# The Impacts of Knowledge Worker and Skills in the Industrial Revolution 4.0: Empirical Evidence from Selected Asean+3 Countries

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## ABSTRACT

The rapid pace of technological change presents significant challenges for academic institutions and professionals. The importance of knowledge workers and skills in enabling businesses to compete in the era of Industry 4.0 is paramount, reshaping the global economy. This study investigated the impacts of knowledge workers and skills on technology from 1990 to 2021. This study utilized pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE) models from dynamic panel techniques. The Hausman test identified the PMG estimator as the most suitable for this research. PMG's findings revealed a substantial, consistent impact of knowledge workers on R&D over time. Additionally, the gap between highly skilled and semi-skilled employees negatively affected R&D. In the short term, FDI exhibited a negative yet significant impact on R&D, while the interaction between high-skilled and nation-dummies positively influences R&D. Thus, policymakers should prioritize enhancing the educational system through new initiatives and support programs. Moreover, increased government funding and support for employer-led training programs are essential to meet the rising demand for skilled workers. Businesses must also foster employee skill development to thrive in the impending industrial revolution.

**Keywords:** Knowledge Worker, Human Capital, Skills, The Industrial Revolution, R&D

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## INTRODUCTION

Industry 4.0, also known as the Fourth Industrial Revolution (4IR), is the term used to describe the widespread adoption of automated processes and cutting-edge technologies across multiple sectors. Automating manufacturing processes and boosting efficiency are hallmarks of this revolution, which is being driven by developments in artificial intelligence, robots, the Internet of Things, and other digital technologies. The growth of Industry 4.0 will have major effects on human capital. Workers in many fields now need to have a broader set of skills and knowledge than was previously necessary as automation and digitization replace manual labour (Hirsch-Kreinsen, 2016). Expertise in areas such as data analysis, programming, and machine operation are all necessities in the modern workplace.

Thus, human capital will play a crucial role in the context of Industry 4.0 in identifying whether workers can adapt to and succeed in the new economy (Hendrik et al., 2019). Workforce members with high levels of technical expertise and a demonstrated capacity for rapid learning will be in great demand, while those with more conventional qualifications may find it difficult to obtain work (Brown et al., 2004). Moreover, maintaining a workforce that can adapt to an ever-evolving economy will depend heavily on investments in human capital. The 4IR characterized by the fusion of technologies across the physical, digital, and biological realms, leading to a transformation in work force (Daley & Cordell, 2021). Knowledge workers, who are intricately to involved in field of technology have crucial role for development in the revolution. They are creative and specialists in their fields, will help to develop in advanced technology. As the 4IR unfolds, knowledge workers face the dual challenges for keeping the phase in evolving technology and recalibrating their roles. This requires a strategic reorientation of skills, ethics, and work paradigms as well as commitment to lifelong learning (Lund et al., 2012).

The 4IR skill is required for the knowledge worker to adapted with new work paradigms that offer an optimum productivity and efficiency through automation, expert systems such as artificial intelligence, smart sensors, internet of Things, big data and analytics, autonomous robots, additive manufacturing, and cloud computing. According to Sarina (2018), this knowledge is crucial for acquiring and constructing in improve project efficiency and cope with massive amounts of data and information. The 4IR refers to the environmental and technological shifts that are revolutionising the way we live and work. In 2016, the founder and executive chairman of the World Economic Forum (WEF), respectively Kayembe and Nel (2019), proposed the ideas of the 4IR. The UNIDO Industrial Development Report named the IoT, big data analytics, sophisticated robotics, AI, cloud computing, and additive manufacturing as characteristics of Industry 4.0. Hussin (2018) used the Education 4.0 framework to help teachers improve their practises. Because of this, teachers now have a greater responsibility to use technology and innovation to open up new horizons for their students.

Ten countries in Southeast Asia form the Association of Southeast Asian Nations (ASEAN), a regional organisation. ASEAN is a multilateral organisation that promotes and supports the political, economic, military, and security integration of its member states in the Asia-Pacific region. It is estimated that 668 million people live within the union's total area of 4,522,518 km2. According to Economic Outlook Asia and Pacific (2022), ASEAN will maintain the region's new status as a global development engine throughout the years 2022 and 2023. Growth in the global economy may be traced in large part to the Association of Southeast Asian Nations (ASEAN) (Vora-Sittha & Chinprateep, 2021). The long-term success of every nation depends on its ability to foster technological innovation. The Government Artificial Intelligence Readiness Index evaluates the level to which governments are prepared to apply AI by providing the appropriate frameworks, skills, resources, and infrastructure. This index of readiness can be used by ASEAN to better prepare for the Fourth Industrial Revolution. The Government Artificial Intelligence Readiness Index 2022 measures how ready a country is to prosper in the Fourth Industrial Revolution.

