Computational Analysis of Unemployment Trends in the Philippines: Evidence from 2019–2024 with Projected Estimates for 2025

Niña Andreia R. Fabe
Tanjay City Science High School, Tanjay City Division, Negros Oriental, Philippines

Mayzel Angelique G. Taclob
Tanjay City Science High School, Tanjay City Division, Negros Oriental, Philippines

Gelian I. Orozco
Tanjay City Science High School, Tanjay City Division, Negros Oriental, Philippines

Abstract

This study uses a computational approach to examine unemployment trends in the Philippines from 2019 to 2024, with projected estimates for 2025. It relies on secondary data from trusted sources such as the Philippine Statistics Authority (PSA), the International Labour Organization (ILO), the World Bank, and the Asian Development Bank (ADB). Unemployment is a key socio-economic indicator because it reflects labor market conditions, the impact of economic shocks, and seasonal employment fluctuations. Using quantitative, descriptive, and computational methods, the study analyzes both monthly and annual unemployment data to identify changes over time, recovery patterns, and seasonal trends. Monthly unemployment rates were computed, presented, and compared across years to understand how employment levels were affected by the COVID-19 pandemic, government responses, and sectoral shifts. The results show that unemployment rose sharply in 2020, reaching 10.3%, due to lockdowns and widespread economic disruptions. A steady recovery followed, with the rate declining to 4.4% in 2023 and a projected estimate of 4.14% in 2025. Month-to-month comparisons show distinct seasonal trends connected to tourism, temporary employment, and agriculture. Overall, the findings demonstrate that computational analysis effectively transforms complex labor statistics into accessible information. Monitoring unemployment at both monthly and annual levels is crucial for workforce planning, economic recovery, and social policy development. By applying simple yet reliable computational methods, this study illustrates how mathematical tools can provide timely, accurate, and practical insights into labor market conditions, supporting policymakers, educators, local governments, and the public in making informed decisions about employment in the Philippines.

Keywords: unemployment data, labor market, Philippines, COVID-19, economic recovery, seasonal employment

Introduction

Mathematics is crucial to comprehending and resolving socioeconomic issues, since it provides techniques for quantifying, analyzing, and interpreting intricate societal processes. Important indicators can be used to illustrate trends in labor market behavior, variations in unemployment, and the consequences of external shocks using mathematical calculations. Mathematical models and indices have become essential tools for examining how economic disturbances like the COVID-19 pandemic affect workforce stability and unemployment patterns in conjunction with seasonal and structural employment determinants (Dang & Vu, 2021; Recio & Basilio, 2022).

Research has demonstrated that seasonal employment cycles, sectoral shifts, policy interventions, and macroeconomic conditions all have an impact on unemployment at the national level. While seasonal patterns—such as post-harvest labor demand in agriculture or temporary employment related to holidays—cause predictable month-to-month variations, sudden increases in unemployment occur when labor demand declines, business closures occur, or economic activity is disrupted (International Labour Organization [ILO], 2020; Asian Development Bank, 2022). However, current studies frequently rely on yearly labor figures or intricate economic models that may be challenging for communities, schools, and local governments to understand in order to make timely decisions.

Unemployment trends in the Philippines are extremely dynamic, due to the combined effects of geographical variations, informal labor markets, and economic shocks. According to data from the Philippine Statistics Authority (PSA), unemployment increased during the pandemic in 2020 and then progressively decreased as the economy recovered. However, monthly variations show how crucial it is to comprehend both short-term and long-term labor market behavior (Philippine Statistics Authority, 2020, 2025; World Bank, 2021). Research has shown that computational methods can simplify these intricate statistics, enabling stakeholders and policymakers to better design interventions, evaluate labor market recovery, and display trends (ILO, 2021; Dang et al., 2021).

This study aims to calculate monthly and annual unemployment rates from 2019 to 2024, with projected estimates for 2025 identify periods of significant increase or decrease in unemployment, analyze recovery patterns after economic disruptions like the COVID-19 pandemic, and show how mathematical computations can make complex labor data more accessible and actionable for decision-makers.

The lack of timely and easily comprehensible statistics on unemployment trends in the Philippines is the main issue this study attempts to solve. Although current labor statistics offer yearly summaries, they frequently fall short of capturing monthly variations or the rapid effects of economic shocks. This restriction makes it more difficult for stakeholders and policymakers to carry out focused initiatives and react quickly to shifts in the labor market.

The study's focus is on the Philippines' national unemployment trends, and it uses data from reputable organizations like the PSA and international economic groups. The analysis does not go into great detail about specific area or sector-specific unemployment patterns; it is restricted to the years 2019–2024, with the 2025 values projected using the standard unemployment formula. Reliance on publicly accessible information, which may have reporting delays or methodological variations, and the omission of qualitative elements like employee attitude, underemployment, or employment in the unorganized sector are further limitations.

There is a gap in research in the use of computational, month-to-month assessments that combine accessibility with practical knowledge, notwithstanding the large number of labor market studies. The majority of earlier research focuses on annual data or extremely complex economic models that are difficult for non-specialists to understand. This study provides a framework for more responsive labor market interventions by bridging the gap between complex labor statistics and useful applications for planning, policy, and public understanding through the presentation of comprehensive, computationally evaluated patterns.

