04	0.29	0.45	-0.14	**0.59*** **	0.00	0.29	-0.01
		(0.11)	(0.12)	(0.10)	(0.21)	(0.38)	(0.08)	(0.13)	(0.09)	(0.22)	(0.09)
	Relationships	-0.14	**-0.29***	-0.41	**-0.53***	-0.16	-0.09	-0.43	-0.49	**-0.84** **	-0.09
		(0.11)	(0.14)	(0.33)	(0.24)	(0.12)	(0.07)	(0.23)	(0.31)	(0.27)	(0.07)
	Personal growth	-0.13	0.03	0.27	0.37	-0.14	-0.16	0.14	0.20	**0.43***	-0.10
		(0.14)	(0.16)	(0.17)	(0.21)	(0.14)	(0.08)	(0.21)	(0.14)	(0.19)	(0.09)
	Constant	0.22	1.48***	2.03***	1.17***	0.15	0.20*	1.57***	2.03***	1.17***	0.12
		(0.13)	(0.11)	(0.09)	(0.14)	(0.14)	(0.08)	(0.11)	(0.06)	(0.16)	(0.10)
	N	79	76	48	54	51	79	76	48	54	51
	R-sq	0.45	0.47	0.18	0.23	0.52	0.66	0.48	0.19	0.28	0.65

Source: Authors' calculations based SEAD data.
Note: Independent variables are dummies taking the value of one if the skills count of a skills category of an occupation is above the meian and thus can be interpreted as percentage point increase (or decrease) towards the probability of being a given occupation digital level. Malaysia does not have one of the 127 occupations of the occupational skills profile (paramedical practitioners, ISCO code 224) according its 2017 labor force survey, so its total number of occupations is 126.

**p < 0.1 **p < 0.05 ***p < 0.01*

Annex 4. Replications of Malaysia-focused analyses about the complementarities between digital, cognitive, and socioemotional skills for the occupational skills profile, Cambodia, Thailand, and Vietnam

Table A.4.1. Correlations between skills (replications of Table 7)

Pairwise correlations based on the number of skills counts of skills categories

A. Occupational skills profile

		Digital			Cognitive			Socioemotional		
		Advanced	Intermediate	Basic	Thinking	Communication	Organization	Emotions	Relationships	Personal growth
Digital	Advanced	1.00								
	Intermediate	**0.45*****	1.00							
	Basic	0.05	**0.31*****	1.00						
Cognitive	Thinking	**0.55*****	**0.40*****	**0.39*****	1.00					
	Communication	**0.22****	0.11	**0.37*****	**0.65*****	1.00				
	Organization	0.14	**0.30*****	**0.44*****	**0.59*****	**0.60*****	1.00			
Socioemotional	Emotions	0.15	**0.28*****	**0.64*****	**0.46*****	**0.40*****	**0.44*****	1.00		
	Relationships	0.06	-0.04	0.08	**0.37*****	**0.59*****	**0.49*****	**0.17***	1.00	
	Personal growth	0.07	**0.64*****	**0.18****	0.07	0.13	**0.35*****	**0.29*****	**0.16***	1.00
Others		0.02	**0.15***	**0.33*****	**0.60*****	**0.66*****	**0.56*****	**0.23*****	**0.33*****	0.09

B. Cambodia

		Digital			Cognitive			Socioemotional		
		Advanced	Intermediate	Basic	Thinking	Communication	Organization	Emotions	Relationships	Personal growth
Digital	Advanced	1.00								
	Intermediate	**0.31*****	1.00							
	Basic	0.10	**0.35*****	1.00						
Cognitive	Thinking	**0.34*****	**0.27*****	**0.64*****	1.00					
	Communication	0.14	0.07	**0.62*****	**0.68*****	1.00				
	Organization	0.09	**0.35*****	**0.54*****	**0.53*****	**0.43*****	1.00			
Socioemotional	Emotions	0.01	**0.46*****	**0.48*****	**0.33*****	0.08	**0.31*****	1.00		
	Relationships	-0.09	0.02	**0.33*****	**0.39*****	**0.49*****	**0.16***	**0.45*****	1.00	
	Personal growth	-0.07	**0.15***	**-0.30*****	**-0.27*****	**-0.25*****	0.06	-0.06	-0.04	1.00
Others		0.08	0.12	**0.58*****	**0.62*****	**0.82*****	**0.43*****	0.05	**0.29*****	-0.13

C. Thailand

		Digital			Cognitive			Socioemotional		
		Advanced	Intermediate	Basic	Thinking	Communication	Organization	Emotions	Relationships	Personal growth
Digital	Advanced	1.00								
	Intermediate	**0.42*** **	1.00							
	Basic	0.12	**0.35*** **	1.00						
Cognitive	Thinking	**0.44*** **	**0.39*** **	**0.60*** **	1.00					
	Communication	**0.15* **	**0.15* **	**0.60*** **	**0.64*** **	1.00				
	Organization	0.10	**0.27*** **	**0.50*** **	**0.61*** **	**0.51*** **	1.00			
Socioemotional	Emotions	**0.15* **	**0.32*** **	**0.63*** **	**0.59*** **	**0.46*** **	**0.41*** **	1.00		
	Relationships	0.01	-0.02	**0.25*** **	**0.36*** **	**0.60*** **	**0.28*** **	**0.33*** **	1.00	
	Personal growth	0.03	**0.31*** **	**-0.22** **	**-0.18** **	-0.10	0.11	-0.14	-0.02	1.00
Others		0.07	**0.21** **	**0.56*** **	**0.57*** **	**0.80*** **	**0.49*** **	**0.30*** **	**0.36*** **	-0.09

