THE IMPACT OF DIGITAL INFRASTRUCTURE ON THE EMPLOYMENT RATE IN ASEAN

A Thesis

Submitted to the Master's Study Program of Economics and Business at the Faculty of Economics and Business in fulfillment of the requirements for the degree of

Master of Arts (M.A)

Universitas Islam Internasional Indonesia

by:

Shellvy Lukito

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ABSTRACT

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Neglecting the exponential expansion of digital infrastructure in ASEAN is impossible. This study investigates digital infrastructure's influence on the employment rate in ASEAN, where Singapore and Timor Leste are regarded as outliers. The variables that are being measured are as follows: fixed broadband subscriptions, fixed telephone subscriptions, internet usage, mobile cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, GDP deflator, and employment to population ratio. The quantitative technique employed is panel regression data analysis, which is conducted using the Stata 17.0 application. this study employs the Heteroscedastic Panels Corrected Standard Errors (HPCSE) method to address the issue of heteroscedasticity in panel data. Additionally, the study utilizes the Feasible Generalized Least Squares (FGLS) approach in regression to obtain parameter estimates that are both efficient and consistent. This study reveals that Fixed broadband subscriptions positively affect the employment rate with a coefficient of 0.5211926 and a p-value of 0.000. Mobile cellular subscriptions also have a coefficient of 0.0359148 and a p-value of 0.064. However, GDP per person employed has a negative coefficient of -3.039084 and a p-value of 0.005. The findings of this study suggest that digital infrastructure is essential for developing job opportunities. Policies that prioritize the development of broadband and cellular access and consider the influence of productivity on the labor market can assist in developing strategies to increase work participation.

Keywords: *ASEAN, employment rate, digital infrastructure*

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ABBREVIATION DIRECTORY

ASEAN	: Association of Southeast Asian Nations
IMF	: International Monetary Fund
IoT	: Internet of Things
AI	: Artificial Intelligence
FGLS	: Feasible Generalized Least Squares
GLS	: Generalized Least Squares
COVID	: Coronavirus Disease
GMV	: Gross Merchandise Volume
DFS	: Digital Financial Services
SMEs	: Small and Medium-sized Enterprises
ILOSTAT	: International Labour Organization's Statistical Database
NEET	: Not in Education, Employment, or Training
ITU	: International Telecommunication Union
OECD	: Organisation for Economic Co-operation and Development
IT	: Information Technology
GDP	: Gross Domestic Product
ILO	: International Labour Organization
ICT	: Information and Communication Technology
FEM	: Fixed Effect Model
CEM	: Common Effect Model
REM	: Random Effect Model

APPENDIX

CHAPTER 1

INTRODUCTION

In the dynamic landscape of ASEAN's digital era, where technology flourishes and connectivity expands, the influence of digital infrastructure on employment is significant. With the expansion of fiber-optic cables and mobile networks, employment opportunities are growing in even the most remote corners of the region. The digital infrastructure has brought about the birth of new industries and the transformation of existing ones, impacting both bustling cities and rural communities. The rapid development of digital infrastructure has created many changes in work patterns and lifestyles. Work patterns which are now increasing in the form of freelance or gig economy, online lifestyles, online shopping, and online services are making many significant changes throughout the world. In Southeast Asia, many workers are currently being replaced by AI, self-checkout shopping systems, e-cash systems and many more. We cannot close our eyes to this because it has become a daily lifestyle. Apart from that, the field of work is also diverse, so this modern job must be balanced with the necessary skills. There will definitely be obstacles that will become obstacles. Therefore, this matters more deeply and carry out in-depth research regarding the impact of increasing digital infrastructure on employment levels. It is also hoped that there will be some input from the government, society, and other stakeholders to minimize possible challenges and be ready to face them.

1.1 Background of the Research

The region of Southeast Asian countries cannot avoid the rapid development of digital infrastructure. ASEAN countries such as Singapore, Malaysia, Indonesia, Philippines, Thailand, Vietnam, Myanmar, Brunei Darussalam, Laos, Cambodia and Timor Leste are countries that continue to encourage the development of digital infrastructure. The Internet and advanced technology, including mobile technology, virtual reality, big data, artificial intelligence, and the Internet of Things (IoT), have facilitated connections between consumers, suppliers, businesses, regulators, devices, data, and processes globally (Ha & Chuah, 2023). The International Monetary Fund (IMF) describes the digital economy as a broad range of new applications of information technology in business models and products that are reshaping the economy and social interactions. Digitalization has the power to both empower and shake up businesses (Ducharme et al., n.d.). The digital economy is experiencing explosive expansion, particularly in developing nations (Bukht & Heeks, 2018), despite the International Monetary Fund (IMF) suggesting that the digital sector contributes less than 10 percent to most economies in terms of value-added, income, or employment (Ducharme et al., n.d.).

Southeast Asian digital infrastructure investments are rising as the digital economy grows. The rising demand for digital services and connectivity in the region and the quick deployment of 5G, AI, and cloud computing are driving the trend. The Southeast Asian data center market is growing rapidly due to increasing demand. The data center business will change in numerous ways as demand grows (J. Wang, 2023). Over the past few years, the digital economy in SEA has garnered significant interest from both public and private organizations. This is primarily due to its immense potential and the far-reaching effects it can have on the economies of SEA countries, as well as their trading partners (Ha & Chuah, 2023) .

In addition, the COVID-19 pandemic has caused a reevaluation of work and the workplace, resulting in an increased reliance on virtual and digital platforms for government services and people's livelihoods (Bukht & Heeks, 2018). The findings unequivocally demonstrate that the disruption caused by COVID-19 is driving the adoption of technology, resulting in automation and collaboration. Furthermore, the current pandemic has resulted in a shift towards remote work, eliminating the limitations of location and reducing the need for physical office spaces. The geographic barrier has the potential to enhance employment opportunities in developing countries (Subramaniam et al., 2021). Yet, the COVID-19 pandemic has compelled businesses, particularly traditional retail companies lacking digital expertise, to transition online during the lockdown. As a result, they have had limited options but to join various business platform ecosystems to sustain their sales (Soto-Acosta, 2020).

Covid also has promoted digital technology for many reasons, in my opinion. First and foremost, the pandemic forced many organizations to adopt digital solutions to maintain remote operations, increasing their dependence on digital tools and platforms. The increasing adoption of digital technology has transformed many businesses, expanding digital infrastructure and services. The need for social distancing and remote work has raised demand for digital communication tools, online collaboration platforms, and e-commerce services.

Digital technology has given businesses and entrepreneurs new opportunities, expanding the digital economy. Telemedicine, remote monitoring, and digital healthcare solutions have also been highlighted by the pandemic. This has increased digital health investment and innovation. The COVID-19 pandemic has accelerated the adoption and expansion of digital technology in several industries, boosting worldwide digitalization and innovation.

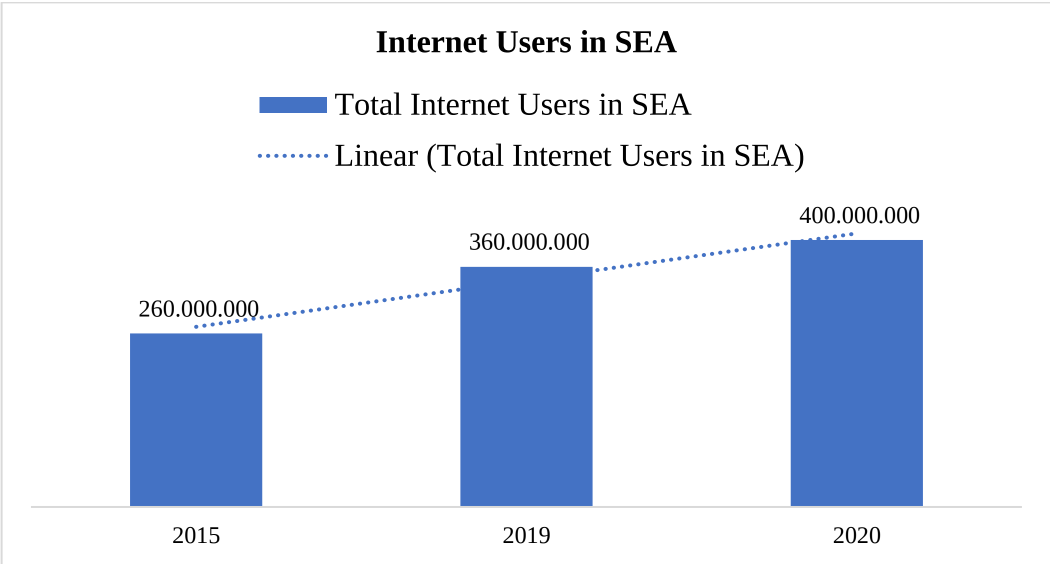

Figure 1. Internet Users in SEA

Source: Google, Temasek, Bain & Company

Based on figure 1, it was shown that projected increase of 40 million new Internet users in 2020. In 2024, the population of Southeast Asia stands at 690,477,368 accounting for approximately 8.54% of the global population (Worldometer, 2024). Over 40 million people, which accounts for 70% of the region's population, are now connected to the internet. The adoption and usage of e-commerce, Online Media, and Food Delivery have experienced a significant surge this year, while the sectors of Transport and Online Travel have faced considerable challenges (Google et al., 2020).

In the end, the Internet sector is expected to maintain its resilience, reaching a Gross Merchandise Volume (GMV) of $100B by the end of 2020 and projected to grow to over $300B by 2025. This growth demonstrates that the sector has not been hindered by the challenges faced in 2020. The crisis will also increase the popularity of Digital Financial Services (DFS), as consumers and SMEs become more open to online transactions(Google et al., 2020).

On the other hand, Employment is of paramount significance for several reasons, including but not limited to the following: economic stability, social well-being, skill development, reduction of inequality, contribution to society, and promotion of general health and well-being. The lives of individuals and the prosperity of societies are both significantly impacted by it through its important function. Within the 2030 Agenda for

Sustainable Development, which emphasizes fostering productive employment and decent work for all, the International Labor Organization (ILO) stated that employment is a vital component (Department of Economic and Social Affairs Poverty, 2007).

Year	Mean weekly hours worked per person employed	Employment-to-population ratio (percentages) Employment (millions)	Unemployment rate (percentages)	Labor force participation rate
2010	42.6	65.4	3.3	67.7
2019	40.6	65.6	2.4	67.2
2022	39.9	64.2	2.6	65.9
2023	39.9	64.5	2.5	66.2
2024	39.9	64.5	2.5	66.1

Table 1. The estimates and forecasts of working hours, employment, unemployment, and labor force in South-East Asia

Source: ILOSTAT, 2023

Weekly hours worked per person employed: Table 1 shows the typical number of hours worked each week by individuals with jobs. The data indicates a decline from 42.6 hours in 2010 to 39.9 hours in 2022, suggesting potential shifts in working patterns or labor market dynamics. The percentage of the working-age population that is employed is indicated by the employment-to-population ratio. According to the data, there has been a consistent employment-to-population ratio of approximately 64-65% over the years, experiencing a slight decline from 2010 to 2022.

- Number of people employed: Table 1 shows the total number of individuals with jobs. According to the data, there has been a decline in total employment from 65.4 million in 2010 to 64.5 million in 2023 and 2024. The decrease could be impacted by a range of factors including shifts in population size, labor force participation, and economic conditions.
- Unemployment rate (percentages): The unemployment rate reflects the percentage of the labor force that is without a job and actively looking for work. Based on the ILOSTAT data provided above, the employment rate has not increased from the initial 3.3% in 2010 to 2.5% in 2024, indicating that unemployment has decreased.
- Additionally, we examine the labor force participation rate, which is a metric that quantifies the proportion of the working-age population that is either employed or

seeking employment. The work participation rate has decreased from 67.7% in 2010 to 65.9%-66.1% between 2019 and 2024, as indicated by the available data.

This is consistent with the findings of Kempert's research. The data indicates a decrease in the average weekly working hours, a consistent ratio of employment to population, a decrease in total employment, a decrease in pressure levels, and a minor decrease in force levels. Occasional employment is required. This can result in changes in economic conditions, demographic factors, and labor market patterns over a specific period (Kampert et al., 2024).

On the one hand, Withing's research in 2021 demonstrates that the World Economic Forum has conducted research on the skills that must be trained in the next 5 to 10 years, as stated in its 2020 report. The following skills are essential: the ability to work independently and collaboratively, multitasking, critical thinking, creativity, leadership, technology utilization, strategy, mental fortitude, and conceptualization (Withing, 2021).

This research concentrates on investigations concerning the challenges induced by the impact of digital infrastructure on employment rates. The study will delve into the potential for job migration as a result of the rapid development of digital infrastructure, which is accompanied by the emergence of artificial intelligence (AI). Additionally, it will examine the impact of these developments on unequal opportunities. employment as a result of demographic and regional factors.

The objective of this research is to offer stakeholders, including the government, companies, and individuals, the ability to develop employment solutions that are responsive to the inescapable emergence of technological advancements. Can offer insight into the potential for the creation of new employment through the adaptation of existing technology. It is anticipated that this research will offer a novel, efficient approach that will be beneficial to all parties and reduce the negative consequences.

1.2 Problem Statement

A technology corporation based in California's Silicon Valley. It is commonly regarded as the epicenter of the digital revolution due to its renowned technological advancements. This hub catalyzes start-up enterprises, playing a crucial role in propelling the global communications and information technology industry forward. According to a study conducted by Jones & Sudlow (2022), this corporation is credited with pioneering the emergence of the digital world, which is currently experiencing fast growth.

The swift advancement of information and communication technology has led to the rise of a new economy characterized by the prevalence of internet-based industry, known as e-commerce. The middle class in Southeast Asia is experiencing economic growth in the digital economy era, shifting towards a cashless transaction system. This change is altering the lifestyle of individuals who rely on the Internet for travel, shopping, and online business activities. It is also fueling the rapid growth of the e-commerce industry (Hastuti & Jauhari, 2021).

Conversely, Industry 4.0, a German effort, has gained worldwide acceptance during the last decade. Several countries have implemented comparable strategic plans, and significant research has been dedicated to creating and integrating Industry 4.0 technology (Xu et al., 2021). The terms "Industry 4.0," "future factory," "smart factory," "digital manufacturing," and "industrial automation" have emerged as contemporary rhetoric among academics and industry leaders (Kumar et al., 2020). The issue of employment in the digital era, especially in the context of Industry 4.0 or the fourth-generation industry, is centered on the digital transformation of the production sector. This change requires establishing a workforce that is ready for upcoming infrastructures, which calls for collaboration between universities, government, and industry to educate workers for the changing productive sector.

The COVID-19 pandemic has intensified employment challenges, emphasizing the importance of conducting a comprehensive study on employment issues. This study should include an examination of the intricate structures and advancements in digital transformations within manufacturing companies (Zyukin, 2020).

To attain sustainable development, enterprises must demonstrate adaptability to the swiftly evolving global markets and consumer demands. Consequently, it is imperative to conform to the progressive fourth industrial revolution, commonly referred to as Industry 4.0, through the adoption and integration of digitally innovative technologies (DI), which empower institutions to attain a sustainable edge throughout the revolution's progression (Gupta & Jauhar, 2023).

As the primary transformation challenge, a dearth of resources and competencies is impeding the education sector's ability to equip students with future-ready competencies in the Asia Pacific. To remain competitive, institutions of higher education are coming to recognize the significance of transformation, with an emphasis on curriculum quality improvement, technological trend alignment, and disruption prevention (Jimenez et al., 2018).

Also, Qi & Chu (2022) investigate the challenge China encounters in surpassing the middle-income trap. The text highlights the necessity of exploring new avenues for economic development, the significance of adjusting to economic evolution, and speeding up digital industrialization to merge the digital and real economies as crucial strategies to address this challenge.

Nevertheless, the issue of information poverty and the absence of digital access among young people in South Africa who are not in education, employment, or training (NEET) is the subject of the study. Due to their limited access to online information services, resources, and digital literacy abilities, these individuals encounter obstacles when attempting to obtain information and opportunities (Matli & Ngoepe, 2022).

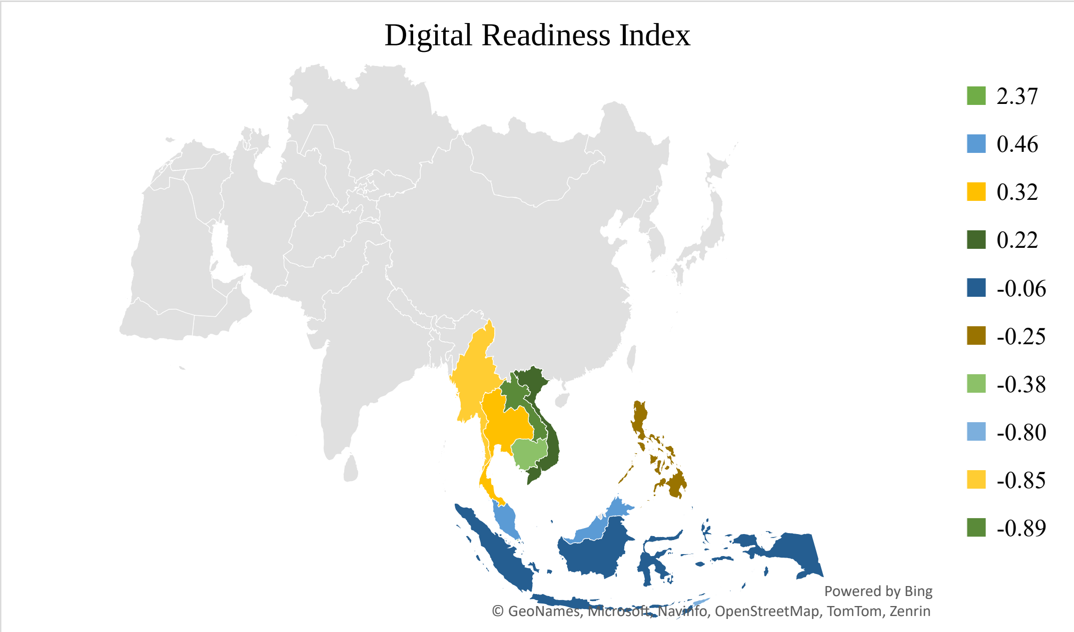

Figure 2. Digital Readiness Index

Source: Authors' elaboration on Cisco data, 2021

According to data from Cisco (2021) in Figure 2 above, the index is determined by seven key indicators: meeting basic needs, investment in technology, business environment, human resources quality, start-up climate, digital technology implementation, and digital infrastructure condition in each country. These seven indicators are then converted into a score ranging from -2.5 to 2.5. A country's digital readiness is considered better with a higher score, and vice versa.

According to the map provided, Singapore has been ranked as having the highest level of digital readiness in Southeast Asia for 2021, scoring 2.37 points. Being at the top globally. Next in Southeast Asia is Malaysia with a score of 0.46, followed by Thailand with 0.32, Vietnam with 0.22, and Indonesia with a lower score of -0.06, The Philippines follows with -0.25, then Cambodia with -0.38, Timor Leste with -0.80, Myanmar with -0.85, and finally Laos with the lowest score of -0.89.

Based on the report stipulated, digital literacy levels across Southeast Asia remain diverse. Some countries like Singapore and Malaysia demonstrate strong digital literacy levels, whereas others may encounter difficulties in this area. Internet access, education levels, and awareness of digital literacy's significance are crucial factors that influence the level of digital literacy in different countries. There is a need to enhance digital literacy through educational initiatives and training programs to bridge this gap.

On the other hand, the main challenge faced by digital infrastructure in Southeast Asia is the disparity in access to technology between various groups within a nation and across developing and developed countries in the area. The contrast is clear in the different broadband Internet speeds seen in various countries and the notable difference in Internet usage rate. Progress in the adoption of mobile broadband services remains inconsistent (Ha & Chuah, 2023; OECD Southeast Asia, 2017).

Factors that contribute to the digital gap within nations encompass age, IT proficiency, income level, expertise, and Internet availability (Ha & Chuah, 2023). With the advancement of the digital era, various sectors are increasingly leveraging digital technologies to enhance their business operations, particularly at the customer level. This trend is creating fresh business prospects and improving overall efficiencies (Wynn & Jones, 2023). The COVID-19 pandemic has significantly affected the quality of education, particularly in the development of literacy skills. During the initial stages of the pandemic, educational institutions in over 190 nations were shut down, impacting the learning of 90% of the global student body totaling 1.57 billion. Approximately 826 million students, or 50 percent, are unable to attend classes due to the pandemic because they lack access to a computer at home.

Furthermore, in light of the COVID-19 school closures, various remote learning strategies were implemented, including the distribution of paper-based take-home materials and the delivery of lessons via digital platforms and broadcast media (e.g., radio and television). Radio constituted the predominant form of media consumption in low-income nations 92%, whereas its usage was considerably lower in high-income countries 25% (UNESCO, 2021). During the peak of the COVID-19 pandemic in 2021, with the shift towards online commerce and remote work, online spending in Southeast Asia surged by 49 percent to $US 174 billion (Google et al., 2020).