**Table 1: The Government AI Readiness Index for 2022**

| World Rank | ASEAN Rank | Country | Index |
|---|---|---|---|
| 29 | 5 | Malaysia | 67.37 |
| 31 | 6 | Thailand | 64.63 |
| 2 | 1 | Singapore | 84.12 |
| 43 | 7 | Indonesia | 60.89 |
| 47 | 8 | Cambodia | 31.17 |
| 9 | 3 | Japan | 75.25 |
| 6 | 2 | South Korea | 76.76 |
| 17 | 4 | China | 70.84 |
| 54 | 9 | Philippines | 55.42 |

Source: IDRC (2022). Government Artificial Intelligence Readiness Index

Table 1 shows nine different East Asian countries with AI readiness indices for 2022. Three other East Asian countries, such as Singapore, Japan, and Korea, emerged as leaders in the 2022 index. These three countries appeared in the top 10 world rankings, with Singapore in the world ranking index. Singapore is powerful in the government's commitment to digital and innovation implementation in a business-friendly legal environment. Pairing works and productive public-private partnerships will open the door for innovation and technology-based industry. Singapore also has partnerships with the National Office for AI and Google Cloud that help the government create AI skills and capabilities for public sector officers and the population. Overall, Singapore is the best example of a regional city with global innovations in East Asia. Technology sectors across the region are growing, with countries with technically skilled workers, such as Taiwan and Malaysia, performing particularly well in this dimension. Japan has expended investment in training, education and human resource development initiatives as the largest economy region (Zhu, 2004).

On the other hand, Thailand and Indonesia introduced the digital nomad in 2022 with a policy of innovation that aimed to attract skilled tech workers. Singapore introduced a flexible visa schema that helps top talent in sectors such as science and technology. One of the challenges for countries is the 4IR approach implemented by the government. Since the COVID-19 pandemic, this issue has been widely used. Malaysia focuses on developing high technology, artificial intelligence (AI) automation. This gives opportunities to hire a skilled worker that can solve problems critically thinking, people management, cognitive, flexibility and creativity. High-skilled workers with technology skill are worth investing in as their skill help in business and economic growth. Robots and machines might replace human force, but human emotion, thinking and skilled worker are unreplaceable. This situation will help enhance training to be more efficient with fast-change technology with high expectations from the customer. Maintaining a highly skilled worker with a sharp mind and curiosity helps develop new ideas and skills. High technology is vital to allow the highly skilled worker to create jobs.

The IR 4.0 is reshaping the global economy and posing new difficulties for training and education. There are a few difficulties, as indicated by empirical evidence from a number of ASEAN+3 countries.

One difficulty is the requirement for a curriculum that is both current and useful in order to adequately educate students for the dynamic nature of the modern workplace. Traditional educational programmes may not provide students with the skills and information essential to thrive in the modern economy when new technologies and industries develop. Raising the bar for students and workers in terms of digital literacy and technical abilities is another obstacle. Technical proficiency and digital literacy are essential for embracing Industry 4.0 technology. In the ASEAN+3 countries, where a large proportion of the workforce is engaged in low-skill, labour-intensive industries that are vulnerable to automation, this is of paramount importance. Creating opportunities for people to keep their skills and knowledge current over the course of their careers is a third obstacle. Workers need to be able to adapt to new technologies and gain new expertise as industries evolve if they want to keep their jobs. This calls for a change away from more rigid forms of education and training in favour of more malleable educational frameworks. Last but not least, we need to close the digital divide and provide everyone the opportunities the digital economy offers. Included in this category are high-speed internet connections, digital tools, and appropriate educational resources.

This research contributes to the existing body of knowledge and provides guidance to policymakers on how to develop a workable policy in this setting. People's knowledge and skillsets are more likely to steadily develop under a strategy that supports technological advancements. It is vital to put money into training and education programmes that emphasise cutting-edge tools and techniques. The following are some of the ways in which this study improves upon previous investigations of education and skilled labour on technology. In order to reach IR4.0, education and trained labour are crucial. They can aid in research and development, implementation, adoption, data management, business model innovation, and security. Here is where investment in education and training for the next generation of employees is critical. Insights into how best to offer students with the skills and knowledge they will need to succeed in the jobs of the future could be gained from the education and skilled worker's study. Policymakers can ensure that students are getting the knowledge and skills they need to succeed in today's dynamic labour market by reviewing data on the current state of education and workforce development. Increasing access to digital learning materials, expanding apprenticeship and vocational training programmes, and investing in STEM (science, technology, engineering, and mathematics) education are all possible ways to achieve this goal. Research on schools and professionals can also help shape policies that promote diversity and inclusion in the workplace. Policymakers can ensure that everyone has a level playing field in the digital economy by analysing gaps in educational and training opportunities across socioeconomic and demographic categories and implementing targeted programmes to close those gaps. Individuals in the modern world need to be adaptable, quick to learn new things, comfortable with uncertainty, and proficient in digital technologies. Besides, in the age of IR4.0, it is important to have well-informed policies that promote economic growth and social well-being. This research is the first to utilise the Panel ARDL method to examine the impacts of education and skilled worker on the IR4.0.

There are five main divisions to this article structure. In the second, we discuss the relevant background research, and in the third, we focus on the methodological and theoretical underpinnings of the model. In the following section, we explain the findings. The final part summarises the most important facts presented in the fifth segment.