D. Vietnam

		Digital			Cognitive			Socioemotional		
		Advanced	Intermediate	Basic	Thinking	Communication	Organization	Emotions	Relationships	Personal growth
Digital	Advanced	1.00								
	Intermediate	**0.46*** **	1.00							
	Basic	**0.16* **	**0.46*** **	1.00						
Cognitive	Thinking	**0.44*** **	**0.44*** **	**0.67*** **	1.00					
	Communication	**0.20** **	**0.25*** **	**0.70*** **	**0.72*** **	1.00				
	Organization	**0.15* **	**0.39*** **	**0.55*** **	**0.60*** **	**0.60*** **	1.00			
Socioemotional	Emotions	0.14	**0.40*** **	**0.62*** **	**0.57*** **	**0.47*** **	**0.45*** **	1.00		
	Relationships	-0.00	-0.02	**0.31*** **	**0.34*** **	**0.52*** **	**0.20** **	**0.33*** **	1.00	
	Personal growth	-0.03	0.07	**-0.32*** **	**-0.23*** **	**-0.20** **	0.05	**-0.27*** **	-0.02	1.00
Others		0.12	**0.28*** **	**0.60*** **	**0.69*** **	**0.77*** **	**0.57*** **	**0.32*** **	**0.23** **	-0.10

Source: Authors' calculations based SEAD data.

**p < 0.1 **p < 0.05 ***p < 0.01*

Table A.4.2. Exploratory factor analysis of skills for the occupational skills profile, Cambodia, Thailand, and Vietnam (replications of Table 8)

Exploratory factor analysis based on skills counts of skills categories

A. Occupational skills profile

	Skills category	Skill subset	Factors 1	2	3	4	Uniqueness
1	Digital	Advanced	0.03	-0.03	0.94	0.10	0.11
2	Digital	Intermediate	-0.08	0.20	0.48	0.78	0.11
3	Digital	Basic	0.09	0.90	0.04	0.11	0.16
4	Cognitive	Thinking	0.50	0.39	0.68	0.02	0.13
5	Cognitive	Communication	0.79	0.33	0.24	-0.03	0.21
6	Cognitive	Organization	0.68	0.41	0.12	0.29	0.27
7	Socioemotional	Relationships	0.18	0.83	0.10	0.17	0.24
8	Socioemotional	Emotions	0.91	-0.07	-0.02	0.05	0.17
9	Socioemotional	Personal growth	0.14	0.09	-0.07	0.95	0.07

B. Cambodia

	Skills category	Skill subset	Factors 1	2	3	Uniqueness
1	Digital	Advanced	0.24	0.18	0.79	0.29
2	Digital	Intermediate	0.09	0.83	0.28	0.23
3	Digital	Basic	0.78	0.35	-0.06	0.27
4	Cognitive	Thinking	0.85	0.24	0.14	0.20
5	Cognitive	Communication	0.87	-0.03	-0.05	0.25
6	Cognitive	Organization	0.49	0.52	0.04	0.48
7	Socioemotional	Relationships	0.28	0.68	-0.36	0.32
8	Socioemotional	Emotions	0.51	0.16	-0.62	0.33
9	Socioemotional	Personal growth	-0.54	0.45	-0.12	0.49

C. Malaysia

	Skills category	Skill subset	Factors 1	2	3	Uniqueness
1	Digital	Advanced	0.15	0.74	-0.07	0.43
2	Digital	Intermediate	0.20	0.87	0.07	0.20
3	Digital	Basic	0.76	0.09	-0.26	0.34
4	Cognitive	Thinking	0.80	0.36	0.07	0.22
5	Cognitive	Communication	0.82	-0.02	0.32	0.23
6	Cognitive	Organization	0.80	0.14	0.23	0.29
7	Socioemotional	Relationships	0.74	0.16	-0.06	0.42
8	Socioemotional	Emotions	0.34	-0.25	0.78	0.22
9	Socioemotional	Personal growth	-0.12	0.43	0.75	0.24

D. Thailand

			Factors			
	Skills category	**Skill subset**	**1**	**2**	**3**	**Uniqueness**
1	Digital	Advanced	0.03	0.78	-0.04	0.39
2	Digital	Intermediate	0.19	0.78	0.35	0.24
3	Digital	Basic	0.71	0.32	-0.26	0.32
4	Cognitive	Thinking	0.73	0.49	-0.18	0.19
5	Cognitive	Communication	0.87	0.02	-0.05	0.25
6	Cognitive	Organization	0.71	0.20	0.22	0.41
7	Socioemotional	Relationships	0.67	0.31	-0.20	0.41
8	Socioemotional	Emotions	0.73	-0.31	0.12	0.36
9	Socioemotional	Personal growth	-0.07	0.09	0.95	0.08

E. Vietnam

			Factors			
	Skills category	**Skill subset**	**1**	**2**	**3**	**Uniqueness**
1	Digital	Advanced	0.06	0.78	-0.03	0.38
2	Digital	Intermediate	0.28	0.81	0.09	0.26
3	Digital	Basic	0.76	0.28	-0.32	0.24
4	Cognitive	Thinking	0.75	0.43	-0.18	0.22
5	Cognitive	Communication	0.88	0.08	-0.10	0.21
6	Cognitive	Organization	0.72	0.30	0.20	0.36
7	Socioemotional	Relationships	0.66	0.24	-0.31	0.41
8	Socioemotional	Emotions	0.70	-0.36	0.10	0.37
9	Socioemotional	Personal growth	-0.10	0.04	0.96	0.07

Sources: Authors' calculations based on SEAD data.
Note: The factor analysis is based on varimax rotation for orthogonal factors.