Why is it vital to consider the consequences of digital infrastructure on employment in Southeast Asia? To fully unlock the potential of Southeast Asia's digital economy, it is crucial to enhance the region's digital infrastructure. This guarantees that all individuals in the area can enjoy top-notch internet connectivity. Regrettably, digital infrastructure in

Southeast Asia continues to fall behind that of other regions. Recent statistics indicate that just three countries in Southeast Asia (Singapore, Brunei, and Malaysia) have internet penetration rates exceeding 80%. Moreover, Southeast Asia boasts a dynamic emerging market with more than 400 million internet users and a thriving digital economy. Southeast Asia has a high internet penetration rate, with over 70 percent in all countries except for Laos, Myanmar, and Timor-Leste (Statista, 2023).

The upcoming sections provide a comprehensive overview of the unique aspects and areas for further research in the study. This will help in formulating research questions and objectives that are easily understandable to the reader. Now, we will break down and analyze the framework supporting the argument more thoroughly.

1.3 Area of Research Gap

This research makes a substantial contribution to its field by investigating novelty using a bibliometric technique that integrates data from Scopus and Semantic Scholar. This research successfully identified growing trends and patterns in linked scientific literature using meticulous bibliometric analysis. It also highlighted elements that distinguish this research from earlier investigations.

This research can provide a robust foundation in scientifically validated literature by using data from Scopus. This research can use bibliometric analysis from Semantic Scholar to broaden its investigation. This research offers a detailed analysis of the originality of its findings and contributes significantly to enhancing our knowledge of the most recent advancements in this sector. This research contributes theoretically and establishes a solid platform for future knowledge and innovation.

Figure 3. Network Visualization - Scopus Data

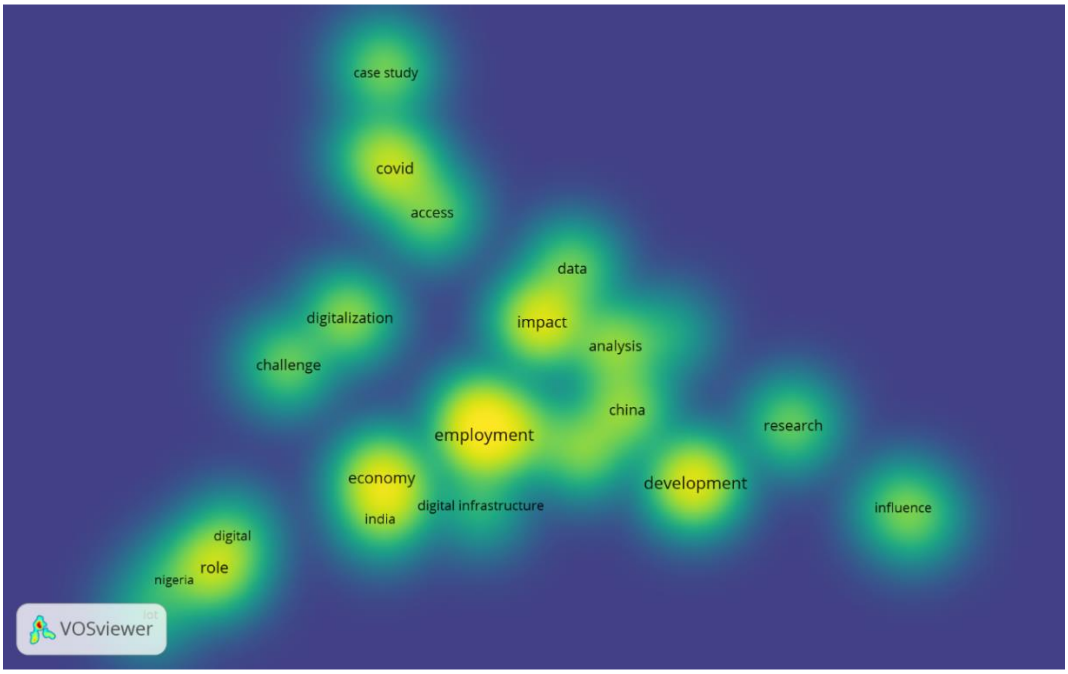

Figure 4. Density Visualization - Scopus Data

Following the analysis of Scopus data from Publish or Perish, the network visualization results were obtained using VOS Viewer. The keywords used for the analysis were "Digital Infrastructure and Workforce". From the depicted image, it can be inferred that there is a correlation between "Digital Infrastructure" and many factors such as "Labor", "effects", "evidence", "services", and "China". There is an evident correlation between the outcomes of the aforementioned subjects in scientific research. Comprehending the aforementioned findings can yield significant insights in this study, particularly with regards to digital infrastructure, employment, and other pertinent topics.

An intriguing study might be conducted in this digital era by thoroughly examining the correlation between "digital infrastructure" and "employment". The study conducted by Ndubuisi et al. (2021) corroborates the findings as mentioned above. Simultaneously, both "effects" and "evidence" in the scientific literature point towards a focus on issues related to digital infrastructure. Conversely, it is intriguing to thoroughly examine the connection between digital infrastructure and "services." This encompasses all-digital technology services, all-electronic services, and internet-related services.

At last, a connection with "China" might suggest a specific emphasis on digital infrastructure linked to the Chinese state, as demonstrated by the research conducted by (Ren et al., 2023; Q. Wang et al., 2023; Z. Zhang et al., 2023) whether in terms of development, implementation, or impact. There is a possibility that not many discussions have been made regarding digital infrastructure and employment in Southeast Asia.

In Figure 4, the digital infrastructure is depicted in a faded color, suggesting that discussions on this topic are limited. Additionally, the absence of the term "Southeast Asia" indicates a lack of research on digital infrastructure in that region.

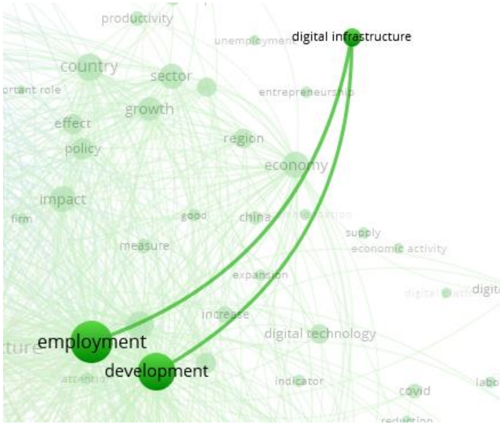

Figure 5. Network Visualization - Semantic Data

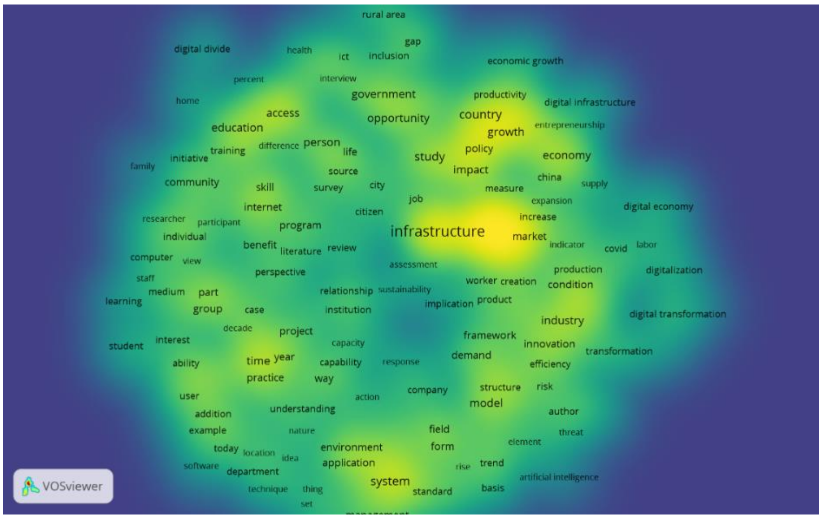

Figure 6. Density Visualization - Semantic Data

When using VOS Viewer to analyze data from Semantic Scholar, the findings reveal connections between "digital infrastructure," "employment," and "development," shedding light on their relationship in scientific literature. Exploring the connection between "digital infrastructure" and "employment" could involve investigating how digital infrastructure influences job opportunities, workforce requirements, or shifts in employment patterns due to advancements in digital infrastructure. Research conducted by Tashiro & Choi (2021) provides support for this.

Based on Figure 6, the visualization of density reveals that the topic of "digital infrastructure" remains relatively underrepresented in scientific literature. It is evident from the distribution of associated terms and phrases, as seen in the density visualization, that there is a lower density around "digital infrastructure". Based on the results, it seems that the topic of "digital infrastructure" is not extensively covered in the scientific literature available through Semantic Scholar. This could help highlight the importance of additional research in this field and the opportunity to address specific gaps in knowledge.

The study titled "The Impact of Digital Infrastructure on The Employment Rate in ASEAN" introduces novelty. This study specifically examines the ASEAN countries, with Singapore and Timor Leste being seen as exceptions. It investigates the impact of digital infrastructure on employment within the area. By concentrating on this specific area, one can gain a comprehensive comprehension of the effects of various technical advancements in ASEAN nations.

This study utilises datasets sourced from the World Bank to analyse the correlation between digital infrastructure and employment. This analysis incorporates multiple variables as metrics, such as fixed broadband subscriptions (per 100 individuals), fixed telephone subscriptions (per 100 individuals), internet usage (% of population), cellular subscriptions (per 100 individuals), secondary school enrollment (% gross), GDP per employed person (constant PPP $ 2021), inflation, GDP deflator (%), and employment to population ratio for individuals aged 15 and above (ILO model estimates).

This research is of utmost importance as it can offer a comprehensive understanding of the correlation between digital infrastructure and employment prospects in the dynamic ASEAN region. This research seeks to offer extensive insights into the influence of infrastructure on employment trends in the ASEAN region. It attempts to analyse the creation of new jobs and economic inclusion, while also proposing solutions to address the existing gaps in information.

This research can also offer valuable understanding regarding the influence of digital transformations in ASEAN countries on future employment trends. This includes the emergence of novel job positions, the need for updated skills training to align with digital advancements, and the potential for new employment prospects available through digital platforms. This research aims to offer valuable insights into the influence of digital infrastructure on employment by including novel features of innovation.

An intriguing aspect of this study is its emphasis on ASEAN member countries, offering a comprehensive analysis of how the digital realm affects employment in the region. The aim is to mitigate economic inequality and ensure equitable distribution of the benefits of this progress by enhancing digital infrastructure in ASEAN countries. Consider analyzing various factors such as fixed network, mobile network, traffic, internet, broadband, quality of service, and ICT Household to provide a thorough understanding of the impact.

In the future, the study may provide valuable insights into the impact of the evolving digital landscape in Southeast Asia on the job market, including the emergence of new roles, the necessity of acquiring fresh skills, and the potential for expanding job opportunities through digital platforms. Introducing new elements can offer valuable insights into the complex connection between digital infrastructure and employment patterns in Southeast Asia.

1.4 Research Inquiries

The issue at hand is the necessity of addressing the subsequent fundamental inquiries:

1. How does the state of digital infrastructure, including aspects such as fixed broadband subscriptions, fixed telephone subscriptions, internet usage, cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, GDP deflator, and employment to population ratio in ASEAN countries?
2. What is the correlation between the level of digital infrastructure development and the employment rate in ASEAN countries?
3. What are the challenges and advantages associated with the process of digital transformation in ASEAN, particularly concerning the development of human and physical resources?
4. How do government policies, regulatory frameworks, and public-private partnerships contribute to the enhancement or hindrance of digital infrastructure development and its impact on employment rates in ASEAN?

1.5 Purpose of the study

This study aims to quantify the influence of digital infrastructure on the employment rate in ASEAN. The research specifically intends to examine the present condition of digital infrastructure in Southeast Asian countries, encompassing aspects such as fixed broadband subscriptions, fixed telephone subscriptions, internet usage, cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, GDP deflator, and employment to population ratio. Examine the correlation between digital infrastructure and the employment rate in the region. Yet, Examine the difficulties and advantages brought about by the process of digital transformation in ASEAN, specifically in regards to the development of people and physical resources.

The study also suggests policy prescriptions for ASEAN countries to enhance their management of the digital revolution and bolster the employment rate. This study seeks to enhance comprehension of how digitalization might foster economic growth and job creation in ASEAN by analyzing the influence of digital infrastructure on the employment rate in the region.

1.6 Scope and Limitation

Scope:

1. The study will specifically examine the influence of digital infrastructure on the employment rate in ASEAN.
2. The data collection would cover many elements of digital infrastructure, such as fixed broadband subscriptions, fixed telephone subscriptions, internet usage, cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, GDP deflator, and employment to population ratio
3. A quantitative analysis will be performed to investigate the association between the growth of digital infrastructure and the changes in the employment rate in the region.

Limitation:

1. The findings of this study could be affected by the constraints and availability of data pertaining to digital infrastructure and employment rates in ASEAN nations. Divergences in data might impede the analysis and precision of interpretation.
2. Given the ever-evolving nature of technology and economic circumstances, the conclusions of the study may be susceptible to alterations as time progresses. Hence, the research will offer valuable perspectives derived from the facts accessible during the investigation.
3. The study's scope may not thoroughly encompass all facets of digital infrastructure or job dynamics in Southeast Asia. Some elements or subtle details may be disregarded because of constraints in data accessibility or research capabilities.
4. The research will primarily apply quantitative analysis to investigate the association between digital infrastructure and employment rates, potentially constraining the exploration of qualitative aspects of the topic.
5. The study's generalizability is restricted to ASEAN countries that were part of the analysis, and the findings may not be relevant to other locations or settings without additional validation.

1.7 The flowchart of the study

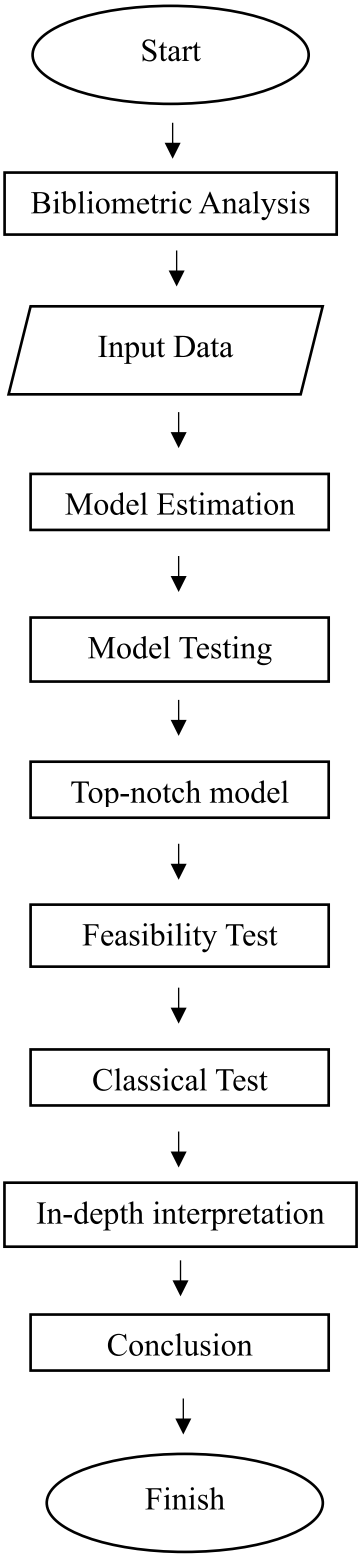

Figure 7. The flowchart of the study

1.8 Significance of Study

The study's policy implications lie in its ability to shed light on the influence of digital infrastructure on employment rates in ASEAN, hence offering significant information for policymakers in the region. The results can guide the formulation of plans and projects focused on encouraging investment in digital infrastructure and stimulating job creation to bolster economic progress and social advancement.

Conversely, in the field of Economic Development, The findings of the study can aid in utilizing digital technology as catalysts for economic development, as Southeast Asian countries progress in their digital transformation. By measuring the impact of digital infrastructure on employment rates, policymakers and businesses may make well-informed choices to utilize the promise of digitalization for the development of jobs and innovation. Regarding Regional Integration The study can promote enhanced regional integration by emphasizing the significance of aligning digital infrastructure policies and actions across Southeast Asian nations. By fostering cooperation and the exchange of information, the discoveries can bolster initiatives to narrow the gap in access to technology and foster all-encompassing development throughout the region.

The findings of this study can offer valuable insights for businesses operating in ASEAN countries, enabling them to strategically leverage digital infrastructure to enhance productivity and gain a competitive edge in the market. This, in turn, can have a multitude of positive effects, including increased opportunities for growth. One can explore job prospects and analyze potential sectors for investment and advancement in the future.
The objective of this study effort is to provide significant insights and contribute to the advancement of scientific literature in the field of digital infrastructure and its impact on employment patterns, particularly in ASEAN countries. By enhancing our understanding of this association, it is anticipated that it can catalyze the emergence of scientific research of digital infrastructure and employment trends in ASEAN countries.

The success of this research can be measured by its ability to influence stakeholders and authorities in shaping policies that promote economic growth, foster regional integration, shape business strategies, and enhance academic understanding of digital infrastructure and employment in ASEAN.

1.9 Thesis Organisational Structure

This thesis has crucial components. The initial section comprises an introductory segment that will provide a comprehensive elucidation of the context and concrete instances of digital infrastructure's impact on employment in the Association of Southeast

Asian Nations (ASEAN). This research will also provide a full explanation of its objectives. In addition, this research will also address its limits.

The second component of the study involves doing a literature analysis that specifically examines the transformations in developing digital infrastructure in the workplace. This review will also explore the difficulties and harmonization that digital infrastructure might bring to the world of work.

The third aspect is the research methodology, which provides a comprehensive explanation of the research design employed, the procedures and techniques used for data collecting, the advanced software utilized, and the ethical considerations addressed in the study.

Next, we have the findings and discussion section, which includes the identification of the most suitable model and can be analyzed in great detail.

Lastly, the fifth section is the Conclusion, which provides a concise review of the entire research series, outlining the outcomes achieved by meticulous computations.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The significant interest in studying and further investigating the impact of digital infrastructure on employment, workforce creation, and a country's economic progress has been sparked by the rapid progress of digital infrastructure in the Southeast Asian region, including ASEAN countries. It is crucial to further investigate the relationship between digital infrastructure, which is highly intricate and encompasses a variety of disciplines of knowledge and employment in this region, and the increasing integration of digital technology into various social and economic aspects of life. The objective of this literature review is to elucidate the comprehensive analysis that will be conducted on the impact of digital infrastructure on employment levels. By examining the intricacy and repercussions of environmental changes across a variety of domains.

The labor market in ASEAN may be altered by the rapid expansion of digital infrastructure, including internet connectivity, mobile phone technology, and innovation in digital-based government services. The objective of this study is to investigate the correlation between employment dynamics in Southeast Asia and the development of digital infrastructure. In addition to exposing the economic impact of opportunities and challenges on a country. Additionally, this investigation will offer recommendations and the necessary skills to confront the obstacles of the digital economy. Offer the perspective on the necessary labor market structure, job prospects, and adaptation.

This observation offers detailed information on critical topics, including the transition from traditional to digital labor patterns and employment opportunities, as well as the advantages of digital infrastructure development on job creation and economic growth. This review also offers valuable insights for decision-makers, entrepreneurs, and researchers by examining the existing literature. The primary objective is to offer decision-makers advice and input that is supported by evidence to promote sustainable, inclusive economic growth.

This literature review delves into the effects of digital infrastructure on employment rate in ASEAN, aiming to enhance comprehension of the opportunities and challenges brought about by the digital transformation. It sets the stage for future research, policy-making, and practical efforts to cultivate a vibrant and diverse workforce in the region.

2.1 Theoretical Framework

2.1.1 Definition of Digital Infrastructure

Grounded in digital technologies, Digital Infrastructure (DI) is a socially ingrained mechanical system that encompasses technological and human elements, networks, systems, and processes that create feedback loops that reinforce themselves. When it comes to operational aspects, particularly managing information system services, it's crucial to treat DI accordingly. Nevertheless, when it comes to building a digital business model, DI ought to be viewed as a crucial component of the digital business ecosystem (Sussan & Acs, 2017).

According to Sustainable Digital Infrastructure Alliance (2022), Digital Infrastructure encompasses the complete physical and software-based infrastructure essential for providing digital goods, products, and services. This covers data centers, fiber infrastructure, server hardware, staff, IT cloud computing & the infrastructure software, systems for operating systems, and more.