## LITERATURE REVIEW

The role of education and training in preparing individuals for the digital age has been thoroughly studied, as has been the relationship between human capital and technology. Using technology in the classroom has been shown to improve students' performance in a variety of ways. Technology-enhanced teaching, for instance, was found to have a moderate to considerable positive effect on student achievement in a meta-analysis of 58 research by Tamim et al. (2011). Means et al. (2010) also discovered that pupils who incorporated technology into their education were more successful overall. Voogt et al. (2013) discovered a favourable correlation between the use of technology in the classroom and students' ICT abilities, which are essential for success in the digital economy, demonstrating the importance of incorporating technology into education in order to prepare students for Industry 4.0. In addition, Harris et al. (2016) discovered that students' academic performance and attendance were significantly influenced by technological tools. Given the increasing technological change of educational institutions, these findings are of special significance.

Since the 4IR will happen whether we like it or not, “education in 4.0” has gained popularity in recent years (Hussin, 2018). Among the many novel concerns addressed in research into adapting the programme to the realities of industry 4.0 is their relationship to the program’s fundamental pedagogical tenets and objectives (Ellahi et al., 2019). The research demonstrated that students are more engaged when teachers use strategies that emphasise active communication and digital infrastructures. As a result, educational institutions must devote greater resources to preparing the next generation to use growing IT networks for data collection, analysis, and sharing. Digital education has been shown to be more effective at improving students’ healthcare knowledge than either traditional or online instruction (Kyaw et al., 2019). The purpose of Devi et al. (2020) was to investigate how IR4.0 might affect the teaching of literature in higher education. Most legal ideas from the physical world’s corpus of knowledge are obsolete in the IR4.0 age. People during the Industrial Revolution needed to learn new skills in order to succeed in the job market.

According to Azmi et al. (2020), traditional approaches that emphasise teaching law graduates are obsolete because such tasks can be easily performed by bots such as those found in Learning Management Systems (LMS) like MyGuru and BeSmart at universities like Malaysia’s Sultan Idris University of Education (UPSI) and Indonesia’s Yogyakarta National University (UNY). Malaysia is still on the cusp of implementing Education 4.0 in its higher learning institutions. According to Halili et al. (2021), they could provide students with more access to opportunities to acquire skills necessary for success in the workplace during the 4IR. According to the estimates of Balaj et al. (2021), the way in which fathers are educated and the way in which their children are educated vary significantly across generations. The gap between the two is large. The work of Wang (2019), analysed the current state of integrating education about innovation and entrepreneurship into Shaanxi’s professional curriculum. He delves into Shaanxi’s experience in naturally combining innovation and entrepreneurship education with professional education to find out its real-world consequences. Hussin (2018) outlined the nine 21st-century teaching abilities educators need, as well as many techniques for adopting Education 4.0 that are supported by student feedback.

Ellahi et al. (2019) research on improving curriculum in light of industry 4.0's stressed on new difficulties and fundamental aspects with pedagogical aims. In order for educational institutions to advance, they must take into account developments like Big Data Analytics, AI, AR, IoT, Cloud Computing, and more. In order to ensure that students are equipped with the technical skills necessary for the developing Industry 4.0, Ellahi et al. (2019) suggested a matrix that may be used by schools to alter their curricula. Mehta et al. highlighted the need of continuing education when making a job change (2013). This is a province where educators are actively looking for new ways to improve students' soft skills. According to Hayes (2016), English is being prioritised as a future-proof skill at Thai universities. Research by Pholphirul (2017) supported the idea that preschools contribute to lasting improvements in later school success. Thai students benefitted greatly from the opportunities to increase their skill set, knowledge, and aptitude (Du et al., 2019).

Students' ability to learn and work together in groups are just two of the characteristics that Trung et al. (2009) identified as influencing students' skill development at Vietnamese universities. Knowing the course objectives and material also aided in skill development. Part-time work and extracurricular activities appeared to be boosting graduates' skills in Vietnam. Di Gropello et al. (2010) research into the demand skills that examined the Asian labour force backs this up. The results indicated that the government should focus policies promoting education access, specialised curriculum activities, and design for wide variety of abilities in order to keep up with the rising demand for skilled workers. Tran (2013) explored the problem of graduate and student skill development in Vietnam's higher education system by looking at curriculum design, content, and pedagogical strategies. The results indicated that students are more likely to be passive when exposed to centrally managed curricula and conventional teaching methods. Graduates are ill-prepared for the workforce because of limitations on their ability to acquire new skills while in school. There is a mismatch between graduates' skills and employers' needs, which is indicative of the changing nature of the job market in the age of Industry 4.0 (Demombynes et al., 2018). The dearth of qualified workers in Vietnam, especially those with technical and professional backgrounds, presents an opportunity for higher education to expand the country's knowledge base in preparation for an increasingly globalised economy (Montague, 2013). As a result, HRM now has the chance to forge connections between training for essential jobs and the management of talent (Connell et al., 2014).