Annex 5. Occupations' classification in exploratory factor analysis of skills categories

Table A.5.1. Occupations' scores of factors from exploratory factor analysis of digital, cognitive, and socioemotional skills subsets in Malaysia

Occupation						
Name	Code	Digitalization level	Factor 1	Factor 2	Factor 3	Employment share in Malaysia
Architects, planners, surveyors and designers	216	High	-0.5	7.8	3.9	0.4
Software and applications developers and analysts	251	High	0.5	7.2	-0.2	0.3
Database and network professionals	252	High	1.3	6.5	-0.6	0.3
Creative and performing artists	265	High	-0.3	6.1	3.5	0.1
ICT operations and user support technicians	351	High	1.1	4.9	-0.4	0.3
Telecommunications and broadcasting technicians	352	High	0.3	4.5	2.3	0.1
Information and communications technology service managers	133	High	1.4	4.0	0.4	0.1
Electrotechnology engineers	215	High	0.4	3.3	-0.4	0.5
Printing trades workers	732	High	-0.5	2.3	0.5	0.1
Electronics and telecommunications installers and repairers	742	High	0.1	2.0	-0.3	0.1
Mathematicians, actuaries and statisticians	212	High	2.3	1.7	-0.3	0.0
Physical and engineering science technicians	311	High	-0.5	1.1	-0.9	2.3
Keyboard operators	413	High	2.3	-0.3	-3.3	0.1
Regulatory government associate professionals	335	Medium	2.9	-0.1	-0.5	0.9
Chemical and photographic products plant and machine operators	813	Medium	2.4	0.4	0.3	0.2
Administration professionals	242	Medium	2.3	0.6	0.4	0.3
Administrative and specialised secretaries	334	Medium	2.1	-0.2	0.1	0.9
Librarians, archivists and curators	262	Medium	1.6	-0.1	1.6	0.0
Numerical clerks	431	Medium	1.3	-0.2	-1.3	1.2
Authors, journalists and linguists	264	Medium	1.3	2.2	2.6	0.1
Sales, marketing and public relations professionals	243	Medium	1.1	1.4	1.3	0.2
Secretaries (general)	412	Medium	1.1	-0.5	-0.2	0.1
Ship and aircraft controllers and technicians	315	Medium	1.1	-0.2	0.0	0.1
General office clerks	411	Medium	1.1	-0.3	-1.5	4.8
Financial and mathematical associate professionals	331	Medium	0.9	0.1	-1.2	0.3
Engineering professionals (excluding electrotechnology)	214	Medium	0.7	1.2	-0.3	1.0
Protective services workers	541	Medium	0.6	-0.2	-0.5	2.8
Process control technicians	313	Medium	0.6	0.8	-0.4	0.1
Other clerical support workers	441	Medium	0.3	-0.4	-1.6	0.5
Ships' deck crews and related workers	835	Medium	0.1	0.4	-0.3	0.1
Other health associate professionals	325	Medium	0.1	0.0	-0.9	0.4
Physical and earth science professionals	211	Medium	0.0	0.6	-0.1	0.0
Building frame and related trades workers	711	Medium	0.0	0.9	-0.8	1.8
Other craft and related workers	754	Medium	-0.1	0.2	-0.3	0.1
Food and related products machine operators	816	Medium	-0.1	0.7	-0.3	0.3
Assemblers	821	Medium	-0.2	0.1	-0.8	1.1
Vocational education teachers	232	Medium	-0.2	0.4	-0.5	0.1
Metal processing and finishing plant operators	812	Medium	-0.3	0.5	-0.3	0.2
Rubber, plastic and paper products machine operators	814	Medium	-0.3	0.8	-0.1	0.6
Manufacturing labourers	932	Medium	-0.4	0.2	-0.7	0.5
Paramedical practitioners	224	Medium	-0.4	-0.1	-0.6	
Wood treaters, cabinet-makers and related trades workers	752	Medium	-0.5	0.5	-0.4	0.5
Sheet and structural metal workers, moulders and welders, (…)	721	Medium	-0.6	0.6	-0.9	0.9
Painters, building structure cleaners and related trades workers	713	Medium	-0.6	-0.1	-0.9	0.4
Wood processing and papermaking plant operators	817	Medium	-0.7	0.5	-0.5	0.5
Handicraft workers	731	Medium	-0.7	0.5	-0.3	0.1
Other stationary plant and machine operators	818	Medium	-0.7	-0.2	-0.9	3.2
Blacksmiths, toolmakers and related trades workers	722	Medium	-1.3	1.9	-1.4	0.1
Finance professionals	241	Low	2.4	0.2	0.0	1.5
Managing directors and chief executives	112	Low	2.1	0.0	1.7	1.1
Business services and administration managers	121	Low	2.1	-0.2	0.5	1.5
Other services managers	143	Low	2.0	-1.0	3.2	0.2
Professional services managers	134	Low	1.8	-0.3	0.3	0.2
Manufacturing, mining, construction, and distribution managers	132	Low	1.6	0.0	0.1	0.9
Sales, marketing and development managers	122	Low	1.5	0.4	2.1	0.4