2.1.2 Components of Digital Infrastructure

Based on Forrester (2022) & Sustainable Digital Infrastructure Alliance (2022), digital infrastructure includes:

1. Fiber infrastructure: The network of fiber-optic cables that allows high-speed data transfer and communication; Server hardware is the computers and servers that process, store, and execute applications and services
2. Staff: IT experts who manage the digital infrastructure and ensure its security and smooth operation
3. Infrastructure software and IT virtualization: software that creates and manages servers, networks, and virtual machines for resource efficiency and scalability
4. Operating systems: Programs that manage a computer or server and provide a foundation for programs and services
5. Storage equipment: Solid-state drives, tape libraries, and hard drives for digital data storage and retrieval; Processing hardware and software: CPUs, GPUs, and other hardware accelerators perform computational tasks, along with software that uses them
6. Networks: LANs, WANs, the internet, and other physical and virtual infrastructure that connects systems and devices

7. Business applications: Project management, accounting, and customer relationship management programs
8. Virtualization software: Programs that provide virtual environment setup and management, enabling service and application deployment and resource efficiency
9. Mobile telecom and broadband infrastructure includes cellular networks, Wi-Fi, and satellite links
10. Cloud computing and SaaS/PaaS apps: Online application and service distribution services that enable scalability and on-demand access
11. Security: Intrusion detection and prevention systems, firewalls, and encryption protect digital infrastructure
12. Connectivity is the physical and virtual infrastructure, such as fiber-optic cables, routers, switches, and network protocols, that allows data transfer between devices and systems (Forrester, 2022; International Telecommunication Union, 2022; Sustainable Digital Infrastructure Alliance, 2022).

However, The study will limit the discussion in this section to the infrastructure elements which involve fixed broadband subscriptions, fixed telephone subscriptions, internet usage, cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, and GDP deflator that will be included as independent variables in this study.

The term "fixed network" typically denotes the wired networks utilized to provide telephone and fixed broadband services. These modes of communication can be conceptualized as a cable connection that enables the user to establish a phone call or access the internet with the end consumer. Fixed data, also known as fixed broadband, encompasses the transmission of high-speed data to a residential or commercial location via a variety of technologies. Internet access via cable modem, digital subscriber line (DSL), fiber optic cable, and other fixed broadband technology connections are examples of transmission methods. A landline telephone, also known as a fixed phone line, employs metal wire or fiber optic cable to transmit signals, in contrast to mobile phones which utilize wireless transmission (Taylor, 2024).

Yet, A mobile network is a communication network built with interconnected components to enable wireless communication among mobile devices such as smartphones, tablets, and other cellular-enabled devices. Crucial components of mobile networks include base stations for wireless communication with devices, Mobile Switching Centers (MSC) for call and data routing, and Home Location Registers (HLR) for storing subscriber information like service details and current location. Mobile networks allow devices to connect and access various services like voice calls, text messaging, multimedia messaging, and internet services, regardless of their location within the network's coverage area (Forte & de Donno, 2010).

Furthermore, in computer networks and the Internet, Traffic describes the movement of data packets between devices. Various types of data exchanges are involved, such as web page requests, email transmissions, file downloads, and streaming services. Understanding traffic characteristics, including packet size, arrival timing, flow directionality, and protocol usage, is essential for optimizing network performance and resource management (Lee & Lee, 2013; Williamson, 2001).

Also, In the context of telecommunications and information technology, the term "Internet" denotes a worldwide network of interrelated computer systems that facilitate the exchange of data, voice, and video communications among devices across the globe. This infrastructure is quite intricate, enabling users to access a plethora of information, interact with others, and utilize a variety of applications and services through the Internet (Definitions of World Telecommunication/ICT Indicators, 2010).

Further, broadband denotes high-speed internet access that is consistently available and quicker than conventional dial-up access. It covers a range of high-speed transmission technologies including DSL (Digital Subscriber Line) - Fiber-optic cable, Cable modem, Wireless, Satellite. Also, High-speed internet access through broadband enables quicker web browsing, file downloading, video streaming, and online gaming for homes and businesses. It plays a crucial role in facilitating access to digital services and information (Definitions of World Telecommunication/ICT Indicators, 2010; Telecommunication Union, 2021).

Next, Quality of Service (QoS) is all about the overall performance of a telecommunication service from the user's perspective, especially in meeting stated and implied needs under specific conditions. This encompasses a variety of factors, including the quickness, dependability, accessibility, and transparency of services. Quality of Service (QoS) is a critical factor in ensuring the seamless operation of a variety of aspects, including business operations, employment, fundamental community services, education, entertainment, and social interaction. The development of digital platforms, which are founded on dependable modern technology services, is crucial in addressing the health, social, and economic availability crisis. This development fosters innovation and enhances resilience in the face of the challenges associated with the rapid advancement of digital infrastructure in the future. (Definitions of World Telecommunication/ICT Indicators, 2010; Telecommunication Union, 2021).

Lastly, it is associated with Information and Communication Technology (ICT), which is employed in daily domestic tasks. This encompasses the utilization of digital services and internet connections, as well as the utilization of technological devices like tablets, smartphones, and computers. In certain populations, the ICT use index in household activities can serve as a benchmark for digital inclusion. This can offer a comprehensive perspective on the household's capacity to access and employ digital technology to facilitate daily activities. This index can also be used to measure employment levels, as it can offer a comprehensive overview of the cost-effectiveness and accessibility of digital services that can facilitate job creation and increase productivity. (OECD Southeast Asia, 2017; Low et al., 2021).

Therefore, the advancement of telecommunications and connections in this contemporary, digital era is contingent upon the presence of digital infrastructure components, including fixed broadband subscriptions, fixed telephone subscriptions, internet usage, cellular subscriptions, secondary school enrolment, GDP per employed person, inflation, and GDP deflator. These components are crucial for establishing the foundation of society in the face of the digital economy, which is characterized by ongoing advancements that facilitate the seamless exchange of data, the sharing of information, and the accessibility of information across a variety of platforms and devices.

2.1.3 Employment levels as the primary indicator of economic growth and development

The utilization of available labor resources is quantified by the employment rate. The results of these figures are ascertained by comparing the number of employed individuals with the total working-age population. A population that is still actively employed and entering working age is defined as those between the ages of 15 and 64 (OECD, 2023).

Among the most important indicators of economic growth and development is the employment rate, which shows how well an economy can create enough job opportunities for its people. Having a high employment rate suggests that a significant portion of the labor force is working, potentially resulting in enhanced productivity, increased wages, and better living conditions. It also indicates a robust and thriving economy, demonstrating business growth and job creation (International Labour Office, 2015).

On the other hand, Having a high employment rate is crucial for decreasing poverty by enabling more individuals to earn a respectable income and attain financial security. This plays a crucial role in the United Nations Sustainable Development Goals (SDGs), particularly SDG 8, which strives to encourage continuous, inclusive, and sustainable economic growth, as well as full and productive employment, and decent work for all (Department of Economic and Social Affairs Poverty, 2007).

Additionally, the quality of life ratio can be employed to assess an individual's quality of life, as a stable and sustainable occupation can enhance one's quality of life. Consequently, this ratio can be employed to assess a nation's capacity to enhance the quality of life of its citizens. In general, the employment level is a critical indicator of a country's economic progress, as it demonstrates the extent to which the economy is capable of generating significant employment opportunities and enabling individuals to earn a sufficient income, meet their basic requirements, and enhance their quality of life.

2.2 Empirical Investigation of Employment Levels and Digital Infrastructure

It is impossible to deny the current inextricable connection between the advancements in technology and the development of the digital world, which governs business and daily life. It has revolutionized our way of communication, work, business operations, and our perception of the world. In 2024, the internet was accessed by 5.35 billion people, representing around 66.2 percent of the global population. There has been a 1.8 percent increase in internet users in the prior year, with 97 million new users incorporating online for the first time in 2023 (Kemp, 2024).

The upward trajectory indicates a growing incorporation of digital technologies into daily life, impacting communication, work, business operations, and global viewpoints. It highlights the increasing significance of digital infrastructure in supporting and maintaining this interconnectedness. The digital world has become a crucial aspect of modern society and business, influencing our interactions, commercial activities, and perceptions of the world. Due to its accelerated development, digital has evolved into an element that is now inseparable from the human world.

On the other hand, distinguishing between digitization and digitalization, these processes are often confused with each other. Digitization is a technical process that entails converting analog information into a digital format. This involves transforming physical products into digital codes and formats to make them programmable or communicable. However, digitalization is defined as a socio-technological process that utilizes digitization methods in wider social and institutional settings. This process involves incorporating digital technologies' infrastructures into different aspects of society and institutions (Bican & Brem, 2020). There is a new theory in the digital realm called Digital Transformation. Creating a business model that is constantly learning and adapting, driven by AI and empowered by humans, aims to identify, codify, and put into action valuable insights about customers, products, and operations to improve efficiency, customer value, risk management, and revenue generation (Schmarzo, 2020). Plenty more to digital information than just digitalization. It involves incorporating digital technologies like web-based apps, mobile devices, and sensors into current operational processes. Digital transformation improves or substitutes human-centered processes with digital technologies (Schmarzo, 2020). To enhance comprehension, refer to the table 2 below illustrating Digital transformation, which involves reinventing the business model:

Conventional	**Modern**
Walkman	Spotify
Conventional Transportation	Gojek (Indonesia)
Fairmont Hotel	Airbnb
DVD Rental	Netflix
Gunung Agung (Indonesia)	Gramedia (Indonesia)
Job Vacancies in Newspapers	LinkedIn

Table 2. Digital Transformation

On the other hand, at least three channels exist for digital transformation to increase wage inequality: Initially, advancements in digital technology often require more skills, leading to a higher wage gap between skilled and unskilled workers. Additionally, automation resulting from digital technology can replace jobs that involve routine tasks. Lastly, investments in digital sectors tend to benefit workers with higher skills and education levels (Wihardja et al., n.d.).

According to a study conducted in China, employment is a crucial aspect of the digital economy for ensuring sustainable development. Furthermore, the study reveals that digital employment policies positively influence digital employability, digital employment capital, and digital employment intentions (Yu et al., 2023). Another intriguing study highlighted how the digital economy has increased women's employment opportunities and advanced gender equality in the workforce (W. Wang et al., 2023).

Additionally, the paper discusses the findings of an empirical analysis that highlights technological lag as the primary factor contributing to the low demand for digital employment in Ukraine (Azmuk et al., 2022). Another study conducted on European economies from 2009 to 2014 revealed that job creation in industries is positively correlated with a growing proportion of digital goods and services in total intermediate inputs, while it is negatively associated with ICT capital deepening (Reljic et al., 2021).
Findings from Geng & He (2021; Reljic et al., 2021) indicate that digital financial inclusion plays a crucial role in promoting sustainable employment in upper-middle-income economies, demonstrating a distinct threshold effect. Yet, the research conducted by

Petrova et al. (2020) During the digitalization process, employment gains a new level of flexibility with various outcomes, both beneficial and challenging. Considering the outcomes is essential for governing the economic and social spheres.

However, the findings from X. Zhang et al. (2022) indicate that the growth of the digital economy has led to a rise in labor market polarisation. Advancements in technology are further widening the gap in the labor market of the digital economy, leading to employment disparities. Informational effects and efficient governance play a crucial role in addressing employment polarization in the digital economy. This research enhances the emphasis on equal employment and opportunities for employees with varying skill levels. Likewise, provides support with Zhu et al. (2023) research indicating that enhancing the digital economy can lead to a notable enhancement in the employment structure through improvements in the industrial sector. Further, it has been observed that labour efficiency in the finance sector rises in correlation with the level of digital finance, providing evidence for the concept of technological unemployment (Deng & Liu, 2022).

On the flip side, research conducted in China indicates that digital advancements have a positive impact on job creation and income increase. Additionally, the rapid growth of e-commerce results in lower product prices and increased transaction volume. The impact of Fintech adoption on loan interest rates remains uncertain, yet it is evident that banks' lending activities are poised to grow significantly as they become more intertwined with the digital economy. The theoretical findings align well with extensively documented observations on China (Liu et al., 2022)..

One of the study in China demonstrates that the digital economy has both favorable and unfavorable effects on employment. It positively increases job opportunities, innovates job structures, improves job quality and pay levels, and provides flexible and varied job choices. On the downside, it may result in the decline of conventional employment, exacerbate income inequality, and favor individuals with advanced education and expertise compared to those with fewer skills (X. Wang et al., 2022).

In summary, this research has provided a comprehensive understanding of the intricate and diverse relationships between technological advancements and labor patterns through the analysis of numerous empirical studies on digital infrastructure and employment. This research offers valuable insight into the ways in which digital infrastructure, such as advanced technologies, e-commerce platforms, and expanding broadband networks, are influencing the labor market, job opportunities, and changing work behavior patterns in the digital era by incorporating deeper data and general trend patterns. This is the case.

It is highly beneficial to our comprehension of the labor market and technological empowerment to further investigate the influence of digital infrastructure on job creation. Furthermore, this research underscores the significance of developing mature policies and conducting ongoing research to leverage the potential of digital infrastructure to promote inclusive growth, increase employment opportunities, and generate jobs that are both sustainable and easily adaptable to technological advancements.

Digital infrastructure is currently in the process of ongoing development in society and has even become an integral component of an all-digital lifestyle. The findings of empirical studies serve as a foundation for ongoing research, which is beneficial for the development of innovative strategies and innovations that emphasize the use of digital technology to enhance job opportunities and facilitate more responsive and user-friendly workforce applications.

2.2.1 Fixed broadband subscriptions on employment level

Today, there is a widespread belief in the workplace that increased internet speed correlates to increased productivity. Despite this, crucial nuances are overlooked. The rapid expansion of internet networks has the potential to enhance communication and efficiency. While this can lead to an increase in work productivity, it can also result in a significant workload, creating a sense of urgency among employees to complete the task. Consequently, employers are obligated to evaluate the capabilities of their employees by In essence, the work load must be equitable and not induce tension, as it must adhere to the principle of justice between the employer and employee.

In the most recent research, general policies regarding internet availability in the context of increasing employment opportunities continue to raise concerns regarding their actual effectiveness. This research demonstrates that, in contrast to conventional wisdom, the development of employment opportunities in the region is not statistically significantly influenced by broadband access. A review of the impact of digital infrastructure on local employment opportunities and the measurement of economic development are necessary in light of the findings of this research (Bai, 2016, 2017, 2018).

In contrast to the research of other authors, the availability of high-speed internet facilities has the potential to increase employment opportunities (Bu & Tang, 2023). In addition, Houngbonon and Liang (2021) noted that broadband internet can contribute to the reduction of income inequality by increasing the number of online job opportunities. This is corroborated by research conducted in the United States, which indicates a positive correlation between the expansion of employment and numerous businesses in specific regions and the expansion of digital infrastructure (Lai et al., 2020; Lapointe, 2015).

Then, in another intriguing study conducted by Dettling et al. (2018), which concentrates on the labor force participation of married women in the United States, it is demonstrated that the rapid advancement of the internet has benefited working women by enabling them to work more flexibly, remotely, and with easy access to information and resources. about strength.Given the abundance of evidence available, a hypothesis has been formulated:

H1: The presence of fixed broadband subscriptions has positive impact to the employment rate.

2.2.2 Fixed telephone subscriptions on employment level

Fixed telephone subscriptions at the employment level are calculated by dividing the total number of fixed and mobile telephone subscriptions by the total number of employees. This statistic quantifies the effectiveness of telecommunications services in relation to the labor force engaged in delivering them. This data indicator is sourced from the Telecommunication Union, a constituent of the World Development Indicators database (Worldbank, n.d.).

Fixed telephone subscribers in this metric positively impact the employment rate. Research indicates that fixed telephone subscriptions have the potential to positively impact the employment rate. This claim is substantiated by research indicating that a growth in fixed telephone subscriptions can positively influence the advancement of the digitization process, leading to enhanced work productivity and the potential for creating new job prospects. In addition, this fixed telephone subscription can enhance connectivity and facilitate communication, so promoting commercial transactions and social interactions, ultimately fostering employment expansion (Amaghionyeodiwe & Annansingh-Jamieson, 2017; Raeskyesa & Lukas, 2019). Therefore, according to the aforementioned explanation, the following is the second hypothesis that can be inferred.

H2: The presence of fixed telephone subscriptions has positive impact to the employment rate.

2.2.3 Individuals using the Internet on the employment level

Advancements in the field of internet networks have significantly impacted the employment market in Southeast Asia. A business must operate efficiently and for employees who work remotely to have access to high-speed internet. Additionally, there will be a new trend that implies work-life balance, in which work and life coexist in harmony.

In Feldmann et al. (2020)'s research, which investigates the effects of the COVID-19 pandemic on internet networks, particularly in terms of employment. The results of this research are quite intriguing, as they indicate that numerous workers utilized the internet network to conduct business operations and work activities during the Covid-19 pandemic. The majority of these activities were conducted at home or through what could be referred to as "work from home."

In addition, the COVID-19 pandemic has established a novel work pattern, in which each work activity is contingent upon the internet network. This research is also consistent with the research described in the preceding paragraph, which posits that the internet network plays a significant role in facilitating work activities during the pandemic. Alternatively, it show that may be acquainted with the remote work system. An internet network demand that is significantly increased is accompanied by a storage system that is readily accessible and a flexible system that can be accessed from anywhere. Subsequently, there are numerous requests for cloud-based applications that are beneficial for supporting work operations. This indicates that these applications are crucial in the facilitation of remote work systems and current work operations (Feldmann et al., 2020).

Employees in various sectors, including those that are not typically technology-focused, now need digital skills to succeed in the current economy. Job-seekers of all levels, from high school students seeking part-time work to experienced executives exploring new opportunities, turn to the Internet to find job openings and apply. There has been a consistent rise in the percentage of Americans using the Internet to search for employment opportunities, increasing from 19 percent in 2013 to 27 percent in 2015 among Internet users aged 15 and above. For numerous individuals, the digital economy presents the ideal platform to discover their next job or business prospects (National Telecommunications and Information Administration, 2016).

One study conducted in China suggests that the development of broadband internet will not impact the employment rate for workers with varying skill levels. Moreover, the advancement of broadband internet benefits low-skilled workers while showing no notable effect on high-skilled workers (Jin et al., 2023). Moreover, after engaging extensively with unemployed graduates, the research from Oyedemi & Choung (2020) revealed that the lack of internet access for job hunting continues to be a significant obstacle, leading to frustration and demotivation among young job seekers. Another study, Dutz et al. (2017) shows that increased Internet access does not have a statistically significant overall impact on aggregate employment. It also negatively affects average wages, leading to a decrease in wage dispersion measures. Employment impacts are favorable and most noticeable in manufacturing, transport and storage, finance and insurance, and hospitality industry sectors. Within the manufacturing sector, having access to the Internet leads to favorable impacts on employment and wages for workers in medium- and high-skill positions.

On the flip side, Based on the research from Radu (2022), it is evident that the rise in the number of internet users within the population has a notable impact on the employment rates of the countries studied, including Austria, Belgium, Cyprus, Czech Republic, Estonia, Spain, Croatia, Italy, Netherlands, Norway, Portugal, Romania, and Sweden from 2010 to 2020. Additionally, it is confirmed that an expansion in mobile internet coverage positively affects employment, leading to an increase in jobs across skilled and unskilled occupations (Ankrah Twumasi et al., 2021; Caldarola et al., 2023; Dutz et al., 2017). Nevertheless, the regression results indicate that residential internet access has a positive impact on both nonstore retail employment and the number of nonstore retail entities (Khan, 2023).

The influence of the Internet on productivity, job satisfaction, and worker flows is undisputed. As companies navigate through the digital world, it's crucial to leverage the advantages of Internet technologies while avoiding possible drawbacks. Cooperation is required among a variety of components that promote work activities, flexible and structured skill training, and the development of new digital employment.

Balgobin and Dubus (2022) conducted research in Uganda and discovered a correlation between employment and the use of traditional cell phones. Additionally, emphasizing the significance of mobile phone access in order to expand employment opportunities. Then, intriguing research revealed that internet use encourages individuals who tend to choose informal work, such as freelancers and part-time work, as supported by research conducted in China. This research also underscores the substantial correlation between the labor market and the expansion of digital connections. The emergence of online work platforms, remote work opportunities, skill upgrading, and the expansion of the internet have all played a significant role in the influence of formal workers in China (Li & Si, 2023)

Another study conducted in China utilized tourism-related employment data from a general social survey to determine that the primary factor contributing to the inverted-U-shaped tourism employment polarization was the internet use of workers. This relationship demonstrates that the internet's influence causes other variables to increase, reach a zenith, and then decrease (Guo et al., 2024). In the interim, research was conducted in India regarding the influence of internet usage on work methods and efficacy. This research also indicates that the internet is a valuable resource for completing assignments. This leads to more efficient and effective work methods, which are also simple to adapt to (Shrivastava et al., 2016).