Teachers have a hard time making the leap from more straightforward, conventional techniques to those that emphasise creativity, innovation, and problem-solving. This not only provides skills and knowledge necessary for the IR4.0 revolution, but also offers problems. According to Fisk (2017), shifting responsibility for learning to students might help them grow into creative, resourceful adults who will be in high demand in the global economy of the future. The technologically savvy students of Generation Z (Gen Z) have propelled education into the 21st century, thanks to the IR4.0 revolution. According to Kozinsky (2017), modern digital tools and online forums may shape the way Generation Z students like to study. Eighty percent of members of Generation Z want jobs that include using cutting-edge technology, finds Dell Inc. research. For their first jobs, they want to do something comparable to what they did in school, so they look for IT jobs. According to Azman and Ibrahim (2018), the Malaysian Ministry of Higher Education has designed a framework for public higher education institutions (IPT) to produce a workforce that is ready for Industry 4.0. Teachers must meet the challenges of the 4IR by remaining competitive and adapting to the opportunities and demands of digital change. Rahim and Shamsudin (2019) argued that communication and technology will be crucial in accommodating the various learning styles of the millennial generation. To further improve the student's learning experience, classroom procedures should not just revolve around the use of computers and electronic materials (Oke & Fernandes, 2020). Rashid and Hanan (2016) argued that digital technology can boost students' education, but that teachers are necessary to make this happen through timely guidance and individualised lessons. By taking this tack, educators can better prepare their pupils to meet the societal demands that will be created by 4IR technologies.

The concept of knowledge workers in the context of the industry 4.0 is important. In the era of Industry 4.0, organizations are increasingly relying on knowledge and its exploitation to sustain a long-term competitive advantage (Manesh et al., 2020). This revolution is characterised by the integration of digital technologies, automation, and data exchange, leading to a knowledge-intensive work environment where manual jobs are being replaced by high-skilled jobs (Anshari et al., 2022). A study published in the

IEEE Transactions on Engineering Management emphasized the critical role of knowledge management in the 4IR. It highlighted the need for a precise understanding of knowledge management processes and how knowledge is created, shared, acquired, stored, and applied throughout an organizational system in the era of Industry 4.0

Furthermore, the shift towards Industry 4.0 is expected to lead to an increased demand for knowledge workers and a decreased need for skilled and unskilled workers (Kurt, 2019). Knowledge workers are seen as the drivers of innovation and creativity in this new industrial era, playing a central role in leveraging digital technologies and contributing to the overall success of organizations. The role of knowledge workers in driving innovation, leveraging digital technologies, and contributing to the long-term competitive advantage of organizations. As Industry 4.0 continues to reshape the industrial landscape, the demand for knowledge workers is expected to rise, highlighting the increasing importance of their role in the modern workforce Li (2022). Besides, Kuo et al. (2018) found that higher education correlates with increased R&D investment. Other than that, the impact with knowledge worker is the introduce towards Knowledge Management (KM) which is the skill for 4IR, as it involves acquiring, constructing, managing, and disseminating knowledge throughout an organization to improve project efficiency and cope with massive amounts of data in times of crisis (Sarina, 2018). This helps knowledge workers to have a basic knowledge management for fundamental to the success of the 4IR.

According to Singaram et al. (2023), the positive impact can be seen in the change of teaching and learning methods with more access and technology advancement that needed for students to digitally literate to adapt to a digital world. In addition, The Asian Development Bank highlighted that need for evidence-based solution for skills and talent development. This emphasizes a greater economic value to societies for effective and greater productivity. However, they are some challenges that need to be addressed towards the changes a requiring educator to understand the new skills and knowledge needed in the workforce. It also calls for the updating of curricula and the development of students' creative, collaborative, and critical thinking skills (Gous, 2019). The 4IR affects not only economic activities but also student mobility and higher education. It may lead to increased demand for study abroad due to changes in the global knowledge stock. However, it also poses challenges such as the rapid obsolescence of knowledge and the high costs of education (Sekiyama, 2020). Furthermore, Al-Maskari et al. (2024) found that organisational dimensions have the greatest influence on students' readiness. Additionally, organisational dimensions significantly affected students' knowledge of 4IR technologies. Students' characteristics related to 4IR are also significantly influenced by their knowledge of these technologies and organisational dimensions.

Neil and Clarke (2019) found that increases in high-tech skilled personnel at low cost and with high equality are made possible. In the Silicon Valley, for instance, the high-tech business pays well due to its numerous and its low-wage, highly equal workforce. The government is putting money into the tech industry so that it can expand. A religious economy can benefit from a sectoral growth approach. The result will be a boost in local output. High productivity in the high-tech industry can be gained through innovation and STEM skills, leading to higher compensation. The need for educated and experienced tech employees has grown substantially in tandem with the expansion of the sector. Even though the tech business is undergoing substantial changes, skilled computer employees remain in high demand. Skills in software development, data analytics, and engineering are highly prized by today's top executives in the technology industry. Although many anticipate radical changes in the sector as a result of automation in the future years, most top executives disagree that this will result in the loss of tech jobs (Holmes, 2019). Soft skills like communication, teamwork, and problem solving are just as important as technical expertise in the computer business. Due to the ever-increasing competition for open positions in the IT industry, it's crucial to hone both hard and soft abilities (Makinde, 2023).