Occupation						
Name	Code	Digitalization level	Factor 1	Factor 2	Factor 3	Employment share in Malaysia
Material-recording and transport clerks	432	Low	1.4	-0.2	-0.7	0.9
Legal, social and religious associate professionals	341	Low	1.4	-0.6	-1.2	0.2
Legislators and senior officials	111	Low	1.4	-0.1	0.6	0.1
Client information workers	422	Low	1.3	-0.4	-0.3	0.5
Business services agents	333	Low	1.2	-0.2	0.7	0.4
Social and religious professionals	263	Low	1.1	-0.6	0.6	0.2
Life science professionals	213	Low	1.0	0.0	0.4	0.1
Tellers, money collectors and related clerks	421	Low	0.8	-1.1	0.9	0.5
Travel attendants, conductors and guides	511	Low	0.6	0.3	1.4	0.1
Other teaching professionals	235	Low	0.6	-0.7	2.0	0.7
Mining, manufacturing and construction supervisors	312	Low	0.5	-0.2	-0.1	1.3
Transport and storage labourers	933	Low	0.4	-0.2	-1.0	0.2
Shop salespersons	522	Low	0.4	-0.3	0.4	5.7
Production managers in agriculture, forestry and fisheries	131	Low	0.4	-0.3	0.2	0.1
Mining and construction labourers	931	Low	0.4	0.1	-0.6	2.2
Life science technicians and related associate professionals	314	Low	0.4	-0.1	-0.7	0.1
Sports and fitness workers	342	Low	0.3	-0.2	1.4	0.1
Personal care workers in health services	532	Low	0.0	-0.7	-0.3	0.2
University and higher education teachers	231	Low	-0.2	-0.1	0.5	0.6
Traditional and complementary medicine associate professionals	323	Low	-0.2	-0.3	-1.1	0.1
Veterinary technicians and assistants	324	Low	-0.2	-0.5	-0.5	0.0
Locomotive engine drivers and related workers	831	Low	-0.2	0.1	-0.3	0.0
Traditional and complementary medicine professionals	223	Low	-0.3	-0.5	-0.4	0.0
Medical and pharmaceutical technicians	321	Low	-0.3	-0.5	-0.9	0.1
Nursing and midwifery associate professionals	322	Low	-0.3	-0.5	-1.4	0.7
Mining and mineral processing plant operators	811	Low	-0.3	0.2	-0.5	0.2
Medical doctors	221	Low	-0.4	-0.7	-0.1	0.4
Artistic, cultural and culinary associate professionals	343	Low	-0.4	2.5	2.3	0.3
Refuse workers	961	Low	-0.6	0.1	-0.9	0.5
Cashiers and ticket clerks	523	Low	-0.6	-0.3	-0.8	0.8
Machinery mechanics and repairers	723	Low	-0.8	0.0	-0.8	2.2
Building finishers and related trades workers	712	Low	-0.9	0.2	-0.9	0.9
Electrical equipment installers and repairers	741	Low	-1.0	0.0	-0.8	1.2
Heavy truck and bus drivers	833	Low	-1.1	-0.4	-0.7	3.2
Primary school and early childhood teachers	234	Very low	-1.1	-0.9	2.8	1.9
Secondary education teachers	233	Very low	-0.8	-1.1	2.7	1.4
Retail and wholesale trade managers	142	Very low	1.1	-0.8	1.7	0.5
Child care workers and teachers' aides	531	Very low	0.5	-0.4	1.6	1.6
Food processing and related trades workers	751	Very low	-0.4	0.2	1.3	1.2
Hotel and restaurant managers	141	Very low	1.0	-0.9	1.2	0.5
Other sales workers	524	Very low	0.1	-0.7	0.9	1.6
Food preparation assistants	941	Very low	0.6	-0.7	0.8	0.5
Sales and purchasing agents and brokers	332	Very low	0.5	-0.6	0.6	2.3
Building and housekeeping supervisors	515	Very low	0.3	-1.0	0.5	0.2
Hairdressers, beauticians and related workers	514	Very low	-0.7	-0.7	0.4	0.8
Market gardeners and crop growers	611	Very low	-1.3	0.3	0.3	5.1
Animal producers	612	Very low	-1.3	0.3	0.3	0.2
Mixed crop and animal producers	613	Very low	-1.3	0.3	0.3	0.0
Forestry and related workers	621	Very low	-1.3	0.3	0.3	0.0
Fishery workers, hunters and trappers	622	Very low	-1.3	0.3	0.3	0.7
Subsistence crop farmers	631	Very low	-1.3	0.3	0.3	0.0
Subsistence livestock farmers	632	Very low	-1.3	0.3	0.3	0.0
Subsistence mixed crop and livestock farmers	633	Very low	-1.3	0.3	0.3	0.0
Subsistence fishers, hunters, trappers and gatherers	634	Very low	-1.3	0.3	0.3	0.2
Agricultural, forestry and fishery labourers	921	Very low	-1.3	0.3	0.3	4.8
Waiters and bartenders	513	Very low	-0.4	-0.6	0.3	2.6
Garment and related trades workers	753	Very low	-0.2	0.3	0.3	1.1
Cooks	512	Very low	-1.2	-0.3	0.2	1.5
Street and market salespersons	521	Very low	-0.2	-0.5	0.2	4.2
Street and related service workers	951	Very low	-0.2	-0.5	0.2	0.0
Street vendors (excluding food)	952	Very low	-0.2	-0.5	0.2	0.3