In the interim, Vayre and Vonthron (2019) conducted research that indicates an increasing number of internet users are utilizing the internet for personal purposes during work hours. In order to achieve a fusion of personal interests and general professional interests in internet use. Executives have devised methods to balance work and personal life by limiting their Internet usage for work purposes, both in the office and at home. It was observed that using the Internet for work purposes is not strongly linked to absorption, a sub-dimension of work engagement. The research revealed a strong correlation between utilizing the Internet for work and developing addictive behaviors towards it.

Meanwhile, a research project in China delved into the impact of Internet usage on job satisfaction among 83,012 Chinese workers. The results revealed a notable 3.2% increase in job satisfaction due to Internet use. Analysis of differences reveals that the Internet has a greater positive effect on individuals residing in urban areas with higher incomes and education levels (D. Zhou et al., 2022)

A separate investigation revealed that higher income levels were observed among individuals residing in rural regions. People in rural areas engaged in non-agricultural activities or entrepreneurship contribute to the relationship between internet usage and income growth, resulting in a positive effect. The use of the internet has a more significant effect on income growth than engaging in entrepreneurship or non-agricultural jobs (X. Zhou et al., 2020).

Finally, the job market in Southeast Asia is significantly influenced by internet network traffic. The availability of high-speed internet access can stimulate the need for industrial development to generate new employment and support the operations of new jobs.

Drawing from this copious collection of data, the subsequent hypothesis has been developed:

H3: Individuals using the Internet influences positive impact to the employment rate

2.2.4 The impact of mobile cellular subscriptions on the employment levels

Cellular networks offer data transmission and communication capabilities without the need for cables to be connected to a variety of devices, including laptops, tablets, and cellphones. Infrastructure in the field of cellular networks is crucial in the employment sector, as it serves as a foundation for devices such as laptops, tablets, and cellphones that are connected to the internet network. This connectivity enables users to easily access jobs, create new ones, and increase their productivity.

An investigation conducted by Telenor Asia Digital Lives Decoded (2022) revealed that mobile connectivity has the potential to significantly enhance careers, as indicated by a higher number of women and C-suite executives who believe that their mobile phones help them access improved job and career prospects This research demonstrates that the success of their work is truly bolstered by the cellular networks that each individual in a given area believes in. Nevertheless, there are disparities in the utilization of technology among rural and urban residents, small and large businesses, and employees of different levels.

In addition, other research indicates that the adoption and availability of broadband have a beneficial effect on the level of employment in rural areas, as it significantly enhances the success of their work. For instance, there are numerous current trends in remote or long-distance work that necessitate only a laptop, cellphone, or iPad, as well as an internet connection. This demonstrates that the rural economy can be enhanced and new job market opportunities in non-agricultural sectors can be created by the presence of digital infrastructure (Isley & Low, 2022).

In the final analysis, digital infrastructure, particularly in the context of mobile networks, is crucial for the expansion of employment opportunities in Southeast Asian countries. It enables mobile devices and applications to promote the creation of new jobs and increase job productivity, particularly in rural areas. A robust cellular network infrastructure can substantially enhance productivity in the industrial sector, thereby creating a plethora of new employment opportunities.

The following can be formulated from the exhaustive explanations of the numerous material references provided above:

H4: Employment levels are positively affected by Mobile cellular subscriptions.

2.3 Education, Productivity, and Inflation as Control Variable

Attaining advanced levels of education may result in enhanced digital skills and more efficient utilization of digital tools, ultimately leading to increased productivity and decreased inflationary impacts. An educated workforce is more adept at using digital tools effectively, which boosts productivity in the economy. As productivity rises, it can result in decreased production costs and, in turn, lower prices for consumers, helping to alleviate inflationary pressures (Emara & Zecheru, 2024). Additionally, this dynamic is a major factor in the fact that, although making up just 8.2 percent of the US GDP, the digital economy has recently contributed 86 percent of the growth in labor productivity in the country. Because they are more productive, workers with higher degrees of digital skills—often found in the ICT industry—tend to command higher compensation (Ezell, 2021).

On the other hand, there appears to be a correlation between inflation and the employment rate, specifically in terms of how inflation affects employment. A policy aimed at maintaining inflation could potentially lead to a temporary decrease in unemployment. This suggests that while inflation might have a temporary effect on employment rates, the connection between the two is more complex in the long run and does not result in a simple trade-off between higher inflation and lower unemployment (Lucas, & Rapping, 1969).

Last but not least, cost-push inflation has the potential to affect the employment rate through an initial escalation in production costs. Also, cost-push inflation may result from supply disruptions in particular sectors. Should such inflation become significant and enduring, it has the capacity to diminish the present and prospective output levels of an economy. This can lead to a phase known as "stagflation," characterized by elevated levels of inflation accompanied by stagnant development and high unemployment. cost-push inflation may result in elevated levels of unemployment as companies make adjustments to escalated production expenses through output reductions and potentially workforce downsizing (Bank of Australia, 2023).

Considering the vast amount of data that is currently accessible, the following hypothesis has been established for the control variable:

Z1: The employment rate is impacted by school enrolment tertiary

Z2: The employment rate is impacted by GDP

Z3: The employment rate is impacted by inflation

2.4 Employment in service as the supplementary variable

Another supplementary variable, Employment in services (% of total employment) is introduced as a novel proxy to assess the reliability of the findings. This variable encompasses employment opportunities in the service sector, offering a more comprehensive perspective and is closely linked to economic expansion. By introducing this variable as a novel proxy, it is anticipated to verify whether the computation outcomes differ in the presence of the new proxy. This approach not only evaluates the dependability of the model but also provides valuable understanding into economic progress.

CHAPTER 3

RESEARCH METHODOLOGY

An effective research methodology is a key determinant of study success. Given the information provided in the previous explanation and literature analysis, it is crucial to conduct a more comprehensive investigation into the influence of digital infrastructure on the employment rate. This study use panel data regression analysis, focusing on countries in the Southeast Asia region, specifically the ASEAN countries. Panel data regression offers a robust approach that takes into account variations among ASEAN countries and their changes over time. This study aims to present a comprehensive analysis of various factors including Fixed broadband subscriptions (per 100 people), Fixed telephone subscriptions (per 100 people), Individuals using the Internet (% of population), Mobile cellular subscriptions (per 100 people), School enrollment, secondary (% gross), GDP per person employed (constant 2021 PPP $), Inflation, GDP deflator (annual %) in relation to Employment to population ratio, 15+, total (%) (modeled ILO estimate).

The objective of this research is to offer empirical evidence and understanding of how digital infrastructure affects employment in ASEAN. By employing systematic panel data analysis, this study yields statistical findings that offer a more comprehensive insight into the process of digital transformation in ASEAN countries.

3.1 Quantitative Analysis

In economic theory, quantitative analysis pertains to the methodology that is predicated on statistical techniques and numerical data to comprehend and resolve economic dilemmas. To supplement pure economic theory with statistics, quantitative analysis frequently employs the accumulation, processing, and interpretation of numerical data to construct economic models and test hypotheses (Mitchell, 1925).

Quantitative data analysis encompasses utilizing statistical methods to interpret numerical data gathered from a sample, converting unprocessed data into outcomes or proof. The approach commences by formulating a well-defined analysis plan to guarantee that the statistical analyses are congruent with the research inquiries. Statistics have two main roles in quantitative analysis: descriptive and inferential. Descriptive statistics provide a summary of the variables in a dataset, revealing the typical characteristics of the sample. On the other hand, inferential statistics investigate the connections between variables and conclude whether observed effects, correlations, or differences are likely to be true and exist in reality (Kotronoulas et al., 2023).

In order to guarantee the accuracy and dependability of data estimates, this study employs the Heteroscedastic Panels Corrected Standard Errors (HPCSE) method to address the issue of heteroscedasticity in panel data. Additionally, the study utilizes the Feasible Generalized Least Squares (FGLS) approach in regression to obtain parameter estimates that are both efficient and consistent. This combination of approaches is designed to generate a comprehensive and precise examination of the relationship between the variables under investigation.

Three model techniques were employed in this study to assure the trustworthiness of the analysis outcomes. The initial model is a comprehensive model computed using Driscoll-Kraay standard errors, specifically developed to address autocorrelation and heteroscedasticity in panel data with cross-sectional dependency. By employing Driscoll-Kraay standard errors, this model guarantees that the parameter estimates stay constant even in the presence of potential dependence between observations over time and among individuals (Hoechle, 2007).

Additionally, a robustness check is conducted to assess the durability and consistency of the findings. The goal of this robustness check is to ascertain the consistency of the acquired results when different assumptions or model specifications are altered. This process enhances confidence in the validity of the conclusions drawn from the model.

The third model employed is an outlier-free model, wherein the outliers, namely Singapore and Timor Leste, are excluded because to their significantly disproportionate digital infrastructure gap compared to other ASEAN countries. This involves excluding observations that are deemed outliers from the analysis. The purpose of eliminating outliers is to guarantee that the estimation results are not influenced by extreme values that may not accurately represent the entire population. Therefore, this approach enhances the precision of the association between the examined variables by mitigating the potential bias arising from atypical or extreme data.

This study aims to enhance the strength, accuracy, and dependability of outcomes in examining the relationship between the variables under investigation by employing these three methodologies.

3.2 Data Collection

3.2.1 Data Source Description

This study utilizes secondary data sources from international organizations. Collect information from well-known international organizations such as the World Bank and compare data across countries and enhance national-level data. Furthermore, delve into academic research by reviewing existing studies and literature on related topics to pinpoint important variables, methodologies, and potential data sources.

The study explored ASEAN, encompassing countries such as Thailand, Vietnam, Singapore, Philippines, Indonesia, Malaysia, Myanmar, East Timor, Brunei, Cambodia, and Laos (refer to the figure 8 below) This study also includes a comparison with ASEAN countries, except Singapore and Timor Leste, which are considered outliers. Delving into this varied region, the research sought to explore the complex connection between digital infrastructure and employment from 2010 to 2022.

ASEAN, with its diverse cultures, languages, and landscapes, was on the brink of a digital revolution during this time. With the widespread adoption of smartphones and the expansion of internet access, the region experienced a significant change in people's lifestyles, work habits, and social interactions.

Figure 8. Southeast Asia Map

Source: Ontheworldmap.com.

Singapore and Timor-Leste are digital infrastructure outliers as a result of the substantial disparities in their infrastructure development and digital connectivity indicators. Singapore has made substantial investments in digital infrastructure, such as submarine cables, satellites, optical fiber cables, and mobile base stations. This has resulted in a robust digital ecosystem in the country, with high rates of mobile and high-speed internet penetration (Ministry of Communications and Information, n.d.; Singapore Business Review, 2023; statista, 2024)Singapore has a high level of digital adoption, with a significant increase in digital usage, notably in the business sector (Singapore Business Review, 2023). And in terms of government support, the government has adopted a proactive approach to the development of digital infrastructure, emphasizing forward-thinking investments, adopting a comprehensive perspective on the digital infrastructure stack, and capitalizing on Singapore's distinctive circumstances. This has allowed the nation to preserve its status as a global epicenter of digital innovation (Ministry of Communications and Information, n.d.)

Timor-Leste is considered an outlier in the context of digital infrastructure development due to its comparatively low level of development, which is characterized by limited access to electricity, internet, and mobile services This country is encountering significant obstacles in the advancement of its infrastructure, particularly in the energy sector, and its infrastructure quality falls below established norms (International Monetary Fund, 2024; Rohman et al., 2024). The country's digital infrastructure development is comparatively inadequate, characterized by low levels of internet penetration and poor ranks in the digital adoption index (International Monetary Fund, 2024; Rohman et al., 2024).

The administration of this country has recognized the significance of investing in digital infrastructure and has actively pursued partnerships with neighboring countries like Indonesia and Australia to facilitate digital transformation within its borders. Nevertheless, the task at hand is challenging since the country is currently grappling with a crisis in the development of digital infrastructure and the promotion of digital adoption (antaranews.com).

On the other hand, Singapore stands out due to its quick growth in digital infrastructure development. However, Singapore boasts a significantly higher internet speed of 72.18 Mbps. According to the sources cited (Rohman et al., 2024; Singapore Business Review, 2023), Singapore has the highest digital adoption index, whereas Timor Leste has the lowest digital adoption index. If we compare ASEAN countries, the lowest digital infrastructure is in Timor Leste because it is still in the initial development stage compared to Laos and Myanmar which are slightly more advanced in this regard.

Ultimately, Singapore attains the top ranking because to its government's profound commitment to global digital technology advancement, resulting in exceptional levels of digital adoption and robust digital infrastructure. Conversely, Timor Leste's low position can be attributed to the lack of comprehensive distribution of technical advancement, as the government has been unable to enhance digital infrastructure due to inadequate resources. This poses a significant problem for Timor Leste in terms of developing its digital infrastructure in the future.

3.2.2 Structure of Panel Data

Panel data is a form of data that encompasses both time series and cross-sectional observations. This has the potential for monitoring the same entity, such as an individual, company, or country throughout a specific timeframe. The data consists of two crucial elements, geographical and temporal dimensions, which enable a more thorough examination of diversity and patterns in the observed entities (Gujarati, 2008).

Panel data, or composite data, is a collection of observations that includes both time series and cross-sectional data. Alternatively, this might be referred to as longitudinal panel data, micro panel, time series analysis, or cohort analysis, depending on the unique research focus (Gujarati, 2008).

The findings of this study will be presented in the form of a pooled ordinary least squares (OLS) model, also referred to as the common effect model, fixed effects model, and random effects model. Subsequently, a meticulous selection process will be conducted to determine the optimal model, followed by rigorous testing to validate the accuracy of the computation findings (Gujarati, 2008).

The fundamental equation for panel data regression can be expressed as follows:

$$y_{it} = \alpha_i + \beta_i X_{it} + u_{it}$$

- α_i represents intercept
- y_{it} represents the dependent variable, where t represents time and α represents the intercept.
- The vector β denotes the coefficients pertaining to the independent variables.
- X_{it} represents the independent variables for individual i at time t.
- u_{it} consists of the individual-specific, time-invariant effect (u_{it}) and the time-varying random component (u_{it}).

Panel data regression models can be estimated using many methodologies, such as fixed effects, random effects, and mixed effects models. These models are employed to examine the correlation between the independent variables and the dependent variable within the framework of panel data, which consists of observations for the same people or units over time (Gujarati, 2008).

This panel data model is intended to investigate the relationship between the ratio of the working population (y) and a variety of independent variables. These variables include fixed broadband subscriptions (x1), fixed telephone subscriptions (x2), internet usage by individuals (x3), and mobile subscriptions (x4), as well as education and economic variables such as secondary school enrollment rates (z1), Gross Domestic Product (GDP) per worker (z2), and inflation based on the GDP deflator (z3).

This model presupposes that the ratio of the working population is influenced by the economic conditions of a country, the level of adoption of communication technology, and access to education. The OLS (Ordinary Least Squares) approach, Fixed Effects Model (FEM), or Random Effects Model (REM) will be employed to estimate this relationship by accounting for cross-sectional and time-series variations in the panel data model.

To ascertain the most suitable model, the methodology employed will be contingent upon the data's characteristics and the outcomes of statistical analysis, including the Hausman test. The estimation of this model will offer a comprehensive understanding of the extent to which each independent variable influences the employment ratio, while also accounting for country-specific variations and temporal fluctuations. Nevertheless, feasible least squares (FGLS) will be implemented to ascertain the optimal model in the event of heteroscedasticity and autocorrelation issues.

$$y_{it}=\alpha+\beta_1 x_{1it}+\beta_2 x_{2it}+\beta_3 x_{3it}+\beta_4 x_{4it}+\gamma_1 z_{1it}+\gamma_2 z_{2it}+\gamma_3 z_{3it}+u_{it}$$

Where:

- y_{it} : Employment to population ratio, 15+, total, for country i at time t.
- x_{1it} : Fixed broadband subscriptions for country i at time t
- x_{2it} : Fixed telephone subscriptions for country i at time t
- x_{3it} : Individuals using the Internet for country i at time t
- x_{4it} : Mobile cellular subscriptions for country i at time t
- z_{1it} : School enrollment, secondary, for country i at time t
- z_{2it}: GDP per person employed for country i at time t
- z_{3it}: Inflation, GDP deflator for country i at time t
- α: The intercept term (fixed effect if using a fixed effects model).
- u_{it} : Error term for country i at time t.

Subsequently, this model incorporates a novel proxy, specifically employment in service:

$$np_{it}=\alpha+\beta_1 x_{1it}+\beta_2 x_{2it}+\beta_3 x_{3it}+\beta_4 x_{4it}+\gamma_1 z_{1it}+\gamma_2 z_{2it}+\gamma_3 z_{3it}+u_{it}$$

Where:

- np_{it} : Employment in services, for country i at time t.
- x_{1it} : Fixed broadband subscriptions for country i at time t
- x_{2it} : Fixed telephone subscriptions for country i at time t
- x_{3it} : Individuals using the Internet for country i at time t
- x_{4it} : Mobile cellular subscriptions for country i at time t
- z_{1it} : School enrollment, secondary, for country i at time t

- z_{2it}: GDP per person employed for country i at time t
- z_{3it}: Inflation, GDP deflator for country i at time t
- α: The intercept term (fixed effect if using a fixed effects model).
- u_{it} : Error term for country i at time t.

This study utilizes panel data from the World Bank spanning from 2010 to 2022 to conduct a comprehensive analysis of the determinants impacting the employment-to-population ratio (specifically, the ratio of employed individuals aged 15 and above to the total population). The employment-to-population ratio is considered as the dependent variable (Y) in this study. The study examines the following independent variables: x1 = Fixed broadband subscriptions, x2 = Fixed telephone subscriptions, x3 = Individuals utilizing the Internet, and x4 = Mobile cellular subscriptions. Furthermore, the control variables included in the analysis include z1, which represents secondary school enrollment, z2, which represents GDP per person employed, and z3, which represents inflation measured by the GDP deflator.

3.2.3 Period Covered

This research spans from 2010 to 2022, during which the impact of digital technologies on the daily lives of ASEAN countries became more noticeable. These technologies not only changed the way people communicate and do business but also affected their job prospects.

3.2.4 Dependent Variable

The employment rate is a metric that quantifies the degree to which the available labor pool is being utilized within an economy. The calculation involves dividing the number of employed individuals by the total number of individuals of working age. The working-age population encompasses individuals between the ages of 15 and 64. Employment rates are responsive to the economic cycle, but they are also affected by factors such as higher education and income support policies, as well as policies that promote the employment of women and disadvantaged groups (OECD, 2023).

The employment rate, which is the dependent variable, is defined as the proportion of the population of working age who are actively employed and earning income. This indicator is based on official labor force surveys and statistical databases, and it measures both the amount and quality of work prospects in each ASEAN countries. The employment rate is a metric used to gauge the correlation between the labor market and economic prosperity.

The calculation can be determined using the subsequent formula:

Employment rate = (Number of employed people / Total labor force) x 100%

This formula is utilized to calculate the current labor participation rate. The aggregate workforce can be acquired from authoritative governmental sources, such as the official website of the National Statistics Agency. The employment rate is determined by dividing the number of individuals who are employed by the total number of individuals who are eligible to work, and then multiplying the result by 100 to express it as a percentage (Calculator Academy Team, 2023; OECD, 2023).

3.2.5 Independent Variables

This exploration examines a range of independent factors to represent the impact of digital infrastructure on the employment rate in Southeast Asia especially in ASEAN countries. The aspects of fixed broadband subscriptions (per 100 individuals), fixed telephone subscriptions (per 100 individuals), internet usage (% of population), cellular subscriptions (per 100 individuals), secondary school enrollment (% gross), GDP per employed person (constant PPP $ 2021), inflation, GDP deflator (%) are crucial in understanding the changing landscape of digital connectivity in the region.

Hypothesis	**Variable**	**Indicator**	**Source**
Y	Dependent	Employment to population ratio, 15+, total (%) (modeled ILO estimate)	International Labour Organization
H1	Independent	Fixed broadband subscriptions (per 100 people)	Lai et al., 2020; Lapointe, 2015
H2	Independent	Fixed telephone subscriptions (per 100 people)	Amaghionyeodiwe & Annansingh-Jamieson, 2017; Raeskyesa & Lukas, 2019
H3	Independent	Individuals using the Internet (% of population)	X. Zhou et al., 2020

H4	Independent	Mobile cellular subscriptions (per 100 people)	Isley & Low, 2022
H5	Independent	School enrollment, secondary (% gross)	Ibarra et al, 2022
H6	Independent	GDP per person employed (constant 2021 PPP $)	Ezell, 2021
H7	Independent	Inflation, GDP deflator (annual %)	Lucas, & Rapping, 1969

Table 3. Hypothesis development

3.2.6 Control Variables

The research focuses on analyzing the influence of digital infrastructure on the employment rate in Southeast Asia. The Study acknowledges the significance of accounting for crucial elements that could affect employment results. The relationship between digitization and employment within the region is influenced by education level and government policies, which are important control variables.