According to Aiyetan and Dillip (2018), several factors include investment, pay, talent management, the work environment, training, experience, and government policy contribute to the lack of skilled labour. This is because people are slow to adapt to changes in technology and the nature of work. Kamal (2018) argued that the lack of diversity in tech is a problem since it makes it harder to find qualified personnel. The prevalence of SDT, which affected 16 percent of adult EU employees but varies greatly between member states, was quantified by Seamus et al. (2021) using data from the European Skills and Jobs Survey. However, the authors discovered evidence that SDT led to dynamic upskilling of workers, and can favourably impact the task content and skill complexity of incumbent workers, refuting assertions that technological development adds to employment deskilling. Still, SDT mostly impacted higher-skilled workers, which maintains inequities in possibilities to improve one's skill set and ultimately leads to employment instability for those affected. It is recommended that all employees be provided with effective training programmes and development programmes in order to increase their skills and expertise, leading to enhanced performance and productivity on the job, as found in a study by Salah (2016).

The primary factor of job creation is education and skill requirements that prepares for challenges of the 21st century (Faiz & Kurniawati, 2020). This requires professional qualifications with vocational education which equips students with job-related abilities that are equal to the highest degree programme. Vocational education is a beneficial development strategy to eliminate education disparities in Cambodia (Miller, 2020). Furthermore, amid the IR4, highly skilled workers from English-speaking developed countries still command higher salaries (Haley & Taengnoi, 2011). ASEAN countries are still investing in 4IR graduates for future development. High-qualified scientists and engineers require high-cost wages, so firms usually seek less qualified scientists and engineers with lower salaries. This helps firms save costs but lose capabilities, skills, and talent. Other than that, Tran et al. (2023) found that high-tech development increased unemployment in Asia; however, the relationship between human capital, institutional conditions, and the unemployment rate varied across different fields. Nor et al. (2023) found that knowledge management, knowledge workers, and Industrial Revolution IR4.0 positively impacted competitiveness. Miah et al. (2024) identified nine critical success factors, including artificial intelligence, digital skills, and big data analytics, that enhance Industry 4.0's productivity and efficiency. Additionally, it highlighted six types of challenges, such as training and development, financial constraints, and regulatory issues, that need to be addressed to fully realise its potential

## Research Framework

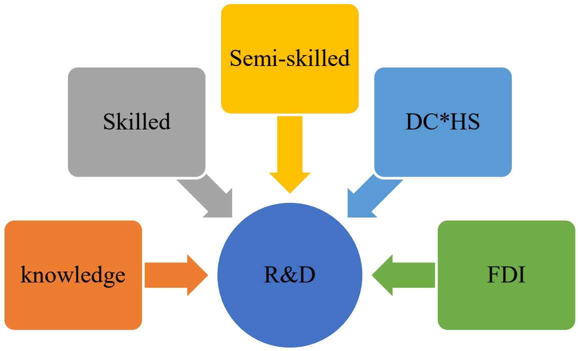


**Figure 1: Research Framework**

Figure 1 presents the research framework, which serves as a visual representation of the structure and components of the research study.

# METHODOLOGY

This research looked at selected ASEAN+3 countries (Singapore, Vietnam, Thailand, Malaysia, Indonesia, Cambodia, the Philippines, China, Japan, and South Korea) from 1990 to 2021 to assess the impacts of education and skilled workers on 4IR in technology. The FDI variable served as the control variable in this study. The International Labour Organization (ILO), the World Bank, and UNESCO all contributed data to this analysis. Mean group (MG), pooled mean group (PMG), and dynamic fixed effect (DFE) calculations were carried out independently using a dynamic panel approach to analyse the data. PMG, MG, and DFE panel analysis can shed light on both the short- and long-term dynamics of a connection. The theoretical framework adopted for this study was based on endogenous growth theory (Romer, 1994). The models of endogenous growth facilitates the internal generation of new technology through R&D and the internal accumulation of human capital. Endogenous growth theory posits that technological advancements are outcomes of internal factors like human creativity and continuous learning. The theory also incorporates the concept of increasing returns to scale, suggesting that larger economies may experience efficiency and productivity gains as a result of scaling up production.

Here are some details about the model:

$$R\&D_{it} = \beta_0 + \beta_1\, YoS_{it} + \beta_2\, HS_t + \beta_3\, SS_{it} + \beta_4\, DC{*}HS_{it} + \beta_5\, FDI_{it} + \varepsilon_{it} \quad (1)$$

Research and development (R&D) stand in for technology here, while years of schooling (YoS) stands in for how long someone has been in school. High-skilled (HS) labour, semi-skilled (SS), and the country-by-country interaction (DC*HS) are all measures of human capital. While the FDI showed the net inflow of foreign direct investment. The symbol for the error term was, with I for the country and t for the year. The stationarity of panel data is typically tested with the unit root test. Each variable used in the data panel was tested with the unit root test devised by Levin-Lin-Chu (LLC) (2002) and Im-Pesaran-Shin (IPS) (2003) to ensure that it was stationary at either the I(0) or I(1) levels (1). In contrast, the data must be stationary if and only if all variables reach the value I. (1). The indirect effects of each variable are demonstrated through estimates of the PMG, MG, and DFE. Without considering the fundamental regressor I(0) or I(1), the method developed by Pesaran and Shin (1999) was useful for calculating the long-run coefficient (1). Itis also more flexible in adapting to shifting partnerships. Time series (T) and cross-sectional data (X) were brought together in panel data (N).