Occupation						
Name	**Code**	**Digitalization level**	**Factor 1**	**Factor 2**	**Factor 3**	**Employment share in Malaysia**
Domestic, hotel and office cleaners and helpers	911	Very low	0.0	-0.8	0.0	2.1
Veterinarians	225	Very low	-0.1	-0.6	0.0	0.0
Other personal services workers	516	Very low	-0.6	-0.6	-0.1	0.1
Textile, fur and leather products machine operators	815	Very low	-0.4	-0.2	-0.2	0.1
Vehicle, window, laundry and other hand cleaning workers	912	Very low	-0.4	-0.2	-0.2	0.2
Legal professionals	261	Very low	1.8	-0.4	-0.3	0.2
Other health professionals	226	Very low	0.1	-0.5	-0.4	0.3
Car, van and motorcycle drivers	832	Very low	-0.8	-0.2	-0.7	1.5
Nursing and midwifery professionals	222	Very low	-0.6	-0.8	-0.7	0.2
Other elementary workers	962	Very low	-1.0	-0.3	-1.1	1.5
Mobile plant operators	834	Very low	-0.8	-0.3	-1.4	0.8

Source: Authors' calculations based SEAD data.

Notes: The factor analysis is based on varimax rotation for orthogonal factors of nine digital, cognitive and socioemotional subsets of skills (three each). Clusters are described in section 6. Darker red and blue colors show higher and lower magnitudes, respectively.

Annex 6. Distribution of occupations across job postings and employment in the four countries

Table A.6.1. Share of job vacancies and employment by digital occupation level of the 127 occupations

Occupation name	ISCO code	Share in job vacancies	Share in employment				Digital occupation level
			Cambodia	Malaysia	Thailand	Vietnam	
Software and applications developers and analysts	251	6.0	0.1	0.3	0.1	0.1	High
Database and network professionals	252	1.8	0.0	0.3	0.1	0.1	High
Information and communications technology service managers	133	1.0	0.0	0.1	0.0	0.0	High
ICT operations and user support technicians	351	1.7	0.0	0.3	0.2	0.1	High
Electrotechnology engineers	215	1.2	0.0	0.5	0.1	0.2	High
Electronics and telecommunications installers and repairers	742	0.1	0.1	0.1	0.3	0.3	High
Mathematicians, actuaries and statisticians	212	0.1		0.0	0.0	0.0	High
Architects, planners, surveyors and designers	216	2.3	0.0	0.4	0.3	0.1	High
Telecommunications and broadcasting technicians	352	0.1	0.1	0.1	0.0	0.0	High
Physical and engineering science technicians	311	1.7	0.2	2.3	0.4	0.3	High
Printing trades workers	732	0.0	0.1	0.1	0.1	0.1	High
Creative and performing artists	265	0.2	0.3	0.1	0.2	0.1	High
Keyboard operators	413	0.1		0.1	0.1	0.0	High
Engineering professionals (excluding electrotechnology)	214	5.9	0.0	1.0	0.3	0.5	Medium
Assemblers	821	0.1	0.1	1.1	1.6	0.8	Medium
Sheet and structural metal workers, moulders and welders (…)	721	0.1	0.9	0.9	0.6	1.0	Medium
Protective services workers	541	0.3	1.2	2.8	1.4	0.9	Medium
Administration professionals	242	2.7	0.0	0.3	0.3	0.8	Medium
Vocational education teachers	232	0.0	0.0	0.1	0.1	0.1	Medium
Handicraft workers	731	0.0	1.0	0.1	1.3	0.9	Medium
Painters, building structure cleaners and related trades workers	713	0.2	0.1	0.4	0.4	0.3	Medium
Librarians, archivists and curators	262	0.0	0.0	0.0	0.0	0.1	Medium
Paramedical practitioners	224	0.1	0.0		0.0	0.0	Medium
Chemical and photographic products plant and machine operators	813	0.0	0.1	0.2	0.2	0.0	Medium
Physical and earth science professionals	211	0.2		0.0	0.1	0.0	Medium
Process control technicians	313	0.0	0.0	0.1	0.1	0.1	Medium
Ships' deck crews and related workers	**835**		0.0	0.1	0.1	0.2	Medium
Other craft and related workers	**754**		0.0	0.1	0.5	0.5	Medium
Other clerical support workers	441	0.1	0.1	0.5	0.4	0.9	Medium
Food and related products machine operators	**816**		0.3	0.3	0.5	0.2	Medium
Other health associate professionals	325	0.4	0.1	0.4	0.3	0.1	Medium
Administrative and specialised secretaries	334	5.2	0.2	0.9	0.2	0.2	Medium
Other stationary plant and machine operators	818	0.1	0.1	3.2	0.5	0.7	Medium
Regulatory government associate professionals	335	0.1	0.0	0.9	0.2	0.5	Medium
Wood processing and papermaking plant operators	**817**		0.0	0.5	0.1	0.2	Medium
Wood treaters, cabinet-makers and related trades workers	**752**		0.9	0.5	0.3	0.8	Medium
Rubber, plastic and paper products machine operators	**814**		0.1	0.6	0.6	0.3	Medium
General office clerks	411	6.0	2.1	4.8	1.5	0.1	Medium
Secretaries (general)	**412**		0.0	0.1	0.0	0.0	Medium
Manufacturing labourers	932	1.0	0.4	0.5	1.3	1.3	Medium
Sales, marketing and public relations professionals	243	4.9	0.2	0.2	0.4	0.5	Medium
Authors, journalists and linguists	264	0.5	0.2	0.1	0.1	0.1	Medium
Metal processing and finishing plant operators	**812**		0.0	0.2	0.3	0.2	Medium
Ship and aircraft controllers and technicians	315	0.1	0.0	0.1	0.0	0.0	Medium
Building frame and related trades workers	711	0.0	4.5	1.8	1.2	4.2	Medium
Numerical clerks	431	0.8	0.1	1.2	0.5	0.1	Medium
Financial and mathematical associate professionals	331	5.4	0.6	0.3	1.5	0.4	Medium
Blacksmiths, toolmakers and related trades workers	722	0.3	0.2	0.1	0.5	0.1	Medium
University and higher education teachers	231	0.3	0.0	0.6	0.2	0.2	Low
Sports and fitness workers	342	0.1	0.0	0.1	0.1	0.0	Low
Electrical equipment installers and repairers	741	0.1	0.4	1.2	0.9	0.5	Low
Managing directors and chief executives	112	1.9	0.0	1.1	0.1	0.0	Low
Medical doctors	221	0.1	0.1	0.4	0.1	0.2	Low