Education as a control variable

Education is a potent means of reducing poverty as it has the ability to transform an individual's mindset. Unlike simply providing funds for immediate consumption needs, education offers a more effective approach by fostering intelligence and productivity. Education has a crucial role in fostering economic growth and development within a nation. Education significantly impacts work prospects and employment outcomes.

Research conducted by Ibarra et al (2022) affirms that employing consistent educational techniques can yield favorable long-term outcomes. The study conducted by Ibarra et al. (2022) offers a comprehensive analysis of how education influences employment, socio-economic factors, and economic growth.

The reason for this is that education can exert a significant impact on both employment prospects and the potential for a substantial income. The aforementioned study conducted by Ibarra et al (2022) confirms that education significantly impacts employment prospects and income, making it an effective long-term strategy for reducing poverty (Jorda & Alonso, 2015).

Productivity and inflation as control variable.

The control variables that follow are productivity and inflation, which are considered in the context of wage policies aimed at sustaining employment levels. According to the Lehment (2000) model, if wages rise less than the combined effect of productivity and inflation, it suggests that it can lead to increased employment. This variable holds significant importance as it has the potential to exert an impact on the employment rate (Lehment, 2000; Meager & Speckesser, 2011).

Gross Domestic Product (GDP) as control variable.

Next, Gross Domestic Product (GDP) is frequently employed as a control variable in research conducted in both economic and social. This is due to GDP's ability to accurately depict a country's economic state. Gross Domestic Product (GDP) encompasses the aggregate value of all goods and services generated within a specific timeframe, hence offering a comprehensive overview of economic activity. Statistical analysis uses GDP as a control variable to isolate the impact of independent factors on the dependent variable, taking into account the overall economic effect. By considering the broader economic conditions, study findings are enhanced in terms of accuracy and reliability.

Employment in Service as the supplementary variable for robustness check

Employment in services (% of total employment) is introduced as a Alternative proxy to assess the reliability of the findings. This variable encompasses employment opportunities in the service sector, offering a more comprehensive perspective, and is closely linked to economic growth.

CHAPTER 4
RESULT AND DISCUSSION

These findings will be explicated in this chapter after meticulous computations. It is expected that these findings will have a beneficial effect on the government, society, and other pertinent shareholders. Starting with quantitative bibliometric analysis to identify novel topics, the process continues with panel data calculations using Stata 17.0. This analysis investigates three econometric models: the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). One model will be distinguished from another, and we will determine which model is most appropriate for this research.

In an additional effort to guarantee the validity of the data or results, a conventional assumption test will be implemented. This measure, which encompasses heteroscedasticity, autocorrelation, and multicollinearity, can ascertain the model's accuracy. This study also employs the Heteroscedastic Panels Corrected Standard Errors (HPCSE) method to address the issue of heteroscedasticity in panel data. Additionally, the study utilizes the Feasible Generalized Least Squares (FGLS) approach in regression to obtain parameter estimates that are both efficient and consistent.

This chapter will also offer conclusions by considering the government, society, and other pertinent stakeholders that it can serve as a foundation for decision-making.

4.1 Descriptive Analysis

Variable	Obs	Mean	Std. Dev	Min	Max
y	143	64.7165	5.577679	52.8	76.07
x_1	140	7.165643	8.316174	0	37.36
x_2	142	10.46007	10.66956	0	38.66
x_3	136	46.19125	28.54251	.25	98.08
x_4	143	116.9724	36.52358	0	181.77
z_1	113	85.72956	18.83049	47.47	134.44
z_2	143	52212.84	64280.59	6197.47	215377.8
z_3	142	4.436549	8.006474	-19.15	59.03

Table 4. Descriptive Analysis

Presented in Table 4, the data set includes various variables related to employment, telecommunications, education, and economic indicators, as indicated by the descriptive statistics provided. The employment-to-population ratio (y) for individuals aged 15 and older, has an average value of approximately 64.72%, with a standard deviation of 5.58%.

On average, it appears that about 64.72% of the population aged 15 and above is employed. There is some variation in the data, with the lowest observed employment rate being 52.8% and the highest being 76.07%.

The first explanatory variable, x1 (Fixed broadband subscriptions), has an average value of around 7.17 subscriptions per 100 people. It also has a relatively high standard deviation of 8.32, which means that there is a significant amount of variation in broadband subscription rates. Some areas have no subscriptions at all, while others have as many as 37.36 subscriptions per 100 people. The second variable, x2 (Fixed telephone subscriptions), has an average of 10.46 subscriptions per 100 people, with a standard deviation of 10.67. This means that there is a significant range of variability, with the number of subscriptions ranging from 0 to 38.66.

According to the data from variable x3 (Individuals using the Internet), the average percentage of the population using the Internet is 46.19%, with a high level of variation indicated by a standard deviation of 28.54%. These numbers show that internet usage varies greatly among different regions or populations, ranging from as low as 0.25% to as high as 98.08%. The number of mobile cellular subscriptions, denoted as x4, has an average of 116.97 subscriptions per 100 people. This means that, on average, there are more mobile subscriptions than there are people in the population. The standard deviation of this data is 36.52, indicating the variability in the number of subscriptions. The range of values for this data spans from 0 to 181.77 subscriptions per 100 people.

Regarding the education-related variable, z1 (School enrollment, secondary), the average enrollment rate is 85.73%, and it has a standard deviation of 18.83%. It seems that a large majority of secondary-school-age students are currently attending school. The enrollment rate varies between 47.47% and 134.44%, with the higher rate possibly suggesting that some areas have more students enrolled than they can accommodate. The economic indicator z2, which measures GDP per person employed, reveals a wide range of values. On average, the value is 52,212.84, but there is a significant amount of variation with a standard deviation of 64,280.59. This indicates that there is considerable disparity in economic productivity per worker across different regions. The lowest recorded value is 6,197.47, while the highest is 215,377.8.

Finally, the inflation rate (measured by the GDP deflator) is found to have a mean value of 4.44%, with a standard deviation of 8.01%. The range of inflation rates varies widely, with some areas experiencing deflation of -19.15% and others seeing a significant increase of 59.03% in the general price level. The wide range of inflation values in the data set reflects the different economic conditions that exist.

Overall, the data set shows that there is a significant amount of variation in the key economic, educational, and telecommunications indicators. This variation is important to take into account when conducting further analysis, especially when trying to understand how these factors affect employment outcomes.

4.2 A correlation analysis

Variable	Y	x1	x2	x3	x4	z1	z2	z3
y	1.0000							
x1	0.2065	1.0000						
x2	-0.0719	0.7429	1.0000					
x3	0.0009	0.7852	0.6499	1.0000				
x4	0.2965	0.5617	0.2791	0.6169	1.0000			
z1	0.1801	0.6628	0.3839	0.5300	0.7158	1.0000		
z2	-0.1874	0.7613	0.8506	0.8019	0.4097	0.6279	1.0000	
z3	0.0295	-0.1329	-0.065	-0.186	-0.166	-0.266	-0.138	1.0000

Table 5. A Correlation analysis

Presented in table 5, The variables analyzed exhibit numerous significant relationships, as indicated by the correlation matrix. The correlation values of the working population ratio (y) are 0.2065, 0.2965, and 0.1801, respectively, and they are weakly positive with respect to the majority of the independent variables, including fixed broadband subscriptions (x1), mobile subscriptions (x4), and secondary education enrollment rates (z1). This suggests that the working population ratio is generally correlated with increases in these variables, albeit the relationship is not particularly robust.

Conversely, a moderate negative correlation was observed between y and fixed telephone subscriptions (x2) and GDP per worker (z2), with correlation values of -0.0719 and -0.1874, respectively. This suggests that decreases in the working population ratio are generally associated with increases in fixed telephone subscriptions and GDP per worker, although this relationship is not particularly significant.

Many of the independent variables exhibit fairly robust correlations. For instance, there is a robust positive correlation of 0.7429 between fixed broadband subscriptions (x1) and fixed telephone subscriptions (x2), as well as a correlation of 0.8506 between GDP per worker (z2) and fixed telephone subscriptions (x2). This suggests a robust correlation between economic indicators and the adoption of communication technology.

Nevertheless, inflation (z3) exhibits a very weak or even negative correlation with other variables, suggesting that inflation is either indifferent or negatively related to the development of communication technology, education, and other economic conditions in the context of this data.

In general, the interpretation of these correlations offers an initial understanding of the relationship between the ratio of the employed population and a variety of technological, educational, and economic factors. Nevertheless, a more comprehensive analysis is required to elucidate the causal effects and interactions in greater detail, utilizing suitable panel data regression methods.

4.3 Driscoll-Kraay standard errors

At the beginning of the study, Driscoll-Kraay's standard errors were employed together with a comprehensive model to address potential issues of autocorrelation and heteroscedasticity in panel data that exhibit cross-sectional dependency. The Driscoll-Kraay standard errors were selected because to their ability to yield reliable and effective estimates, despite the presence of interdependence across observations across time and persons. By employing this methodology, the estimation outcomes in the comprehensive model are anticipated to be more resilient and precise, so ensuring that the deductions derived from the research are more dependable and indicative of the phenomenon under investigation (Hoechle, 2007).

4.3.1 Hausman Test

The subsequent data presents the outcomes of the Hausman test computations for the Full model:

Chi-Square	Prob
15.56	0.0295

Table 6. Hausman Test (Full Model)

As mentioned table 6, The Hausman test findings for the whole model show a Chi-Square statistic of 15.56 and a p-value of 0.0295. The p-value is below the standard significance level of 0.05, indicating that we can reject the null hypothesis. The null hypothesis of the Hausman test states that the random effects model is the preferred model. Based on the p-value, there is evidence to support the fixed effects model over the random effects model. This is because the coefficient variations are consistent and not due to chance. Therefore, it may be inferred that the fixed effects model is more suited for the data under examination.

4.3.2 Heteroskedasticity Check

The subsequent data presents the outcomes of the Heteroskedasticity test computations for the Full model:

Chi-Square	Prob
547.05	0.000

Table 7. Heteroskedasticity check (Full Model)

According to the heteroscedasticity study results in table 7, the Chi-Square value is 547.05, and the probability value (Prob) is 0.000. This demonstrates an exceedingly low probability value, falling below the generally employed significance level of 0.05. Therefore, this computation demonstrates the presence of heteroscedasticity in the model, indicating that the variance of errors varies between data and cannot be considered constant. Heteroscedasticity can lead to inefficiency and bias in the statistical conclusions drawn from estimates obtained by the Ordinary Least Squares (OLS) method. Thus, the subsequent stage necessitates the use of a rectification technique, such as the utilization of Heteroscedasticity-Consistent Standard Errors or other alternative methodologies like Feasible Generalized Least Squares (FGLS), in order to get parameter estimates that are more precise and dependable.

4.3.3 Multicollinearity test

The results of the VIF calculation are as follows:

Variable	**VIF**	**1/VIF**
X1	4.55	0.219837
X2	5.28	0.189525
X3	1.15	0.870234
X4	3.25	0.307873
Z1	3.64	0.275102
Z2	7.48	0.133739
Z3	1.15	0.870234
Mean	**4.25**	

Table 8. Multicollinearity test (full model)

Presented table 8 above, The Variance Inflation Factor (VIF) is employed in the multicollinearity analysis of independent variables in the regression to determine the degree to which each variable is collinear with other variables. The data provided indicates that X1 (Fixed broadband subscriptions) has a VIF of 4.55 and a 1/VIF of 0.219837, which suggests a moderate level of multicollinearity with other independent variables. X2 (Fixed telephone subscriptions) exhibits a VIF of 5.28 and a 1/VIF of 0.189525, suggesting that it also experiences a moderate level of multicollinearity, albeit slightly higher than X1.

In contrast, X3 (Individuals using the Internet) has a very low VIF of 1.15 and a 1/VIF of 0.870234, suggesting that it is a variable that is quite distinct from the other independent variables and has very low multicollinearity. A relatively low level of multicollinearity is indicated by the VIF of 3.25 and the 1/VIF of 0.307873 for X4 (Mobile cellular subscriptions).

Z1 (School enrollment, secondary) has a VIF of 3.64 and a 1/VIF of 0.275102, which suggests a relatively moderate level of multicollinearity. Lastly, Z2 (GDP per person employed) has the highest VIF of 7.48 and a 1/VIF of 0.133739, which suggests that it is highly multicollinear with other variables. X3 and Z3 (Inflation, GDP deflator) have the same VIF of 1.15, with a 1/VIF of 0.870234, suggesting very low multicollinearity.

The average VIF of all variables is 4.25, which suggests that the model has a moderate level of multicollinearity. It is still below 10, which is still considered acceptable.

4.3.4 Wooldridge test for autocorrelation

The Wooldridge test for autocorrelation is employed in this study to determine whether there is an issue with autocorrelation.

F	Prob
12.763	0.0051

Table 9. Wooldridge test for autocorrelation (Full Model)

Based on the F test results in table 9, the probability (Prob) is 0.0051, with a F value of 12.763. The probability that results is less than the significance level of 0.05. This suggests that the regression model employed in its entirety is statistically significant. So this demonstrates that there is an adequate amount of evidence to reject the null hypothesis, which asserts that the coefficients of all independent variables are zero. Subsequently, the dependent variable is significantly influenced by the independent variables in the model. Consequently, the regression model that was developed can be regarded as a valid representation of the relationship between these variables in the context of the analyzed data.

4.3.5 Regression with Driscoll-Kraay Standard Errors

Based on the previous calculation findings, it is evident that there is an issue with heteroscedasticity. To address this problem, the next step would be to utilize Regression with Driscoll-Kraay standard error. This approach can effectively handle the issues of heteroscedasticity, autocorrelation, and cross-sectional dependency in panel data.

The findings of the Regression with Driscoll-Kraay standard errors are as follows:

y	Coef	p-value
x_1	.5211926	**0.000**
x_2	-.0684917	0.173
x_3	-.0296985	0.153
x_4	.0359148	**0.064**
z_1	.0007369	0.990
z_2	-3.039084	**0.005**
z_3	.0441729	0.336
Note(s): $*p < 0.10$; $**p < 0.05$; $***p < 0.01$		
Source(s): Author's computation using Stata version 17.0		

Table 10. Driscoll-Kraay standard errors

Table 10 above displays the results of the Driscoll-Kraay standard errors regression estimation. It provides the coefficient and p-value for each independent variable in the model, while the dependent variable is the employment to population ratio (Employment to population ratio, 15+, total). The variable for fixed broadband subscriptions (x1) has a coefficient of 0.5211926, indicating a positive relationship with the employment ratio. The p-value of 0.000 suggests a significant effect at the 1% level. This means that for every increase in the number of fixed broadband subscriptions, there is a corresponding increase in the employment ratio.

In addition, the variable for Fixed telephone subscribers (x2) has a coefficient of -0.0684917, which is negative. However, its p-value of 0.173 suggests that its effect is not statistically significant. Similarly, the variable representing individuals utilizing the Internet (x3) has a coefficient of -0.0296985 with a p-value of 0.153, indicating that it is not statistically significant.

Similarly, the variable for Mobile cellular subscriptions (x4) has a coefficient of 0.0359148 with a p-value of 0.064, which is statistically significant at the 10% level. This suggests that an increase in the number of cellular subscriptions has a positive effect on the employment ratio, although the impact is not particularly strong in this case.

The control variable "School enrollment, secondary (z1)" has a coefficient of around zero (0.0007369) with a p-value of 0.990. This suggests that it does not have a significant impact on the employment ratio. On the other hand, the variable GDP per person employed (z2) has a notable negative coefficient of -3.039084, with a p-value of 0.005, which is statistically significant at the 5% level. This suggests that higher productivity per worker is significantly impact linked to a reduction in the employment ratio. Ultimately, the coefficient of 0.0441729 for Inflation, GDP deflator (z3) is positive. However, the p-value of 0.336 suggests that the impact of inflation on the employment ratio is not statistically significant.

These findings suggest that among the factors examined, Fixed broadband subscriptions and GDP per person employed have a notable impact on the employment ratio. Additionally, Mobile cellular subscriptions also have a significant, albeit less pronounced effect. Although the other variables do not exhibit a statistically significant impact.

Lastly, the explanation of the significance of this variable is the coefficient for fixed broadband subscriptions is 0.5211926, with a p-value of 0.000. This indicates that a one-unit increase in fixed broadband subscriptions will result in a 0.5211926 increase in the employment ratio. In this instance, one fixed broadband subscription is intended for every 100 individuals. In other words, the employment ratio increases by approximately 0.521 for every 100 additional broadband subscriptions, provided that all other variables remain constant. Then also, The coefficient for mobile cellular subscriptions is 0.0359148, with a p-value of 0.064. This indicates that a one-unit increase in mobile cellular subscriptions will result in a 0.0359148 increase in the employment ratio. In this instance, one mobile cellular subscription is intended for every 100 individuals. In other words, the employment ratio increases by approximately 0.359 for every 100 additional mobile subscriptions, provided that all other variables remain constant. And lastly, The coefficient of -3.039084 indicates that a decrease in the employment ratio of 3.039084 is associated with every one-unit increase in GDP per person employed (in constant 2021 PPP dollars). This suggests that in constant PPP terms, one unit is equivalent to one dollar. This suggests that a decrease in the employment rate is the result of an increase in productivity per worker, as evidenced by the GDP per person employed.

4.3.6 R- Square

The R-squared value of the Full model is 0.4246. This implies that the independent variables inputted account for 42.26% of the variation. This implies that this model can serve as a reference and elucidate the complete range of fluctuations in the employment rate. and that this variation effectively explains nearly half of the current model. This model has failed to account for the remaining 57.54% of the variation in the employment rate variable. This is likely due to the absence of other factors in the analysis. This study has a reasonably moderate predictive power in explaining the dependent variable, as evidenced by the R-square of 0.4246, which is still acceptable. In this scenario, FGLS does not provide the R-square value (Umar et al., 2024).

4.4 Robustness Check

The subsequent action is After doing regression analysis using the Driscoll-Kraay standard error method to address issues of heteroscedasticity, autocorrelation, and cross-sectional dependence in panel data, the subsequent crucial step is to conduct a robustness check. A robustness check is conducted to assess the consistency and stability of the estimation results of the regression model when modifications are made to the model parameters or assumptions. In this instance, employment in service will serve as a Alternative proxy for conducting a robustness assessment.

4.4.1 Robustness Check with Alternative Proxy

The subsequent step in the robustness check is to perform supplementary analysis by incorporating a Alternative proxy, "employment in service," into the regression model. The objective of this phase is to assess the impact of modifications to the variable's definition or measurement on the overall analysis results. This study will offer insight into the consistency of the relationships observed in the initial model when a specific aspect of the workforce, specifically the service sector, is explicitly considered by replacing or adding this variable.

4.4.1.1 Hausman Test

The subsequent data presents the outcomes of the Hausman test computations for in robustness check:

Chi-Square	Prob
13.09	0.0700

Table 11. Hausman Test (Alternative Proxy)

In Table 11, The Chi-Square value is 13.09, with a probability value (Prob) of 0.0700, as indicated by the Hausman test results in the robustness check. The results are on the border between insignificant and significant at the 10% level, as the probability value is marginally higher than the significance level of 0.05 but still below the significance level of 0.10. Consequently, the null hypothesis, which asserts that the random effects model is more suitable, can be accepted at the 5% significance level but may be refuted at the 10% significance level. Nevertheless, this result suggests that a random effects model can still be considered, despite the fact that fixed effects may be more applicable, due to the marginal significance factor.

4.4.1.2 Lagrangian Multiplier Test

The subsequent data presents the outcomes of the LM test computations in robustness check:

Chibar2	Prob
359.20	0.0000

Table 12. Lagrangian Multiplier Test (Alternative Proxy)

The robustness check results in table 12 of the Lagrangian Multiplier (LM) test indicate a Chibar2 value of 359.20 with a probability value (Prob) of 0.0000. At a significance level of 1%, this extremely low probability value suggests that the results are significant, which implies that the null hypothesis can be rejected with great force. A simple OLS model without random effects would be more appropriate, as the null hypothesis in the LM test specifies that the individual component variance (random effects) is zero. Nevertheless, it demonstrates that the random effects model is more suitable than the basic OLS model, as there is substantial evidence to support this claim. thereby suggesting that the random effects model is more suitable for application due to the variation between individuals that must be considered.