Later in the investigation, the Hausman test was used to figure out which of PMG, MG, and DFE was the best estimator. Consequently, the MG long-run model is presented as follows:

$$R\&D_{it} = \theta_i + \beta_{0i}\, R\&D_{t-1} + \beta_{1i}\, YoS_{it} + \beta_{2i}\, HS_{it} + \beta_{3i}\, SS_{it} + \beta_{4i}\, DC{*}HS_{it} + \beta_5\, FDI_{it} + \varepsilon_{it} \quad (2)$$

What follows is a long-term illustration of the connection between the PMG and DFE models:

$$\Delta R\&D_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij} \Delta R\&D_{i,t-j} + \sum_{j=1}^{p} \delta_{1ij} \, \Delta YoS_{i,t-j} + \sum_{j=1}^{p} \delta_{2ij} \, \Delta HS_{i,t-j} + \sum_{j=1}^{p} \delta_{3ij} \, \Delta SS_{i,t-j} + \sum_{j=1}^{p} \delta_{4ij} \, \Delta DC * HS_{i,t-j} + \sum_{j=1}^{p} \delta_{5ij} \, \Delta FDI_{i,t-j} + \varepsilon_{it} \tag{3}$$

Where: i represented countries (1, 2…10), t is the optimal time lag, and the fixed effect is given as μ. The model below illustrates the short-run relationship between knowledge worker, skilled, FDI and technology:

$$\Delta R\&D_{it} = \alpha_i + \varphi_i R\&D_{it-1} + \lambda_1 YoS_{i,t} + \lambda_2 HS_{i,t} + \lambda_3 SS_{i,t} + \lambda_4 DC * HS_{i,t} + \sum_{j=1}^{p} \lambda_{ij} \Delta R\&D_{i,t-j} + \sum_{j=1}^{p} \delta_{1ij} \, \Delta YoS_{i,t-j} + \sum_{j=1}^{p} \delta_{2ij} \, \Delta HS_{i,t-j} + \sum_{j=1}^{p} \delta_{3ij} \, \Delta SS_{i,t-j} + \sum_{j=1}^{p} \delta_{4ij} \, \Delta DC * HS_{i,t-j} + \sum_{j=1}^{p} \delta_{5ij} \, \Delta FDI_{i,t-j} + \varepsilon_{it} \tag{4}$$

The parameter in the long term was denoted by λi, while the error correction parameter (φi) represented the rate of R&D on the long-term equilibrium following changes in YoS, HS, SS, and DCHS. Cointegration of R&D with YoS, HS, SS, and DCHS was indicated by a significant and negative value for suggesting the existence of long-term relationships. Long time series and high-dimensional cross-sections are no problem for the MG and PMG estimators when working with panel data. However, if the long-term homogeneity restriction is real, then the maximum likelihood-based PMG methodology is the efficient estimator, not the MG method. When calculating PMG, MG, and DFE, it is vital to set a lag that is reasonable and equitable for a country's population and run the Hausman test to assess whether the methodologies are suitable.

Which of the four models (PMG, MG, PMG, and DFE) was most appropriate for the study was determined by use of the Hausman test. According to Pesaran and Shin (1999), the PMG model gives more weight to the short-term coefficient, which varies from country to country, while assuming that the long-term coefficient is constant. However, the MG estimator does not allow for consistency in country coefficients during the intermediate period. Under the null hypothesis, the PMG estimator is preferred over the MG estimation, and if the null hypothesis is refuted, the preference switches. If the null hypothesis is instead accepted, PMG emerges victorious over DFE.

## RESULTS

Findings can be analysed without concern for autocorrelation, heteroskedasticity, multicollinearity, or data stability. The research used Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effect (DFE) analyses to examine the challenges of education and the skilled workers on technology.

**Table 2: Panel Unit Root Test**

| Variable | Levin, Lin, and Chu (LLC) | | Im, Pesaran and Shin (IPS) | |
|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) |
| R&D | -0.7647<br>(0.2222) | -7.1841***<br>(0.0000) | -0.9190<br>(0.1791) | -13.603***<br>(0.0000) |
| Years of Schooling | -4.8906***<br>(0.0000) | -2.6487***<br>(0.0040) | -0.9764<br>(0.1644) | -4.4635***<br>(0.0000) |
| High skill worker | 1.1014<br>(0.8646) | -1.0831**<br>(0.0394) | -1.4697*<br>(0.0708) | -12.9672***<br>(0.0000) |
| Semi-skilled worker | -2.0937**<br>(0.0181) | -6.4693***<br>(0.0000) | -4.1068***<br>(0.0000) | -12.3966***<br>(0.0000) |
| DC*HS | 1.1014<br>(0.8646) | -1.0831**<br>(0.0394) | -1.4697* | -12.9672***<br>(0.0000) |
| FDI | -3.2390***<br>(0.0006) | -4.8989***<br>(0.0000) | -3.4978***<br>(0.0002) | -5.6720***<br>(0.0000) |

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively

Table 2 displays the outcomes of the unit root test for the LLC. YoS, SS, and DCHS had a strong correlation although R&D, HS, and DCHS do not. The results of the investigation were consistent with the null hypothesis. However, as all variables were significant at the first difference, indicating they were stationary, the null hypothesis was supported. The IPS unit root test confirmed the findings of the LLC unit root test, finding R&D and YoS to be non-significant at the level of significance. The significance of all variables was confirmed by the t-test, demonstrating their importance to the investigation.