Occupation name	ISCO code	Share in job vacancies	Share in employment				Digital occupation level
			Cambodia	Malaysia	Thailand	Vietnam	
Life science professionals	213	0.2	0.0	0.1	0.1	0.1	Low
Heavy truck and bus drivers	833	0.1	0.4	3.2	0.7	0.9	Low
Traditional and complementary medicine associate professionals	**323**		0.0	0.1	0.0	0.0	Low
Personal care workers in health services	532	0.1	0.0	0.2	0.3	0.1	Low
Tellers, money collectors and related clerks	421	0.2	0.5	0.5	0.3	0.2	Low
Machinery mechanics and repairers	723	0.2	1.3	2.2	1.6	0.9	Low
Legislators and senior officials	**111**		0.5	0.1	0.7	0.4	Low
Cashiers and ticket clerks	523	0.1	0.1	0.8	0.4	0.1	Low
Nursing and midwifery associate professionals	322	0.0	0.0	0.7	0.2	0.3	Low
Medical and pharmaceutical technicians	321	0.2	0.0	0.1	0.1	0.1	Low
Mining and mineral processing plant operators	811	0.0	0.0	0.2	0.1	0.2	Low
Veterinary technicians and assistants	**324**		0.0	0.0	0.0	0.0	Low
Professional services managers	134	1.0	0.1	0.2	0.3	0.0	Low
Finance professionals	241	3.1	0.4	1.5	0.2	1.3	Low
Traditional and complementary medicine professionals	**223**		0.0	0.0	0.0	0.0	Low
Other services managers	143	0.5	0.1	0.2	0.1	0.3	Low
Manufacturing, mining, construction, and distribution managers	132	4.6	0.0	0.9	1.0	0.1	Low
Business services and administration managers	121	6.7	0.2	1.5	0.6	0.1	Low
Client information workers	422	3.1	0.2	0.5	0.5	0.2	Low
Other teaching professionals	235	0.1	0.3	0.7	0.2	0.2	Low
Refuse workers	**961**		0.4	0.5	0.3	0.3	Low
Locomotive engine drivers and related workers	**831**		0.0	0.0	0.0	0.0	Low
Material-recording and transport clerks	432	1.4	0.1	0.9	0.8	0.3	Low
Social and religious professionals	263	0.1	0.1	0.2	0.1	0.1	Low
Sales, marketing and development managers	122	5.2	0.1	0.4	0.2	0.0	Low
Production managers in agriculture, forestry and fisheries	131	0.0	0.0	0.1	0.0	0.0	Low
Mining, manufacturing and construction supervisors	312	0.4	0.4	1.3	0.5	0.1	Low
Shop salespersons	522	4.7	9.1	5.7	7.0	5.1	Low
Life science technicians and related associate professionals	314	0.1	0.0	0.1	0.0	0.0	Low
Building finishers and related trades workers	712	0.0	1.2	0.9	1.4	0.2	Low
Mining and construction labourers	931	0.1	2.5	2.2	1.7	2.3	Low
Legal, social and religious associate professionals	341	0.2	0.0	0.2	0.1	0.1	Low
Business services agents	333	0.8	0.2	0.4	0.3	0.2	Low
Artistic, cultural and culinary associate professionals	343	1.4	0.1	0.3	0.2	0.1	Low
Transport and storage labourers	933	0.6	1.0	0.2	1.1	1.0	Low
Travel attendants, conductors and guides	511	0.0	0.0	0.1	0.1	0.0	Low
Market gardeners and crop growers	**611**		9.6	5.1	21.7	4.8	Very low
Animal producers	**612**		6.8	0.2	2.5	1.8	Very low
Mixed crop and animal producers	**613**		0.0	0.0	0.2	0.0	Very low
Forestry and related workers	**621**		0.4	0.0	0.2	0.0	Very low
Fishery workers, hunters and trappers	**622**		1.3	0.7	0.8	1.8	Very low
Subsistence crop farmers	**631**		12.2	0.0	3.1	1.1	Very low
Subsistence livestock farmers	**632**		3.5	0.0	0.0	0.1	Very low
Subsistence mixed crop and livestock farmers	**633**		0.0	0.0	0.0	0.1	Very low
Subsistence fishers, hunters, trappers and gatherers	**634**		1.1	0.2	0.2	0.0	Very low
Agricultural, forestry and fishery labourers	921	0.0	4.8	4.8	2.8	30.0	Very low
Car, van and motorcycle drivers	832	0.2	2.6	1.5	3.3	1.9	Very low
Legal professionals	261	0.2	0.0	0.2	0.2	0.1	Very low
Waiters and bartenders	513	0.2	0.7	2.6	1.0	0.5	Very low
Child care workers and teachers' aides	531	0.1	0.1	1.6	0.2	0.2	Very low
Food preparation assistants	941	0.3	0.2	0.5	0.3	0.2	Very low
Hairdressers, beauticians and related workers	514	0.2	0.6	0.8	0.8	0.7	Very low
Other sales workers	524	0.8	0.8	1.6	3.0	0.5	Very low
Textile, fur and leather products machine operators	815	0.0	0.1	0.1	1.3	3.7	Very low
Vehicle, window, laundry and other hand cleaning workers	**912**		0.7	0.2	0.4	0.1	Very low
Cooks	512	0.1	0.6	1.5	1.9	0.7	Very low
Sales and purchasing agents and brokers	332	6.1	0.1	2.3	0.5	0.1	Very low
Street and market salespersons	**521**		4.8	4.2	3.5	7.1	Very low
Street and related service workers	**951**		0.0	0.0	0.0	0.1	Very low
Street vendors (excluding food)	**952**		0.4	0.3	1.1	0.2	Very low