4.4.1.3 Heteroskedasticity Check

The subsequent data presents the outcomes of the Heteroskedasticity test computations for the robustness check model:

Chi-Square	Prob
2811.58	0.000

Table 13. Heteroskedasticity Test (Alternative Proxy)

Presented in table 13, The heteroscedasticity test findings for the robustness check model indicate a Chi-Square value of 2811.58, with a probability (Prob) of 0.000. This suggests the presence of heteroscedasticity in the regression model under examination. According to the criteria for decision-making, if the p-value is less than or equal to 0.05, then the null hypothesis (H0) that suggests there is no heteroscedasticity is rejected, and it can be inferred that there is heteroscedasticity present in the data. This suggests that there is compelling evidence of heteroscedasticity in the model. Thus, these findings suggest that it may be necessary to make adjustments or modifications to the model to address the issue of heteroscedasticity, thereby ensuring more accurate and dependable analysis outcomes.

4.4.1.4 Wooldridge test for autocorrelation

The Wooldridge test for autocorrelation is employed in this study to determine whether there is an issue with autocorrelation.

F	Prob
28.234	0.0003

Table 14. Wooldridge test for autocorrelation (Alternative Proxy)

The Wooldridge test for autocorrelation in table 14 indicates that the model's robustness is confirmed, with a F value of 28.234 and a probability (Prob) of 0.0003. The probability value is significantly lower than the significance threshold of 0.05, suggesting a strong hint of an autocorrelation issue in the model. Autocorrelation is the condition in which the residuals of a regression model are reliant on each other, leading to biased and inefficient coefficient estimations. Hence, the findings of this examination suggest the necessity for additional modifications to the model in order to address the issue of autocorrelation, thereby enhancing the accuracy and validity of the analysis results.

4.4.1.5 Feasible Generalized Least Squares (FGLS) Analysis

In this instance, Feasible Generalized Least Squares (FGLS) is a regression technique that is employed to address heteroscedasticity in a linear regression model. FGLS is a variation of Generalized Least Squares (GLS).

Alternative proxy	Coef	p-value
x_1	-.0711847	0.675
x_2	-.2962566	**0.034**
x_3	-.0357827	0.465
x_4	.077795	**0.025**
z_1	-.0849629	0.204
z_2	21.00359	**0.000**
z_3	-.1097721	0.405
Note(s): **p* < 0.10; ***p* < 0.05; ****p* < 0.01		
Source(s): Author's computation using Stata version 17.0		

Table 15. Feasible Generalized Least Squares (FGLS) with Alternative Proxy

In table 15, Several significant relationships between the variables examined and the employment ratio to the population aged 15 years and over are apparent in the regression analysis results, which employ the Alternative proxy employment in service. The data presented indicates that variable x2 (fixed telephone subscription) has a coefficient of -0.2962566 and a p-value of 0.034, which suggests a substantial negative impact on the employment ratio to the population. The employment ratio is positively correlated with the increase in cellular subscriptions, as evidenced by the positive coefficient of 0.077795 and the p-value of 0.025 for variable x4. This effect is also significant. On the other hand, variables x1 (fixed broadband subscription) and x3 (internet users) do not exhibit a significant effect, with p-values of 0.675 and 0.465, respectively.

Only z2 (GDP per employed person) in variable z exhibits a significant relationship with the employment ratio, with a p-value of 0.000 and a very high coefficient of 21.00359. This suggests a strong positive effect on the employment ratio. Conversely, variables z1 (secondary school enrolment) and z3 (GDP deflator inflation) failed to demonstrate statistically significant effects, with p-values of 0.204 and 0.405, respectively.

To conclude, this demonstrates that the employment rate is significantly influenced by a number of variables, including x2 (fixed telephone subscription), x4 (mobile subscription), and z2 (GDP per employed person).

4.4.2 Robustness Check with Outliers

After doing the regression analysis using the complete model, the final step in the robustness check involves calculating the model while taking outliers into account. The objective of this stage is to assess whether the existence of atypical data has a substantial impact on the outcomes of the analysis. Anomalies can exert a significant influence on the coefficient estimates and the interpretation of the model, so it is crucial to scrutinise their impact on the results.

4.4.2.1 Hausman Test

The subsequent data presents the outcomes of the Hausman test computations for in robustness check without outliers:

Chi-Square	Prob
3.87	0.6939

Table 16. Hausman Test (without outliers)

In table 16, The Chi-Square value is 3.87, with a probability (Prob) of 0.6939, as demonstrated by the Hausman test results, which evaluate the model's robustness in the absence of outlier values. The null hypothesis is rejected, as evidenced by the high probability value, which is significantly higher than the conventional significance threshold of 0.05. Consequently, the random effect model is rendered more suitable. The independent variable is presumed to be uncorrelated with unobserved inter-unit variations. These findings provide assurance that the random effect model can generate unbiased and efficient estimates in accordance with the characteristics of the data under analysis, following the removal of outliers.

4.4.2.2 Lagrangian Multiplier Test

The subsequent data presents the outcomes of the LM test computations in robustness check without outliers:

Chibar2	Prob
59.37	0.0000

Table 17. Lagrangian multiplier Test (Without Outliers)

Presented in table 17, Chibar2 value is 59.37, with a probability (Prob) of 0.0000, in the Lagrangian Multiplier (LM) test, which is used to verify the robustness of the model in the absence of anomalies. 0.05 is the conventional significance level, and this probability value is exceedingly small. Thus, the random effect model's selection is substantially substantiated by the results of this LM test after the removal of outliers, thereby guaranteeing that the employed methodology generates more precise and dependable outcomes.

4.4.2.3 Heteroskedasticity Check

The subsequent data presents the outcomes of the Heteroskedasticity test computations for the robustness check model without outliers:

Chi-Square	Prob
120.73	0.0000

Table 18. Heteroskedasticity Test (Without Outliers)

According to the analysis results in table 18, the Chi-Square value is 120.73, with a probability (Prob) of 0.0000. This extremely low probability value, which is significantly lower than the significance threshold of 0.05, suggest that there is substantial evidence to reject the null hypothesis. That is, the model's reliability is compromised by heteroscedasticity.

4.4.2.4 Wooldridge test for autocorrelation

The Wooldridge test for autocorrelation is employed in this study to determine whether there is an issue with autocorrelation.

F	Prob
12.563	0.0076

Table 19. Wooldridge Test for Autocorrelation (Without outliers)

The Wooldridge test for autocorrelation, which is used to verify the robustness of the model in the absence of anomalies, yields a F value of 12,563 and a probability (Prob) of 0.0076. 0.05 is the significance threshold, and this probability value is below it. In other terms, these findings suggest that the residual model has an autocorrelation issue. Therefore, the subsequent action is to modify the model to address the autocorrelation issue, thereby enhancing the reliability and accuracy of the analysis results.

4.4.2.5 Feasible Generalized Least Squares (FGLS) Analysis

As an extension of the preceding calculation, the subsequent results of the FGLS calculation are as follows:

y	coef	p-value
x_1	.4520695	**0.006**
x_2	-.0649534	0.535
x_3	-.0244968	0.519
x_4	.0458591	**0.063**
z_1	-.00099	0.982
z_2	-3.15443	**0.007**
z_3	.0422105	0.682
Note(s): **p* < 0.10; ***p* < 0.05; ****p* < 0.01		
Source(s): Author's computation using Stata version 17.0		

Table 20. Feasible Generalized Least Squares (FGLS) without outliers

According to the data in Table 20, the Feasible Generalized Least Squares (FGLS) calculation, when outliers are excluded, reveals many meaningful correlations between the independent variables and the dependent variable. The variable x1, which represents fixed broadband subscribers, has a coefficient of 0.4520695 and a p-value of 0.006. This indicates a statistically significant positive effect on the dependent variable (y) at the 1% significance level. This demonstrates a favorable correlation between the rise in fixed broadband subscriptions and the employment rate.

In addition, the variables x2 (Fixed telephone subscriptions) and x3 (Individuals accessing the Internet) do not exhibit a statistically significant impact, as indicated by their p-values of 0.535 and 0.519, respectively. The variable x4, representing mobile cellular subscriptions, exhibits a degree of significance approaching 10%. It has a positive coefficient of 0.0458591 and a p-value of 0.063. This suggests that a rise in cellular subscriptions may have a positive impact on the dependent variable, but the effect is not particularly large.

In addition, the control variable z2 (GDP per person employed) exhibits a statistically significant negative impact, with a coefficient of -3.15443 and a p-value of 0.007. This suggests that an increase in GDP per person employed is associated with a decrease in the dependent variable. The variables z1 (School enrollment, secondary) and z3 (Inflation, GDP deflator) do not exhibit a statistically significant impact on the dependent variable, as indicated by their respective p-values of 0.982 and 0.682.

In summary, the findings of this FGLS analysis indicate that the results align with those of the previous comprehensive model. Specifically, it is evident that Fixed broadband subscriptions, Mobile cellular subscriptions, and GDP per person employed significantly influence the employment ratio. This analysis offers valuable insights into the key elements

4.5 Discussion

According to the findings of the exhaustive calculation that was conducted earlier. The employment ratio is substantially influenced by the variables Fixed broadband subscriptions, Mobile cellular subscriptions, and GDP per person employed, as evidenced by the analysis that compares the full model with robustness checks that do not include outliers.

This discovery also underscores the critical role of economic productivity and digital infrastructure in shaping the labour market. Access to fixed broadband services is closely associated with an increase in the employment ratio, as evidenced by the substantial impact of fixed broadband subscriptions. Consequently, the expansion of employment opportunities can be achieved by enhancing broadband infrastructure, which will support technology-based industries and facilitate the creation of new positions. This is further confirmed by research conducted by Salsabila & Oktora (2022), which indicates that individuals may find it easier to secure employment as broadband access increases. Currently, numerous job postings are available on social media platforms, as opposed to newspapers, where jobs were previously advertised. Consequently, the process of locating and matching employment to the requirements of both companies and individuals is simplified, more cost-effective, and expedited. This has the potential to mitigate frictional unemployment. The expansion of innovation and entrepreneurship can also be facilitated by broadband, resulting in the creation of new employment. Additionally, the expansion of the labour market to remote regions that were previously denied benefits is facilitated by the increase in broadband. So this has the potential to generate new employment opportunities in remote regions and ensure that they are equitable (Katz, 2018).

The second factor is the substantial impact of mobile cellular subscriptions. This indicates that the employment ratio is positively correlated with the increase in cellular penetration. This demonstrates that enhanced access to cellular technology has a beneficial effect on the expansion of connectivity, the enhancement of communication, and the support of employment opportunities in a variety of sectors. This may be due to the fact that employment rates can be influenced by mobile phone subscriptions for factors such as Mobile phones can expedite and enhance communication among job seekers, employers, and networks. Employers are able to promptly contact candidates, and individuals are able to more easily access job opportunities. In addition, it can furnish employment data. Remote work is the most recent trend. This allows individuals to work from any location without being tied to space or time constraints. Subscriptions to mobile phones can also stimulate economic activity, resulting in the creation of jobs in a variety of industries. As businesses expand and develop as a result of improved connectivity, they frequently require additional employees. Therefore, mobile phone subscriptions can enhance communication, facilitate rapid, inexpensive, and convenient access to information, and generate entrepreneurial opportunities, all of which have a beneficial effect on employment rates (Chege et al., 2020; Jestl, 2024; Ogbonna et al., 2023).

Lastly, it is intriguing that the GDP per person employed exhibits a substantial but detrimental impact. Automation or efficiency that reduces the need for labour, such as the rise of online transportation services, the ability to purchase food online, the implementation of cashless payment systems, the use of QRIS payment systems, the convenience of e-cashiers for depositing and withdrawing money, the availability of self-service supermarkets, the use of e-tolls and e-parking systems, and the utilisation of robots for assembly purposes, may be the reason.

Currently, this study observes a distinctive phenomenon in the global economy: the discrepancy between the growth of GDP and the rise in employment. Historically, an increase in GDP is frequently accompanied by an increase in the number of employees. Nevertheless, it is evident that this partnership is becoming increasingly incompatible.

Rapid technological advancements, particularly in the areas of automation and artificial intelligence (AI), are among the primary factors contributing to this phenomenon.

The rapid advancement of digitalization has been accompanied by the emergence of Artificial Intelligence (AI), which has revolutionized numerous aspects of life for individuals, industries, and other entities worldwide. The impact of digital progress has made it possible to uncover numerous new behaviors. For instance, the lifestyle of the current generation is significantly influenced by the use of the internet and applications at the individual level. For example, the emergence of online transportation, the ability to order food online, cashless payment systems, QRIS payment systems, the use of e-cashiers to deposit and withdraw money, self-service supermarkets, e-tolls, and e-parking, among others. Nevertheless, this may result in a decrease in the demand for human labor, as it is supplanted by machines that are aided by advanced AI technology and possess a higher level of consistency and productivity than humans. This technology replaces a significant amount of human labor. Jobs that are dependent on technology are gradually replacing traditional occupations. For instance, the automotive industry assembly line is transitioning to the use of robots, while customer service systems are being supplanted by AI-based chatbot systems. On the one hand, this digital transformation has a positive impact, such as increased work efficacy, which results in accurate and rapid work. Nevertheless, the challenge is significant in that it results in a decrease in employment opportunities, with a focus on digital fields, information technology (IT), and skills-based positions. It is noted that individuals who are incapable of adapting are unemployed.

Despite GDP growth, employment levels have not risen proportionally, and in some cases, poverty rates have even increased, highlighting that economic development does not always benefit all members of society equally. The global community is concerned about AI's impact on employment. The International Labour Organisation (ILO) and the World Bank provide key statistics: the ILO estimates that about 14% of global workers are at risk of job loss due to automation. AI is expected to significantly impact job polarization, sparing low-skilled and high-skilled jobs while posing a greater risk to medium-skilled roles. Subsequently, the ILO anticipates that AI will generate new employment prospects in sectors such as cybersecurity, digital marketing, and data science (Euronews, 2024).

Conversely, The World Bank observes that the labour market implications of AI have sparked a vigorous debate in response to the accelerated advancements in machine learning. The World Bank's analysis indicates that the demand for non-AI workers may be significantly reduced in the first year following the deployment of AI. This is due to job displacement. While, The World Bank underscores the necessity of retraining programmes to assist employees in adapting to the evolving job market (IBM, 2022).

Consequently, governments and other stakeholders must establish policies that encourage the retraining and education of the workforce in order to enable them to adjust to the evolving needs of the labour market. To effectively integrate technology into the economy without jeopardizing the well-being of the human workforce, a balanced approach is required over the long term. This encompasses the development of skills, investment in education, and the creation of new employment that are pertinent to the digital era. This is the only way to guarantee that technological advancements benefit the entire society, rather than a select few.

This can be proven by several things that can be used as examples of real cases in this digital era, including: In the ASEAN region, technological progress is inevitable, for example in Singapore, Malaysia, and Thailand, many supermarkets in these countries have adopted a self-service system. checkout, where customers can scan and pay for their own items without the need for a human cashier. Then in the manufacturing company sector. Robots are replacing many jobs such as assembly, packaging and quality control, which produce output more quickly and accurately than humans. Then in the manufacturing company sector. Many jobs such as assembly, packaging and quality control are being replaced by robots which produce output more quickly and accurately than humans. and also With the existence of self-checkout systems in banks, the jobs of bank tellers are starting to be replaced by technology. Banks in ASEAN such as Singapore and Malaysia have integrated this technology to facilitate customer transactions (CNBC Indonesia, 2021; CNN Indonesia, n.d.; Standard Chartered, 2021).

Overall, these findings substantiate the parties' assertion that the significance of investing in digital infrastructure and ensuring the equitable and effective management of economic productivity is to positively and effectively address labor market dynamics in the future.

CHAPTER 5
CONCLUSION

5.1 Conclusion

The employment ratio is significantly influenced by the variables Fixed broadband subscriptions, Mobile cellular subscriptions, and GDP per person employed, as determined by a meticulous calculation. Initially, the variable Fixed broadband subscriptions exhibit a positive coefficient of 0.5211926 with a p-value of 0.000, indicating that each increase in fixed broadband subscriptions is associated with an increase in the employment ratio. Investment in broadband infrastructure has the potential to extend employment opportunities and support the growth of the technology sector, which is crucial for increasing workforce participation.

The second variable is mobile cellular subscriptions, which have a coefficient of 0.0359148 and a p-value of 0.064. This indicates a positive effect that is approaching significance at the 10% level. Although not statistically significant at the 5% level, the employment ratio can be enhanced by increasing cellular subscriptions, as it enhances communication and access to job opportunities, particularly in more remote areas, thereby ensuring that all individuals receive the same benefits.

Third, the coefficient is negative at -3.039084 with a p-value of 0.005 about the GDP per person employed variable. This suggests that a decrease in the employment ratio is correlated with an increase in productivity per worker. This can be attributed to the inevitable automation of work, the rapid development of technology, and changes in new work trends that increase GDP but decrease employment.

The findings of this study suggest that digital infrastructure is essential for the development of job opportunities. Policies that prioritize the development of broadband and cellular access and consider the influence of productivity on the labor market can assist in the development of strategies to increase work participation.

5.2 Policy Recommendation

Given the findings of the preceding analysis, the following are policy recommendations that may prove advantageous in terms of employment growth. This investigation emphasizes two primary objectives: productivity impact management and the advancement of digital infrastructure technology. Accelerating investment in broadband infrastructure and mobile services is an essential initial measure that must be taken by the government and stakeholders. as a result of the potential to enhance communications, support the development of the technology sector, and expand employment opportunities, particularly in remote regions, by increasing access to fixed and mobile broadband. Following this, it is crucial to develop policies that mitigate the consequences of heightened productivity. The risk of diminishing employment ratios can be mitigated by the expansion of training and skills development policies and work transition programs, despite the fact that higher productivity is generally indicative of economic progress. Education and training are also included in this investment to equip the workforce for the accelerated pace of technological advancement and automation. Policies can facilitate the creation of new employment and guarantee that the workforce can adjust to the current market requirements, thereby promoting sustainable and inclusive economic growth.

5.3 Constraints of the study

This study utilizes data collected from a reputable institution, World Bank. This research is shaped by the accessibility and precision of data about digital infrastructure and employment rates in Southeast Asia, namely in ASEAN nations. Singapore and Timor Leste are considered outlier countries. Discrepancies and constraints in data have an impact on the precision of the research, as economic advancements are highly fluid. The findings of this study are subject to potential revisions as time progresses. Nevertheless, the supplied insights are derived from precise and dependable information, hence the findings of this research can be trusted. This study is specifically conducted in ASEAN countries, with the possibility of including or excluding outliers. Due to regional variations, the findings of this research may not be applicable to other countries with accuracy. This study used quantitative analysis, hence the potential for qualitative analysis was not investigated.

Potential avenues for future research could involve the use of this study in several geographical areas and historical epochs, as well as the utilization of alternative data sources that are both precise and amenable to rigorous testing of their trustworthiness.

REFERENCES

Amaghionyeodiwe, L., & Annansingh-Jamieson, F. (2017). An Investigation Into The Impact Of Mobile Technologies On Economic Growth And Employment In The Caribbean. *Athens Journal Of Business & Economics*, *3*(3). Https://Doi.Org/10.30958/Ajbe.3.3.3

Azmuk, N., Grishnova, O., & Kuklin, O. (2022). Digital Employment: Ukraine's Rankingin The Global Division of Digital Labour. *Financial And Credit Activity: Problems Of Theory And Practice*, *2*(43). Https://Doi.Org/10.55643/Fcaptp.2.43.2022.3578

Bank Of Australia, R. (2023). *Causes Of Inflation*. Https://Www.Rba.Gov.Au/Education/Resources/Explainers/Pdf/Causes-Of-Inflation.Pdf

Bican, P. M., & Brem, A. (2020). Digital Business Model, Digital Transformation, Digital Entrepreneurship: Is There a Sustainable "Digital"? *Sustainability (Switzerland)*, *12*(13). Https://Doi.Org/10.3390/Su12135239

Bukht, R., & Heeks, R. (2018). Defining, Conceptualising, And Measuring The Digital Economy. *International Organisations Research Journal*, *13*(2). Https://Doi.Org/10.17323/1996-7845-2018-02-07

Calculator Academy Team. (2023). *Employment Rate Calculator*. Calculator Academy. Https://Calculator.Academy/Employment-Rate-Calculator/

Chege, S. M., Wang, D., & Suntu, S. L. (2020). Impact Of Information Technology Innovation On Firm Performance In Kenya. *Information Technology For Development*, *26*(2). Https://Doi.Org/10.1080/02681102.2019.1573717

CNBC Indonesia. (2021). *Daftar Profesi Manusia Yang Terancam Punah, Digantikan Robot*. CNBC Indonesia.

CNN Indonesia. (N.D.). *5 Pekerjaan Yang Akan Digantikan Oleh Teknologi AI Kecerdasan Buatan AI*. 2020.

Definitions Of World Telecommunication/ICT Indicators. (2010).