**Table 3: Kao Cointegration Test**

| | Statistic | P-value |
|---|---|---|
| Modified Dickey-Fuller t | -5.8852 | 0.0000*** |
| Dickey-Fuller t | -6.0707 | 0.0000*** |
| Augmented Dickey-Fuller t | -3.0943 | 0.0000*** |
| Unadjusted modified Dickey-Fuller t | -11.7184 | 0.0000*** |
| Unadjusted Dickey-Fuller t | -7.5851 | 0.0000*** |

Note: *** indicates significance at 1%

Table 3 shows the cointegration test. The Kao test is helpful when the data is non-stationary since it is built to deal with scenarios in which there may be many cointegrating correlations between the time series being examined. When compared to other cointegration tests, the Kao test is less picky about the lag length you use. As the table shows all the statistical values were significant at the 1% level, and it was concluded that R&D and the independent variables were long-term cointegrated and so the the null hypothesis was rejected. Thus, the explanatory variables and R&D were cointegrated over time. This allowed us to use the PMG, MG, and DFE in the regression analysis to better understand the nature of this link.

**Table 4: PMG, MG, and DFE Long-Term Estimate Outcomes**

| | PMG | | MG | | DFE | |
|---|---|---|---|---|---|---|
| Variables | Coefficient | P-value | Coefficient | P-value | Coefficient | P-value |
| YOS | 0.532 | 0.000*** | -0.794 | 0.410 | -0.372 | 0.043** |
| HS | -11.666 | 0.078* | 22.306 | 0.145 | 22.353 | 0.066* |
| SS | -4.920 | 0.000*** | 35.823 | 0.361 | 1.619 | 0.639 |
| DC*HS | 11.124 | 0.078* | -1.887 | 0.108 | -8.957 | 0.255 |
| FDI | -0.456 | 0.181 | 0.411 | 0.377 | 0.031 | 0.681 |
| Hausman Test | 4.61 | 0.4650 | | | 0.26 | 0.9983 |

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively

The ARDL-based PMG, MG, and DFE models are shown in Table 4. (1,1,1,2,2). The Hausman test was used to check for statistical significance between the PMG and MG models. After running all the numbers, the PMG model was deemed to be the best. The Hausman test was also used to compare the PMG and DFE models, and the PMG model was selected since its variability value was larger than the significance level. According to the PMG model, the quantity of years spent in school (YoS) was a significant predictor of R&D spending over the long term in the sample of ASEAN+3 nations. The model predicted that an increase of 0.53 percentage points in R&D activity for every additional year of schooling. This finding emphasizes the significance of higher education in promoting creative thinking, enhancing analytical abilities, and expanding access to learning possibilities. This finding was supported by (Kuo et al., 2018 and Li, 2022). Findings from the MG and DFE models were contradictory, with both suggesting that education has little bearing on R&D. According to the DFE model, there will be a negative relationship between schooling and technology in the long run.

The PMG model predicted that an increase of just 1% in the number of highly qualified people will lead to a 11.67 per cent drop in R&D spending, thus this was a significant negative impact. One possible explanation is a failure to adequately fund technological development. Companies may have the assumption that those they recruit have the expertise to get their jobs done without resorting to technology. Besides, they might not feel compelled to purchase cutting-edge machinery. Because of this, scientific advancement and new inventions may stall. Resistance to change is another possible explanation. Knowledgeable professionals may be reluctant to alter their tried-and-true approaches to completing jobs. Because of this, people may be slow to adopt new technologies, even if they would improve productivity or quality of life. There is also the possibility that a surplus of qualified workers could reduce the need for some forms of advanced machinery. A decline in the development and usage of technology may result if skilled workers are able to complete previously technologically intensive tasks manually. This finding is consistent with study by Kurt (2019).

Additionally, the PMG model indicated that technology was significantly hindered by semi-skilled labour, meaning that a 1 per cent increase in semi-skilled workers will result in a 4.92 per cent decline in R&D. Compared to highly trained individuals, semi-skilled employees often had lower levels of education and experience. So, itis possible that they lacked the technical understanding and competence of their more skilled counterparts. Due to concerns that semi-skilled employees will not be able to properly operate and maintain the new technology, some businesses may be hesitant to adopt it. Moreover, semi-skilled workers may be less adaptable than highly-skilled ones. This is due to the fact that those groups are more likely to experience feelings of insecurity in the face of technological change. Such a lack of openness to change might make it harder for businesses to adopt new technologies. Lack of originality is another possible outcome of employing semi-skilled individuals. Skilled individuals have a higher understanding of the technology and how it may be applied to solve problems, hence they are often more creative and innovative than semi-skilled workers. It is possible that technical advancement will stall if there are less skilled individuals in a sector or company. The results, however, do not align with the predictions made by the MG and DFE models, which show little impact on R&D.