Occupation name	ISCO code	Share in job vacancies	Share in employment				Digital occupation level
			Cambodia	Malaysia	Thailand	Vietnam	
Food processing and related trades workers	751	0.1	1.2	1.2	1.7	1.3	Very low
Nursing and midwifery professionals	222	0.4	0.2	0.2	0.4	0.1	Very low
Veterinarians	225	0.0	0.0	0.0	0.0	0.0	Very low
Other health professionals	226	0.7	0.1	0.3	0.3	0.1	Very low
Hotel and restaurant managers	141	0.3	0.2	0.5	0.3	0.0	Very low
Other personal services workers	516	0.1	0.1	0.1	0.1	0.4	Very low
Retail and wholesale trade managers	142	0.4	0.0	0.5	0.5	0.1	Very low
Mobile plant operators	834	0.0	0.5	0.8	0.5	0.3	Very low
Other elementary workers	962	0.2	0.7	1.5	0.9	0.9	Very low
Primary school and early childhood teachers	234	0.3	0.8	1.9	1.4	1.5	Very low
Building and housekeeping supervisors	515	0.1	0.0	0.2	0.7	0.5	Very low
Domestic, hotel and office cleaners and helpers	911	0.1	0.6	2.1	1.4	0.7	Very low
Secondary education teachers	233	0.1	0.5	1.4	0.6	1.0	Very low
Garment and related trades workers	753	0.0	9.3	1.1	0.6	2.1	Very low

Source: Authors' calculations based on SEAD data.

Notes: The 27 occupations in bold are the ones whose skills profile is imputed from one or several similar occupations (see section 3).

Annex 7. Robustness Checks: Results using the 5 clusters based on ascending digital occupation levels without merging clusters 2 and 3

Table A.7.1 and figures A.7.1. and A.7.2. show that the results presented in Tables 6 and Figures 6 and 7 are robust to merging the clusters based on ascending digital occupation levels.

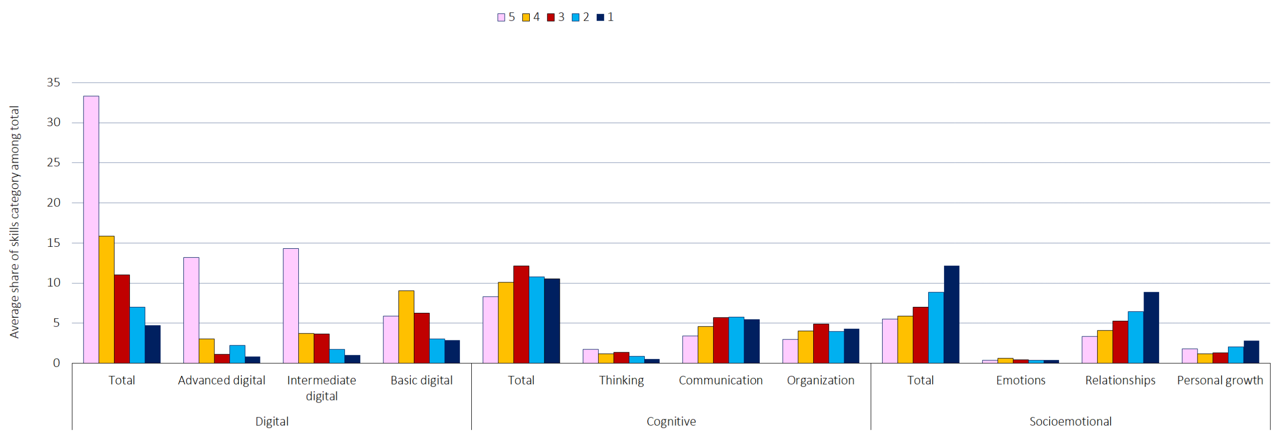
Table A.7.1. Conditional correlations between clusters based on ascending digital occupation levels and cognitive and socioemotional skills requirements (replication of Table 6)