Deng, J., & Liu, Y. (2022). Does Digital Finance Reduce The Employment In The Finance Industry? Evidence From China. *Finance Research Letters*, *48*. Https://Doi.Org/10.1016/J.Frl.2022.102994

Department Of Economic And Social Affairs Poverty, U. N. (2007). *Employment And Decent Work*. Https://Www.Un.Org/Development/Desa/Socialperspectiveondevelopment/Issues/Employment-And-Decent-Work.Html

Ducharme, L. M., Arslanalp, S., Goksu, B., Kostroch, D., Carlos Moreno-Ramirez, J., Martins, M., Matei, S., Cas, S. M., Van Oudheusden, P., Piché, R., Razin, T., Reinsdorf, M., Sánchez-Muñoz, C., Tumbarello, P., Venter, L., Ylä, M., & Jamasali, J. K. (N.D.). MEASURING THE DIGITAL ECONOMY Approved By. In *MEASURING THE DIGITAL ECONOMY INTERNATIONAL MONETARY FUND* (Vol. 3).

Emara, N., & Zecheru, D. (2024). Asymmetric Threshold Effects Of Digitization On Inflation In Emerging Markets. *Financial Innovation*, *10*(1). Https://Doi.Org/10.1186/S40854-023-00545-8

Euronews. (2024, January 15). *Almost 40% Of Jobs Around The World Will Be Impacted By AI, IMF Chief Says*. Euronews. Https://Www.Euronews.Com/Next/2024/01/15/Almost-40-Of-Jobs-Around-The-World-Will-Be-Impacted-By-Ai-Imf-Chief-Says

Ezell, S. (2021). *Assessing The State Of Digital Skills In The U.S. Economy*.

Forrester. (2022). *The Total Economic Impact^tm Of Equinix Digital Services*.

Forte, D., & De Donno, A. (2010). Mobile Network Investigations. In *Handbook Of Digital Forensics And Investigation* (Pp. 517–557). Elsevier Ltd. Https://Doi.Org/10.1016/B978-0-12-374267-4.00010-0

Geng, Z., & He, G. (2021). Digital Financial Inclusion And Sustainable Employment: Evidence From Countries Along The Belt And Road. *Borsa Istanbul Review*, *21*(3). Https://Doi.Org/10.1016/J.Bir.2021.04.004

Google, Temasek, & Bain & Company. (2020). *E-Conomy SEA 2020 Report*.

Gujarati, D. N. , & P. D. C. (2008). *Basic Econometrics: A Practical Guide For Students And Researchers (5th Ed.)*. Mcgraw-Hill.

Gupta, M., & Jauhar, S. K. (2023). Digital Innovation: An Essence For Industry 4.0. *Thunderbird International Business Review*, *65*(3). Https://Doi.Org/10.1002/Tie.22337

Ha, H., & Chuah, C. K. P. (2023). Digital Economy In Southeast Asia: Challenges, Opportunities And Future Development. *Southeast Asia: A Multidisciplinary Journal*, *23*(1). Https://Doi.Org/10.1108/Seamj-02-2023-0023

Hastuti, I. S., & Jauhari, A. K. (2021). MIDDLE ECONOMIC GROWTH TOWARDS TO DEVELOPMENT OF E-COMMERCE IN SOUTHEAST ASIA. *Journal Of Economic Empowerment Strategy (JEES)*, *4*(1).

Hoechle, D. (2007). Robust Standard Errors For Panel Regressions With Cross-Sectional Dependence. *Stata Journal*, *7*(3). Https://Doi.Org/10.1177/1536867x0700700301

IBM. (2022). IBM Global AI Adoption Index 2022. *IBM Corporation*.

International Labour Office. (2015). *Decent Work Country Diagnostics*.

International Telecommunication Union. (2022). *Measuring Digital Development Facts And Figures 2022*.

Jestl, S. (2024). Industrial Robots, And Information And Communication Technology: The Employment Effects In EU Labour Markets. *Regional Studies*. Https://Doi.Org/10.1080/00343404.2023.2292259

Jimenez, D.-Z., Lim, V., Cheok, L., & Ng, H. (2018). Unlocking The Economic Impact Of Digital Transformation In Asia Pacific. *Microsoft*, *31*(November 2018).

Kampert, P., Tobin, S., Horne, R., Feist, L., Ernst, E., & Sánchez Martínez, M. (2024). *World Employment And Social Outlook*. Https://Doi.Org/10.54394/HQAE1085

Katz, R. L. (2018). The Impact Of The Broadband Internet On Employment. In *Digitized Labor* (Pp. 95–108). Springer International Publishing. Https://Doi.Org/10.1007/978-3-319-78420-5_6

Kemp, S. (2024, January 31). *Internet Use In 2024*. Datareportal.

Kotronoulas, G., Miguel, S., Dowling, M., Fernández-Ortega, P., Colomer-Lahiguera, S., Bağçivan, G., Pape, E., Drury, A., Semple, C., Dieperink, K. B., & Papadopoulou, C. (2023). An Overview Of The Fundamentals Of Data Management, Analysis, And Interpretation In Quantitative Research. In *Seminars In Oncology Nursing* (Vol. 39, Issue 2). Https://Doi.Org/10.1016/J.Soncn.2023.151398

Kumar, S., Suhaib, M., & Asjad, M. (2020). Industry 4.0: Complex, Disruptive, But Inevitable. *Management And Production Engineering Review*, *11*(1). Https://Doi.Org/10.24425/Mper.2020.132942

Lee, Y., & Lee, Y. (2013). Toward Scalable Internet Traffic Measurement And Analysis With Hadoop. In *Computer Communication Review* (Vol. 43, Issue 1). Https://Doi.Org/10.1145/2427036.2427038

LIU, N., GU, X., & LEI, C. K. (2022). The Equilibrium Effects Of Digital Technology On Banking, Production, And Employment. *Finance Research Letters*, *49*. Https://Doi.Org/10.1016/J.Frl.2022.103196

Lucas, R. E., & Rapping, L. A. (1969). Real Wages, Employment, And Inflation. *Journal Of Political Economy*, *77*(5). Https://Doi.Org/10.1086/259559

Matli, W., & Ngoepe, M. (2022). Extending Information Poverty Theory To Better Understand The Digital Access And Inequalities Among Young People Who Are Not In Education, Employment Or Training In South Africa. *Higher Education, Skills And Work-Based Learning*, *12*(3). Https://Doi.Org/10.1108/HESWBL-05-2020-0107

Ministry Of Communications And Information, S. (N.D.). *Digital Infrastructure*. Retrieved June 28, 2024, From Https://Www.Mci.Gov.Sg/What-We-Do/Digital-Singapore/Digital-Infrastructure/

Mitchell, W. C. (1925). Quantitative Analysis In Economic Theory. *The American Economic Review*, *15*(1).

OECD. (2023). *OECD Employment Outlook 2023*. OECD. Https://Doi.Org/10.1787/08785bba-En

OECD Southeast Asia. (2017). *Opportunities And Policy Challenges Of Digitalisation In Southeast Asia*.

Ogbonna, A. E., Adediran, I. A., Oloko, T. F., & Isah, K. O. (2023). Information And Communication Technology (ICT) And Youth Unemployment In Africa. *Quality And Quantity*, *57*(6). Https://Doi.Org/10.1007/S11135-022-01600-9

Ontheworldmap.Com. (N.D.). *Map Of Southeast Asia*. Retrieved March 10, 2024, From Https://Ontheworldmap.Com/Asia/Map-Of-Southeast-Asia.Html#Google_Vignette

Petrova, I., Balyka, O., & Kachan, H. (2020). Digital Economy And Digital Employment Appearence. *Social And Labour Relations: Theory And Practice*, *10*(2). Https://Doi.Org/10.21511/Slrtp.10(2).2020.02

Qi, Y., & Chu, X. (2022). Development Of The Digital Economy, Transformation Of The Economic Structure And Leaping Of The Middle-Income Trap. *China Political Economy*, *5*(1). Https://Doi.Org/10.1108/Cpe-09-2022-0012

Raeskyesa, D. G. S., & Lukas, E. N. (2019). Does Digitalization Increase Economic Growth? Evidence From ASEAN8 Countries. *Jurnal Ekonomi Indonesia*, *8*(2). Https://Doi.Org/10.52813/Jei.V8i2.33

Reljic, J., Evangelista, R., & Pianta, M. (2021). Digital Technologies, Employment, And Skills. *Industrial And Corporate Change*. Https://Doi.Org/10.1093/Icc/Dtab059

Ren, J., Gao, T., Shi, X., Chen, X., & Mu, K. (2023). The Impact And Heterogeneity Analysis Of Digital Financial Inclusion On Non-Farm Employment Of Rural Labor. *Chinese Journal Of Population Resources And Environment*, *21*(2). Https://Doi.Org/10.1016/J.Cjpre.2023.06.006

Salsabila, R., & Oktora, S. I. (2022). The Impact Of Broadband Access On Unemployment Rate In Indonesia 2016-2019. *The Asian Journal Of Business Environment (AJBE)*, *12*(3).

Schmarzo, B. (2020). *The Economics Of Data, Analytics, And Digital Transformation*. Packt Publishing.

Singapore Business Review. (2023). *Chart Of The Day: Singapore Is The Outlier In Digital Product Growths*. Https://Sbr.Com.Sg/Information-Technology/News/Chart-Day-Singapore-Outlier-In-Digital-Product-Growths

Soto-Acosta, P. (2020). COVID-19 Pandemic: Shifting Digital Transformation To A High-Speed Gear. *Information Systems Management*, *37*(4). Https://Doi.Org/10.1080/10580530.2020.1814461

Standard Chartered. (2021). *Important Notice: Cessation Of E-Cashier's Order Issuance Facility On Online Banking And SC Mobile*.

Statista. (2023). *Internet Usage In Southeast Asia - Statistics & Facts*. Https://Www.Statista.Com/Topics/9093/Internet-Usage-In-Southeast-Asia/#Topicoverview

Statista. (2024). *Digital & Connectivity Indicators - Singapore*. Https://Fr.Statista.Com/Outlook/Co/Digital-Connectivity-Indicators/Singapore#Digital-Infrastracture

Subramaniam, R., Singh, S. P., Padmanabhan, P., Gulyás, B., Plakkeel, P., & Sreedharan, R. (2021). Positive And Negative Impacts Of Covid-19 In Digital Transformation. *Sustainability (Switzerland)*, *13*(16). Https://Doi.Org/10.3390/Su13169470

Sussan, F., & Acs, Z. J. (2017). The Digital Entrepreneurial Ecosystem. *Small Business Economics*, *49*(1). Https://Doi.Org/10.1007/S11187-017-9867-5

Sustainable Digital Infrastructure Alliance (SDIA). (2022). *Definition For Digital Infrastructure*. Https://Sdialliance.Org/Dictionary/Digital-Infrastructure/

Taylor, P. (2024, January 10). *Fixed-Line Telecoms - Statistics & Facts*. Statista.

Telecommunication Union, I. (2021). *Measuring Digital Development - Facts And Figures 2021*.

Telenor Asia Digital Lives Decoded. (2022). *Decoding Changing Attitudes Towards Mobile Connectivity In South And Southeast Asia*. Https://Www.Youtube.Com/Watch?V=Znszy7ibuo0

Umar, U. H., Baita, A. J., Hamadou, I., & Abduh, M. (2024). Digital Finance And SME Financial Inclusion In Africa. *African Journal Of Economic And Management Studies*. Https://Doi.Org/10.1108/AJEMS-08-2023-0323

UNESCO. (2021). *Literacy For A Human Centred Recovery: Narrowing The Digital Divide*.

Wang, J. (2023, October 3). *Five Trends For Data Center Transformation In Southeast Asia* .

Wang, Q., Xia, X., Lan, S., & Li, M. (2023). Rural Digital Infrastructure And Labor Market: Evidence From Universal Telecommunication Service. *Asian Economic Journal*, *37*(3), 293–325. Https://Doi.Org/10.1111/Asej.12306

Wang, W., Jiang, S., & Li, L. (2023). Understanding The Women's Digital Employment Intentions: The Role Of Policies And Values. *Problems And Perspectives In Management*, *21*(2). Https://Doi.Org/10.21511/Ppm.21(2).2023.29

Wang, X., Liang, T., Wang, Y., Li, L., & Zhou, Z. (2022). Research On Employment Effect Of Digital Economy. *Frontiers In Computing And Intelligent Systems*, *1*(2). Https://Doi.Org/10.54097/Fcis.V1i2.1886

Wihardja, M. M., Pradana, A. T., Wibisana, S., Swarnata, A., & Doarest, A. (N.D.). Digital Transformation In Indonesia's Labour Market: Gainers And Losers. *ISEAS, Yusof Ishak Institute*.

Williamson, C. (2001). Internet Traffic Measurement. *IEEE Internet Computing*, *5*(6). Https://Doi.Org/10.1109/4236.968834

Withing, K. (2021). These Are The Top 10 Job Skills Of Tomorrow – And How Long It Takes To Learn Them. *World Economic Forum*.

Worldbank. (N.D.). *Metadata Glossary*. Retrieved July 31, 2024, From Https://Databank.Worldbank.Org/Metadataglossary/World-Development-Indicators/Series/IT.TEL.TOTL.EM

Worldometer. (2024, February 15). *South-Eastern Asia Population*. Https://Www.Worldometers.Info/World-Population/South-Eastern-Asia-Population/

Wynn, M., & Jones, P. (2023). Corporate Responsibility In The Digital Era. *Information (Switzerland)*, *14*(6). Https://Doi.Org/10.3390/Info14060324

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 And Industry 5.0—Inception, Conception And Perception. *Journal Of Manufacturing Systems*, *61*. Https://Doi.Org/10.1016/J.Jmsy.2021.10.006

Yu, J., Jiang, S., Han, J., Li, L., & Ke, X. (2023). Promoting Digital Employment Intention Among Students Of Chinese Higher Education Institutions. *Problems And Perspectives In Management*, *21*(3). Https://Doi.Org/10.21511/Ppm.21(3).2023.03

Zhang, X., Lin, F., Wang, Y., & Wang, M. (2022). The Impact Of Digital Economy On Employment Polarization: An Analysis Based On Chinese Provincial Panel Data. *Labor History*, *63*(5). Https://Doi.Org/10.1080/0023656X.2022.2133101

Zhang, Z., Xia, Y., & Abula, K. (2023). How Digital Skills Affect Rural Labor Employment Choices? Evidence From Rural China. *Sustainability (Switzerland)*, *15*(7). Https://Doi.Org/10.3390/Su15076050

Zhu, T., Chen, X., Zhang, W., & Sharp, B. (2023). Analysis Of The Spatial–Temporal Evolution Of The Digital Economy And Its Impact On The Employment Structure In China From 2001 To 2020. *Sustainability (Switzerland)*, *15*(12). Https://Doi.Org/10.3390/Su15129619

Zyukin, D. A. (2020). Digital Industry And Manufacturing Automation: Impact On Employment. *Personality & Society*, *1*(2). Https://Doi.Org/10.46502/Issn.2712-8024/2020.2.2

APPENDIX

Appendix 1. Worldbank Data

Country Name	Year	Employment to population ratio, 15+, total (%) (modeled ILO estimate)	Fixed broadband subscriptions (per 100 people)	Fixed telephone subscriptions (per 100 people)	Individuals using the Internet (% of population)	Mobile cellular subscriptions (per 100 people)	School enrollment, secondary (% gross)	GDP per person employed (constant 2021 PPP $)	Inflation, GDP deflator (annual %)	Employment in services (% of total employment) (modeled ILO estimate)
Id	Year	y_1	x_1	x_2	x_3	x_4	z_1	z_2	z_3	np
Brunei Darussalam	2010	62,24	5,48	20,17	53,00	109,86	97,92	190413,13	16,69	80,55
Brunei Darussalam	2011	62,04	5,77	19,88	56,00	110,37	101,30	194325,26	20,18	80,67
Brunei Darussalam	2012	61,42	4,88	17,44	60,27	115,52	106,52	194663,96	1,22	80,90
Brunei Darussalam	2013	60,79	6,69		64,50	113,87	105,06	189345,23	-2,82	81,25
Brunei Darussalam	2014	60,16	7,26	17,20	68,77	108,50	99,63	183563,22	-1,85	81,67
Brunei Darussalam	2015	59,06	8,17	18,03	71,20	109,95	107,58	183319,80	-17,61	81,95
Brunei Darussalam	2016	57,97	8,48	17,42	90,00	122,88	93,41	179405,90	-9,17	82,31

Brunei Darussalam	2017	56,88	9,55	19,47	94,87	126,60	91,66	182623,97	4,95	82,51
Brunei Darussalam	2018	59,70	11,39	19,02	95,00	130,32	91,50	171789,46	9,22	79,53
Brunei Darussalam	2019	59,94	12,37	19,77	95,00	131,22	89,65	175499,10	-3,33	77,28
Brunei Darussalam	2020	58,91	16,09	23,52	96,07	121,48	88,43	178424,86	-10,86	74,95
Brunei Darussalam	2021	60,62	17,83	25,21	98,08	135,50		168595,85	15,47	75,03
Brunei Darussalam	2022	61,51	20,09	27,22		117,76		161527,54	24,24	74,44
Cambodia	2010	68,96	0,25	2,50	1,26	56,75		6197,47	3,12	29,24
Cambodia	2011	68,26	0,15	3,64	3,10	94,39		6570,58	3,36	26,98
Cambodia	2012	67,48	0,20	3,95	4,94	129,21		7010,91	1,44	29,05
Cambodia	2013	68,78	0,22	2,81	6,00	135,10		7260,90	0,78	31,19
Cambodia	2014	69,83	0,43	2,37	14,00	134,46		7528,55	2,63	30,24
Cambodia	2015	71,25	0,54	1,66	18,00	135,24		7762,84	1,79	32,61
Cambodia	2016	72,18	0,62	1,45	32,40	127,46		8060,06	3,48	36,70
Cambodia	2017	73,74	0,84	0,84	32,90	117,32	49,15	8302,56	3,34	36,30
Cambodia	2018	74,86	1,04	0,55		121,17	51,37	8651,11	3,11	36,02
Cambodia	2019	75,95	1,14	0,35	52,31	132,15	52,31	8991,81	3,24	35,66
Cambodia	2020	75,19	1,43	0,34	53,65	128,60	54,84	8663,54	-0,67	37,95
Cambodia	2021	75,77	2,03	0,24	60,15	119,96	57,96	8714,06	1,29	36,45
Cambodia	2022	75,85	3,04	0,23		116,33		9018,68	4,07	36,79
Laos	2010	60,87	0,09	1,63	7,00	63,31	48,93	12707,66	9,20	20,25

Laos	2011	60,41	0,10	1,68	9,00	85,42	47,47	13507,35	10,47	21,18
Laos	2012	59,96	0,12	6,91	10,75	66,06	49,90	14366,05	7,53	22,22
Laos	2013	59,50	0,14	10,63	12,50	69,88	53,24	15286,94	6,47	23,72
Laos	2014	59,07	0,24	13,76	14,26	69,02	58,36	16204,54	5,73	25,44
Laos	2015	58,64	0,21	14,18	18,20	54,91	62,42	17130,39	2,35	26,72
Laos	2016	58,23	0,35	18,38	21,87	57,44	64,88	18076,49	3,02	27,82
Laos	2017	57,83	0,39	16,08	25,51	53,04	66,12	19059,69	1,85	29,22
Laos	2018	57,65	0,64	20,86	36,30	51,55	66,19	19907,51	1,92	28,09
Laos	2019	57,50	1,06	20,15	47,03	64,29	64,99	20639,46	1,20	27,09
Laos	2020	56,66	1,68	18,65	54,00	63,35	62,43	20639,65	5,03	25,58
Laos	2021	56,29	2,03	17,51	62,00	64,96	59,83	20887,90	3,71	24,51
Laos	2022	57,21	0,00	0,00		0,00	56,88	20702,58	15,77	23,26
Malaysia	2010	58,37	7,30	16,05	56,30	117,90	77,24	55227,89	7,27	59,08
Malaysia	2011	59,76	8,59	15,50	61,00	125,62	77,90	55398,84	5,41	59,07
Malaysia	2012	60,76	9,85	15,47	65,80	139,33	82,12	56114,31	1,00	59,17
Malaysia	2013	62,19	9,75	15,05	57,06	142,71	82,51	56098,28	0,17	59,36
Malaysia	2014	62,65	10,00	14,41	63,67	146,79	85,66	57740,22	2,47	59,67
Malaysia	2015	62,71	9,86	14,45	71,06	141,96	84,55	59361,10	1,22	60,01
Malaysia	2016	62,38	8,62	15,34	78,79	137,87	83,70	61074,48	1,66	61,15
Malaysia	2017	62,52	8,41	20,58	80,14	132,41	83,71	63237,91	3,78	61,23
Malaysia	2018	62,98	8,32	22,93	81,20	130,91	79,67	64638,51	0,62	61,74
Malaysia	2019	63,46	9,04	22,57	84,19	135,96	80,59	65850,64	0,07	62,05
Malaysia	2020	62,31	10,12	22,49	89,56	131,70	78,58	62364,37	-0,82	61,71
Malaysia	2021	63,03	11,12	24,56	96,75	140,59	80,27	62723,94	5,71	61,50
Malaysia	2022	62,90	12,44	24,91	97,40	141,29	84,54	67299,89	6,45	61,87