Furthermore, the contact between highly skilled professionals and country dummies had a significant and positive effect on R&D, indicating that high-income nations' R&D expenditures will rise by 11.12 per cent. This is likely because workers in high-income nations are more educated and skilled than those in underdeveloped countries, and they may help to adopt or develop more advanced technologies more quickly. These findings contradict the predictions made by the MG and DFE models, which indicated no significant long-term impact on R&D.

**Table 5: Results of Short-Run Estimation for PMG, MG, and DFE**

| Variables | PMG | | MG | | DFE | |
|---|---|---|---|---|---|---|
| | Coefficient | P-value | Coefficient | P-value | Coefficient | P-value |
| ECT | -0.456 | 0.000*** | -0.631 | 0.000*** | -0.400 | 0.000*** |
| ∆YOS | -0.496 | 0.249 | -0.553 | 0.099* | -0.733 | 0.073* |
| ∆HS | -19.525 | 0.312 | -15.539 | 0.407 | -10.143 | 0.011** |
| ∆SS | -6.751 | 0.454 | -7.742 | 0.441 | -3.313 | 0.043** |
| ∆DC*HS | 4.894 | 0.002*** | 1.312 | 0.348 | 3.464 | 0.012** |
| ∆FDI | -0.084 | 0.044** | -0.066 | 0.042** | -0.006 | 0.718 |

Note: ***, ** and * indicates significance at 1%, 5% and 10% respectively

In Table 5, we can see the results of the PMG, MG, and DFE models' short-term predictions. The ECT value of the estimate was negative at the 1 per cent level of significance, indicating a long-term relationship between the variables and the rate of adjustment required to achieve long-term equilibrium. The PMG model revealed that R&D was relatively indifferent to most variables, but it was significantly influenced by the foreign direct investment and the interaction between highly skilled individuals and nation dummies. It demonstrated that a 1 per cent increase in net inflow of FDI will lead to a drop in R&D by 0.08 per cent in the short run. FDI may reduce R&D activity in certain scenarios. For instance, if foreign investors focus on short-term profitability rather than long-term investment, they may emphasize cost-cutting tactics over R&D investment. Moreover, if foreign corporations bring their own technology and experience to a host country, local firms may feel less incentive to participate in R&D as they can rely on the knowledge and technology of foreign investors. This result was supported by Xu and Li (2021) that FDI had a significant negative impact on productivity.

The result is consistent with the MG estimator, which indicated that FDI had a significant but negative impact on R&D. The DFE estimation showed that all variables had a significant impact on R&D except for FDI. In contrast, the MG estimation indicated that only years of schooling and FDI can affect R&D in the short run.

## CONCLUSION

Examining the impacts of knowledge worker and skills in the context of the 4IR, this study looked at selected ASEAN+3 countries (Malaysia, Thailand, the Philippines, Cambodia, Singapore, Vietnam, Indonesia, China, South Korea, and Japan) from 1990 to 2021. The PMG estimator was preferred over the MG and DFE estimators based on the results of the Hausman test. The selected ASEAN+3 states with the highest levels of workers, knowledge, foreign direct investment and R&D, as found by PMG, all benefitted from the presence of dummy countries in the long run. In the selected ASEAN+3 countries, R&D was significantly impacted in the long run by workers with high and intermediate levels of knowledge. All three estimators (PMG, MG, and DFE) agreed that the ECT was negative and substantial. However, the findings of the MG estimators revealed that only years of schooling and FDI had a short-term impact on R&D. On the other hand, DFE showed that all variables had a significant impact on R&D in the short run, except for FDI, in selected ASEAN+3 countries.

Overall, the impacts of knowledge workers and skills in the I R 40 were complex and multifaceted. Addressing these impacts will require a coordinated effort from governments, educators, employers, and other stakeholders to ensure workers are prepared for the changing global economy demands. To compete in the IR 4.0 era, individuals must possess specific skills and knowledge relevant to the new technological advancements. Individuals need to constantly study and acquire new skills to keep up with the ever-evolving technological landscape and their respective work markets. Workshops, online classes, and other forms of formal education can help them achieve their goals. To thrive in the IR 4.0 era, which is defined by cutting-edge technologies like automation, robots, AI, and the Internet of Things, it is crucial to cultivate human capital with the appropriate set of skills and knowledge (IoT). The rapid pace of technological advancements requires individuals to learn and update their skills continuously. Investing in education and training programs focusing on the latest technologies and skills relevant to the industry is vital. These studies suggested that human capital is critical to adopting and utilising new technologies. Education and training are essential to developing the cognitive skills and digital literacy needed to succeed in the digital age. Additionally, investment in ICT infrastructure and digital literacy programs can help to promote human capital development and bridge the digital divide.

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