		Clusters based on ascending digital occupation levels									
		2 vs. 1	3 vs. 1	4 vs. 1	5 vs. 1	3 vs. 2	4 vs. 2	5 vs. 2	4 vs. 3	5 vs. 3	5 vs. 4
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cognitive	Thinking	0.51	**0.82***	**1.35*****	**2.78*****	0.06	**0.78****	**1.43****	0.14	0.38	0.01
		(0.26)	(0.40)	(0.27)	(0.53)	(0.31)	(0.24)	(0.47)	(0.11)	(0.39)	(0.15)
	Communication	0.21	**0.91***	0.18	-0.12	0.33	-0.19	-0.43	-0.25	-0.52	0.01
		(0.16)	(0.42)	(0.27)	(0.21)	(0.18)	(0.46)	(0.71)	(0.15)	(0.35)	(0.33)
	Organization	-0.11	0.30	-0.27	-0.81	0.26	0.16	1.25	**-0.35****	-0.43	0.12
		(0.19)	(0.37)	(0.27)	(0.55)	(0.22)	(0.35)	(0.76)	(0.12)	(0.34)	(0.10)
Socioemotional	Emotions	0.30	-0.35	**1.30*****	1.08	-0.33	0.78	0.04	**0.49*****	0.47	-0.30
		(0.16)	(0.33)	(0.25)	(0.54)	(0.19)	(0.44)	(0.66)	(0.11)	(0.33)	(0.21)
	Relationships	**-0.43****	-0.12	**-1.44*****	-0.89	0.26	-0.60	-1.00	-0.39	**-0.80***	0.08
		(0.14)	(0.25)	(0.30)	(0.57)	(0.26)	(0.54)	(0.53)	(0.19)	(0.30)	(0.38)
	Personal growth	**-0.32***	0.09	**-1.09*****	-0.73	-0.05	-0.76	-0.92	-0.13	0.22	**0.36***
		(0.13)	(0.30)	(0.29)	(0.54)	(0.31)	(0.48)	(0.68)	(0.17)	(0.31)	(0.18)
	Constant	1.48***	1.17***	2.49***	1.98**	2.22***	2.90***	2.69***	3.79***	4.11***	4.22***
		(0.15)	(0.26)	(0.33)	(0.72)	(0.13)	(0.36)	(0.65)	(0.11)	(0.61)	(0.22)
	N	58	59	72	51	41	54	33	55	34	47
	R-sq	0.34	0.50	0.67	0.44	0.36	0.34	0.26	0.55	0.36	0.13

Sources: Authors' calculations based on SEAD data for Malaysia.

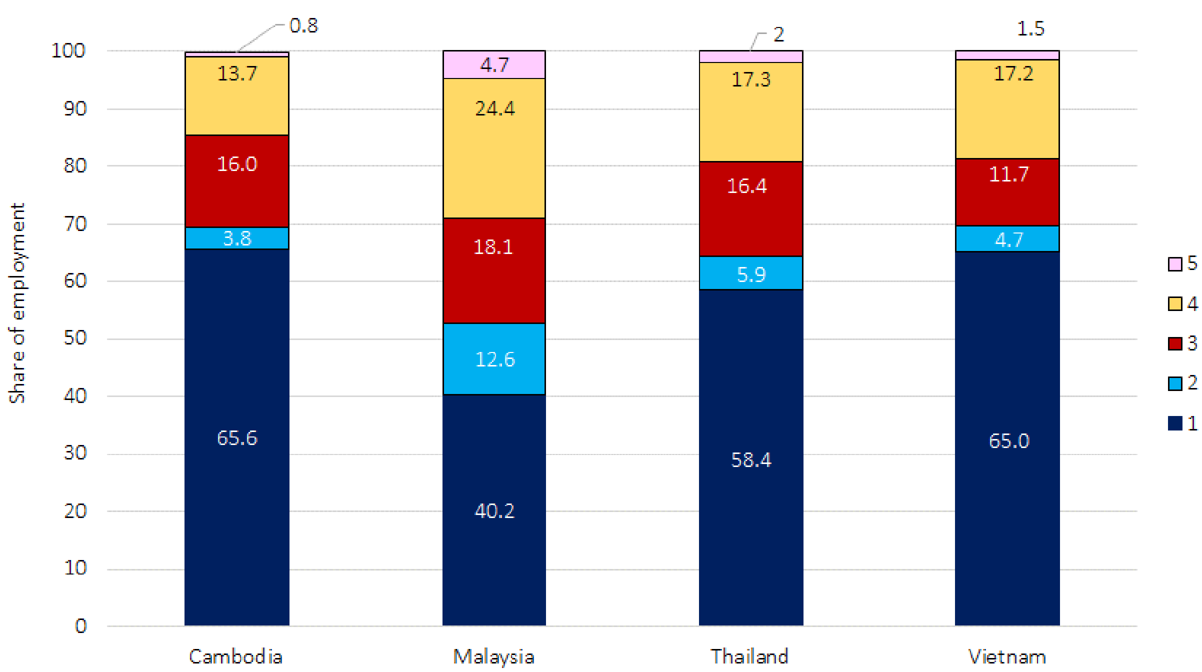
Note: The regressors for the outcome are dummy variables taking the value of one if the skills count of a skills category of an occupation is above the mean. The 2017 Malaysian labor force survey does not report any workers in one of the 127 occupations from our occupational skills profile (paramedical practitioners, ISCO code 224). See subsection 3.2. for details on the clustering.
**p < 0.1 **p < 0.05 ***p < 0.01*

Figure A.7.1. Composition of skills categories and subsets across clusters based on ascending digital occupation levels (replication of Figure 6.B)



Source: Authors' calculations based on SEAD data.
Notes: The share of skills splits between digital, cognitive, and socioemotional, and other skills. Digital skills levels and cognitive and socioemotional skills subsets are subcategories counted in the total. See subsection 3.2. for details on the clustering.

Figure A.7.2. Employment across clusters based on ascending digital occupation levels across countries (replication of Figure 7)



Source: Authors' calculations based SEAD data.
Notes: See subsection 3.2. for details on the clustering.