Myanmar	2010	65,67	0,05	1,00	0,25	1,20	50,89	8207,72	7,04	30,27
Myanmar	2011	65,44	0,04	1,05	0,98	2,50		8584,36	10,25	30,72
Myanmar	2012	65,13		1,04	1,40	7,43		9133,53	3,13	30,92
Myanmar	2013	64,79	0,00	1,06	1,80	13,49		9823,26	4,38	30,99
Myanmar	2014	64,49	0,00	1,03	7,40	56,84	56,90	10522,65	4,17	31,09
Myanmar	2015	64,21	0,06	1,00	10,90	79,62		11169,15	4,14	31,54
Myanmar	2016	62,71	0,17	0,99	16,00	97,48	67,00	11982,18	3,35	32,28
Myanmar	2017	61,18	0,21	1,06	23,62	91,70	71,26	12882,45	5,87	32,96
Myanmar	2018	61,88	0,25	0,99	28,70	116,10	75,65	13381,30	5,34	34,05
Myanmar	2019	60,25	0,92	0,99	30,64	154,50		14488,49	5,42	33,60
Myanmar	2020	59,26	1,29	0,98	41,95	147,03		13255,55	5,34	34,96
Myanmar	2021	52,80	1,66	0,97	44,02	126,27		12957,81	19,52	35,22
Myanmar	2022	53,54	2,08	0,99		106,70		13157,12	6,16	35,67
Philippines	2010	59,21		3,52	25,00	87,86		16463,69	4,37	51,48
Philippines	2011	60,00		3,69	29,00	97,77		16485,24	3,92	52,03
Philippines	2012	59,57	1,86	3,56	30,80	104,03		17349,17	1,99	52,56
Philippines	2013	59,30	2,19	3,16	32,70	103,13		18196,01	2,06	53,38
Philippines	2014	59,93	2,86	3,05	32,70	109,87	86,14	18732,44	3,05	53,64
Philippines	2015	59,53	2,81	3,13	36,90	114,37	86,64	19607,05	-0,72	54,62
Philippines	2016	59,93	2,85	3,61	39,20	114,51	87,13	20386,42	1,28	55,55
Philippines	2017	57,63	3,18	3,90	41,60	112,40	84,50	22161,82	2,32	56,29
Philippines	2018	57,60	3,49	3,81	44,10	123,98	82,04	23073,24	3,74	56,64
Philippines	2019	58,11	5,72	3,86	43,03	151,59	87,57	23759,27	0,70	58,03
Philippines	2020	53,37	7,07	4,22	47,11	133,33	89,25	22918,27	1,65	56,93
Philippines	2021	54,55	8,45	4,10	52,68	143,44	87,13	23249,78	2,28	56,81

Philippines	2022	58,05	7,57	4,23		144,04	93,67	23059,41	5,48	57,38
Singapore	2010	65,87	25,92	38,66	71,00	143,01	109,33	168260,15		77,86
Singapore	2011	66,23	26,66	38,21	71,00	147,58	109,90	173482,72	1,11	78,91
Singapore	2012	66,96	26,63	36,94	72,00	149,93	109,73	174538,65	1,17	79,33
Singapore	2013	66,81	27,26	35,91	80,90	154,03	108,39	176792,66	0,50	80,06
Singapore	2014	67,64	26,46	35,84	82,10	145,48	108,14	178319,46	-0,27	82,20
Singapore	2015	68,45	26,30	35,68	83,20	145,72	107,78	178465,36	3,07	82,53
Singapore	2016	67,99	27,87	34,99	84,45	148,12	107,86	183180,64	0,47	83,69
Singapore	2017	67,62	25,60	34,55	84,45	145,41	107,57	192073,49	2,88	84,00
Singapore	2018	67,60	25,69	34,41	88,17	147,36	105,84	197873,55	3,53	83,87
Singapore	2019	68,26	25,64	32,58	88,95	154,00	104,71	196293,15	-0,20	84,96
Singapore	2020	67,43	25,55	32,00	92,00	142,89	103,20	191449,41	-2,70	85,04
Singapore	2021	67,92	25,69	32,00	96,92	147,48	103,04	215377,79	8,78	85,45
Singapore	2022	68,69	37,36	31,90	95,95	156,48		213146,39	9,05	85,65
Thailand	2010	71,15	4,76	10,01	22,40	105,06	82,55	29266,37	4,08	41,11
Thailand	2011	72,80	5,67	9,69	23,67	112,71	85,12	28495,12	3,74	39,55
Thailand	2012	72,58	6,53	9,22	26,46	122,93	85,04	30292,05	1,91	38,03
Thailand	2013	70,09	7,46	8,70	28,94	134,88	86,84	31850,97	1,78	39,44
Thailand	2014	69,43	7,78	8,13	34,89	138,79	131,60	32171,46	1,44	42,95
Thailand	2015	68,83	8,86	7,55	39,32	146,44	134,44	33192,38	0,72	43,95
Thailand	2016	67,78	10,22	6,67	47,50	169,49	132,96	34586,96	2,64	45,05
Thailand	2017	66,94	11,58	14,04	52,89	171,41	116,02	36212,79	1,90	45,57
Thailand	2018	67,28	12,92	8,52	56,82	175,88	115,47	37315,63	1,43	44,95
Thailand	2019	66,48	14,18	7,59	66,65	181,77	113,04	38349,58	1,01	45,62
Thailand	2020	66,28	16,06	7,00	77,84	162,70	110,96	35932,39	-1,28	46,01

Thailand	2021	66,13	17,35	6,47	85,27	168,78	103,30	36373,77	1,71	45,83
Thailand	2022	66,90	18,45	6,09	87,98	176,32	105,60	36715,73	4,72	47,34
Timor-Leste	2010	65,44	0,05	0,27	3,00	43,46	67,89	10512,52	10,96	34,97
Timor-Leste	2011	65,11	0,05	0,27	4,00	55,18	70,25	10894,69	11,57	34,67
Timor-Leste	2012	64,77	0,05	0,26	7,00	54,58	70,10	11169,27	6,16	34,26
Timor-Leste	2013	64,60	0,06	0,26	11,00	55,96	67,89	11217,05	16,64	34,04
Timor-Leste	2014	64,34	0,09	0,30	17,50	116,11	69,44	11415,99	-0,73	35,18
Timor-Leste	2015	64,15	0,09	0,23	18,60	114,17	73,06	11452,42	7,20	35,53
Timor-Leste	2016	63,95	0,05	0,21	21,20	121,85	77,55	11587,07	0,22	35,79
Timor-Leste	2017	64,52	0,27	0,19	24,20	125,21	81,15	10849,64	-0,15	39,27
Timor-Leste	2018	64,99	0,01	0,17	27,60	116,38	83,10	10433,56	-1,32	42,00
Timor-Leste	2019	64,75	0,01	0,16	28,00	111,31	85,32	12606,43	4,87	43,43
Timor-Leste	2020	64,32	0,01	0,15	34,13	105,99	85,21	16322,17	-19,15	45,39
Timor-Leste	2021	64,26	0,01	0,14	39,45	104,94		16761,82	59,03	50,63
Timor-Leste	2022	65,14	0,01	0,14		110,42		12824,61	11,36	49,03
Viet Nam	2010	75,33	4,20	16,44	30,65	127,64		12762,42	42,30	29,61

Viet Nam	2011	75,51	4,34	11,52	35,07	144,11		13347,83	21,41	30,41
Viet Nam	2012	75,41	5,35	10,70	36,80	147,45		13911,19	9,08	31,44
Viet Nam	2013	76,00	5,71	7,45	38,50	137,08		14371,43	4,04	32,00
Viet Nam	2014	76,07	6,58	7,37	41,00	149,23		15099,99	3,70	32,22
Viet Nam	2015	75,77	8,31	7,95	45,00	130,52	88,20	16030,75	-1,72	33,24
Viet Nam	2016	75,14	9,77	6,01	53,00	129,50	88,64	17048,70	1,82	33,37
Viet Nam	2017	74,71	11,99	4,66	58,14	127,63	88,96	18129,36	4,36	34,07
Viet Nam	2018	74,73	13,69	4,53	69,85	148,17	90,64	19256,16	3,63	35,57
Viet Nam	2019	74,36	15,46	3,82	68,66	142,24	93,15	20547,78	2,42	36,37
Viet Nam	2020	71,74	17,28	3,32	70,30	143,75	93,79	21663,67	1,47	36,32
Viet Nam	2021	71,17	19,83	3,20	74,21	138,87	96,07	22167,71	2,78	37,82
Viet Nam	2022	71,96	21,65	2,43	78,59	139,95	97,25	23462,28	3,86	35,78
Indonesia	2010	62,85	0,93	16,77	10,92	86,59	77,00	19703,19	15,26	42,22
Indonesia	2011	63,46	1,11	15,63	12,28	101,10	79,54	20400,21	7,47	42,82
Indonesia	2012	64,41	1,19	15,18	14,52	112,69	81,53	20991,72	3,75	43,00
Indonesia	2013	63,86	1,28	12,13	14,94	123,67	84,51	22015,96	4,97	44,07
Indonesia	2014	63,92	1,33	10,23	17,14	127,07	85,26	22767,96	5,44	44,32
Indonesia	2015	63,58	1,54	4,01	22,06	130,82	89,54	23676,89	3,98	44,92
Indonesia	2016	63,46	2,00	4,11	25,45	147,25	89,17	24580,34	2,44	46,46
Indonesia	2017	64,17	2,35	4,18	32,34	164,54	91,99	25207,98	4,29	47,19
Indonesia	2018	64,68	3,32	3,11	39,90	119,61	94,18	25967,63	3,82	48,01
Indonesia	2019	65,79	3,81	3,58	47,69	126,59	95,78	26473,93	1,60	48,98
Indonesia	2020	64,54	4,31	3,55	53,73	130,81	98,04	26123,78	-0,40	48,89
Indonesia	2021	63,35	4,54	3,29	62,10	133,65	99,10	27319,41	6,00	49,25
Indonesia	2022	64,70	4,88	3,06	66,48	114,90	98,97	27887,85	9,57	48,85

Appendix 2. Calculation

FULL MODEL

Descriptive statistics

su

```
   Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
          id |          0
        year |        143        2016    3.754809       2010       2022
          y1 |        143     64.7165    5.577679       52.8      76.07
         x11 |        140    7.165643    8.316174          0      37.36
         x21 |        142    10.46007    10.66956          0      38.66
-------------+---------------------------------------------------------
         x31 |        136    46.19125    28.54251        .25      98.08
         x41 |        143    116.9724    36.52358          0     181.77
         z11 |        113    85.72956    18.83049      47.47     134.44
         z21 |        143    52212.84    64280.59    6197.47   215377.8
         z31 |        142    4.436549    8.006474     -19.15      59.03
-------------+---------------------------------------------------------
          np |        143    48.32783    18.56439      20.25      85.65
    outliers |        143    .8181818    .3870503          0          1
     country |        143           6    3.173393          1         11
```

encode id, generate(country)

gen lz21 = log(z21)

pwcorr y1 x11 x21 x31 x41 z11 lz21 z31

```
             |       y1      x11      x21      x31      x41      z11     lz21
```

```
-------------+------------------------------------------------------------
          y1 |   1.0000
         x11 |   0.2065   1.0000
         x21 |  -0.0719   0.7429   1.0000
         x31 |   0.0009   0.7852   0.6499   1.0000
         x41 |   0.2965   0.5617   0.2791   0.6169   1.0000
         z11 |   0.1801   0.6628   0.3839   0.5300   0.7158   1.0000
        lz21 |  -0.1874   0.7613   0.8506   0.8019   0.4097   0.6279   1.0000
         z31 |   0.0295  -0.1329  -0.0651  -0.1862  -0.1660  -0.2665  -0.1382

             |      z31
-------------+---------
         z31 |   1.0000
```

quietly reg y1 x11 x21 x31 x41 z11 lz21 z31

vif

```
    Variable |       VIF       1/VIF
-------------+----------------------
        lz21 |      7.48    0.133739
         x21 |      5.28    0.189525
         x11 |      4.55    0.219837
         x31 |      4.44    0.225012
         z11 |      3.64    0.275102
         x41 |      3.25    0.307873
         z31 |      1.15    0.870234
-------------+----------------------
```

```
   Mean VIF |      4.25

xtset country year
Panel variable: country (strongly balanced)
 Time variable: year, 2010 to 2022
         Delta: 1 unit
quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31, fe
est sto fe
quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31, re
est sto re
hausman fe re, sigmamore
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference       Std. err.
-------------+----------------------------------------------------------------
         x11 |   -.3741211    -.3063055      -.0678156        .0218689
         x21 |    -.084869    -.0749083      -.0099608        .0042603
         x31 |    .0245066     .0105238       .0139828        .0066658
         x41 |   -.0136823    -.0130661      -.0006161        .0007336
         z11 |   -.0185092    -.0221771       .0036679        .0044675
        lz21 |   -2.587519    -.8368847      -1.750634        1.214736
         z31 |    .0077533     .0082262      -.0004729        .0005872
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.
```

Test of H0: Difference in coefficients not systematic

chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 15.56

Prob > chi2 = 0.0295 (FEM)

Chi-square – prob (table)

quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31, fe

xttest3

Modified Wald test for groupwise heteroskedasticity

in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (11) = 547.05

Prob>chi2 = 0.0000 (heteroscedasticity – greater than 0.05 – there is no hetero) cross section

xtserial y1 x11 x21 x31 x41 z11 lz21 z31

Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation

F(1, 10) = 12.763

Prob > F = 0.0051 (serial)

. xtscc y1 x11 x21 x31 x41 z11 lz21 z31

Regression with Driscoll-Kraay standard errors (find theory) Number of obs = 108

Method: Pooled OLS Number of groups = 11

Group variable (i): country F(7, 12) = 123.77

maximum lag: 2 Prob > F = 0.0000

R-squared = 0.4246

Root MSE = 4.0231

```
------------------------------------------------------------------------------
             |           Drisc/Kraay
          y1 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         x11 |   .5211926   .0830324     6.28   0.000     .3402804    .7021047
         x21 |  -.0684917   .0473176    -1.45   0.173    -.1715878    .0346044
         x31 |  -.0296985   .0194869    -1.52   0.153    -.0721568    .0127599
         x41 |   .0359148   .0175812     2.04   0.064    -.0023913    .0742209
         z11 |   .0007369   .0574205     0.01   0.990    -.1243717    .1258455
        lz21 |  -3.039084   .8903916    -3.41   0.005     -4.97908   -1.099087
         z31 |   .0441729   .0440291     1.00   0.336    -.0517582    .1401039
       _cons |   89.79239   9.317883     9.64   0.000     69.49047    110.0943
------------------------------------------------------------------------------
```

ROBUSTNESS CHECK

A. ALTERNATIVE PROXY [np].

```
quietly xtreg np x11 x21 x31 x41 z11 lz21 z31, fe

est sto fe

quietly xtreg np x11 x21 x31 x41 z11 lz21 z31, re

est sto re
```

```
hausman fe re, sigmamore

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference          Std. err.
-------------+----------------------------------------------------------------
         x11 |   -.2298668    -.1874566       -.0424102        .0268122
         x21 |   -.0824409    -.0809871       -.0014537        .0052184
         x31 |       .0605     .0424472        .0180529        .0081778
         x41 |   -.0032876    -.0035796         .000292        .0008989
         z11 |    .0829443     .0699836        .0129607         .005479
        lz21 |    9.489043     13.00401       -3.514965        1.490371
         z31 |   -.0392553    -.0399642         .000709        .0007192
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  13.09
Prob > chi2 = 0.0700

quietly xtreg np x11 x21 x31 x41 z11 lz21 z31, re
```

xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

np[country,t] = Xb + u[country] + e[country,t]

Estimated results:

```
         |       Var     SD = sqrt(Var)
---------+-----------------------------
      np |   347.2718       18.63523
       e |   2.291393       1.513735
       u |   49.03994       7.002852
```

Test: Var(u) = 0

chibar2(01) = 359.20

Prob > chibar2 = 0.0000 (REM)

quietly xtreg np x11 x21 x31 x41 z11 lz21 z31, fe

xttest3

Modified Wald test for groupwise heteroskedasticity

in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (11) = 2811.58

Prob>chi2 = 0.0000 (there is heteroscedaticity)

xtserial np x11 x21 x31 x41 z11 lz21 z31

Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation

F(1, 10) = 28.234

Prob > F = 0.0003

. xtgls np x11 x21 x31 x41 z11 lz21 z31

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: homoskedastic

Correlation: no autocorrelation

Estimated covariances = 1 Number of obs = 108

Estimated autocorrelations = 0 Number of groups = 11

Estimated coefficients = 8 Obs per group:

min = 4

```
                                        avg =   9.818182
                                        max =         13
                                   Wald chi2(7)     =     712.86
Log likelihood          = -359.1251        Prob > chi2      =     0.0000

------------------------------------------------------------------------------
          np | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         x11 |  -.0711847   .1699438    -0.42   0.675    -.4042684    .2618991
         x21 |  -.2962566   .1400969    -2.11   0.034    -.5708415   -.0216716
         x31 |  -.0357827    .049001    -0.73   0.465    -.1318228    .0602574
         x41 |    .077795    .034773     2.24   0.025     .0096413    .1459488
         z11 |  -.0849629   .0669543    -1.27   0.204    -.2161909    .0462652
        lz21 |   21.00359   1.808958    11.61   0.000      17.4581    24.54908
         z31 |  -.1097721   .1319297    -0.83   0.405    -.3683496    .1488054
       _cons |  -164.7241   14.67334   -11.23   0.000    -193.4833   -135.9649
------------------------------------------------------------------------------
```

B. Model without Outliers

```
quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1 , fe
. est sto fe
. quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1 , re
. est sto re
. hausman fe re, sigmamore
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
```

```
             |      fe          re        Difference       Std. err.
-------------+----------------------------------------------------------------
         x11 |  -.3638302   -.3527145      -.0111156       .0106445
         x21 |   -.087418   -.0866526      -.0007654       .0047645
         x31 |   .0239496    .0222487       .0017009       .0047548
         x41 |  -.0159946   -.0155881      -.0004066       .0015501
         z11 |   -.020129   -.0197485      -.0003805       .0044932
        lz21 |  -2.514042   -2.361954      -.1520879       1.153037
         z31 |   .0210149    .0210005       .0000145       .0017137
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.
Test of H0: Difference in coefficients not systematic
   chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
           =   3.87
Prob > chi2 = 0.6939 (REM)
. quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1 , re
. xttest0
Breusch and Pagan Lagrangian multiplier test for random effects
        y1[country,t] = Xb + u[country] + e[country,t]
        Estimated results:
                       |       Var     SD = sqrt(Var)
              ---------+-----------------------------
                    y1 |     31.529       5.615069
                     e |   1.815359       1.347352
```

u | 87.38835 9.348174

Test: Var(u) = 0

chibar2(01) = 59.37

Prob > chibar2 = 0.0000 (REM)

. quietly xtreg y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1 , fe

. xttest3

Modified Wald test for groupwise heteroskedasticity

in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (9) = 120.73

Prob>chi2 = 0.0000 (problem)

. xtserial y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1

Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation

F(1, 8) = 12.563

Prob > F = 0.0076

. xtgls y1 x11 x21 x31 x41 z11 lz21 z31 if outliers==1

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares

Panels: homoskedastic

Correlation: no autocorrelation

Estimated covariances = 1 Number of obs = 86

Estimated autocorrelations = 0 Number of groups = 9

Estimated coefficients = 8 Obs per group:

min = 4

avg = 9.555556

max = 13

Wald chi2(7) = 59.49

Log likelihood = -247.3073 Prob > chi2 = 0.0000

y1	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
x11	.4520695	.1629589	2.77	0.006	.1326759	.771463
x21	-.0649534	.1046713	-0.62	0.535	-.2701053	.1401985
x31	-.0244968	.0379408	-0.65	0.519	-.0988595	.0498659
x41	.0458591	.0246394	1.86	0.063	-.0024332	.0941515
z11	-.00099	.0444978	-0.02	0.982	-.0882041	.0862241
lz21	-3.15443	1.170593	-2.69	0.007	-5.44875	-.86011
z31	.0422105	.1030418	0.41	0.682	-.1597477	.2441688
_cons	90.02597	9.474704	9.50	0.000	71.45589	108.596