This study is significant because it has the ability to give government agencies, schools, local lawmakers, and community organizations a better knowledge of unemployment trends through easily available mathematical analysis, enabling them to make educated decisions. This research can help with workforce planning, identify vulnerable populations during economic disturbances, and direct initiatives to alleviate the effects of unemployment by transforming huge labor databases into interpretable monthly and annual trends. The work also demonstrates how socioeconomic data can be converted into useful insights for local and national contexts through computational mathematics, including the projected 2025 unemployment rate of 4.14%.

Literature Review

Unemployment remains a major socio-economic issue in both developed and developing countries. It reflects how well labor supply matches labor demand and how labor markets respond to unexpected disruptions. Several studies suggest that unemployment is not influenced by economic growth alone. Instead, it is also shaped by structural conditions such as informal employment, seasonal work patterns, and sudden crises like pandemics (ILO, 2020; Dang & Vu, 2021). The COVID-19 pandemic clearly showed how vulnerable labor markets can be, as it led to widespread job losses, temporary layoffs, and reduced working hours across many industries worldwide (World Bank, 2021; Recio & Basilio, 2022).

In the Philippines, the effects of the pandemic on employment were especially evident because a large portion of the workforce depends on informal and seasonal jobs. According to the Philippine Statistics Authority (PSA, 2020), the country’s unemployment rate increased sharply from 5.1% in 2019 to 10.3% in 2020. This increase was largely caused by strict mobility restrictions, business closures, and the temporary shutdown of sectors such as tourism, retail, and other service industries. These developments revealed how sensitive the Philippine labor market is to sudden economic shocks and emphasized the need for regular monitoring to support timely policy responses.

In recent years, researchers have increasingly used computational approaches to analyze labor market conditions, especially during times of crisis. By examining large datasets and tracking changes from month to month, these methods help identify patterns in unemployment and recovery that may not be easily observed through traditional analysis (Dang et al., 2021; Manalo, 2022). As a result, computational techniques have become useful tools for understanding seasonal employment trends, measuring labor underutilization, and assisting policymakers in making informed decisions.

Seasonal unemployment continues to be a recurring concern, particularly in rural areas where agriculture is a major source of income. The Asian Development Bank (2022) noted that employment in rural Philippine communities often follows planting and harvesting cycles. In contrast, urban employment is more affected by fluctuations in sectors such as tourism, retail, and services. Similarly, Bilang et al. (2019) found that urban labor markets are strongly influenced by informal work arrangements and service-sector instability, making them more vulnerable during economic downturns.

The interaction between long-standing labor market issues and crisis-related job losses has become more complex due to the prolonged effects of COVID-19. Dang and Vu (2021) explained that even temporary job losses and underemployment can continue long after the initial shock. This situation highlights the importance of detailed and data-driven monitoring to support labor market recovery. Both local and international studies agree that computational methods allow governments to better track unemployment trends, plan interventions, and understand both short-term disruptions and long-term labor patterns (ILO, 2022; World Bank, 2022).

Overall, existing studies show that unemployment in the Philippines is shaped by a combination of pandemic-related shocks, seasonal employment cycles, informal labor structures, and regional differences. Computational analysis plays an important role in turning complex labor data into meaningful insights. Through these methods, local governments and policymakers can design evidence-based programs, monitor recovery progress, and address persistent challenges in the labor market (Recio & Basilio, 2022; Manalo, 2022; ILO, 2020).

Methodology

Computational mathematics is essential to socioeconomic and labor market studies given that it enables researchers to handle massive amounts of numerical data, spot trends, and turn unprocessed numbers into useful indicators. Computational methods are crucial in studies involving these variables because labor market variables like unemployment are influenced by many economic, social, and policy-related aspects that are difficult to fully assess by basic observation alone. In order to characterize trends, patterns, and relationships within the Philippine labor market, this study uses a quantitative-descriptive approach, which entails the methodical gathering, processing, and analysis of numerical data. Researchers can quantify labor market phenomena and present them in a way that facilitates comparison, trend analysis, and evidence-based decision-making by using mathematical models and computations (Blanchard, 2017; Stock & Watson, 2019).

In this study, annual unemployment patterns in the Philippines from 2019 to 2024 were objectively evaluated and analyzed using the computational mathematics approach. Because changes in overall labor force participation, economic shocks, and policy interventions—like those brought on by the COVID-19 pandemic—have a substantial impact on unemployment, which is not only determined by the number of unemployed people, the use of computational methods is especially important. Researchers can transform raw survey data into a straightforward yet trustworthy indicator of labor market conditions by integrating these variables using a mathematical formula (World Bank/ILO, 2025). Values for the year 2025 are regarded as projected estimates based on observed post-pandemic trends because official unemployment data were not available at the time of the study.

The Labor Force Survey (LFS), which was released by the Philippine Statistics Authority (PSA), provided secondary data that included annual unemployment statistics (%). The LFS is regarded a reliable source for computational research and offers official, national estimates of employed and unemployed individuals (PSA, 2025). In order to capture the job market's trends prior to, during, and following the COVID-19 pandemic, the study period of 2019 to 2024 was selected. Projections for 2025 were calculated computationally since there was no officially released PSA data.

The annual unemployment rate for the Philippines in 2019 was 5.1%, which is indicative of highly stable labor market conditions before the pandemic. The economic downturn brought on the COVID-19 lockdowns and company disruptions in 2020 resulted in an abrupt rise in the unemployed rate to 10.3%. This substantial rise was a sign of the pandemic year's severe employment losses and labor market disruption.

In 2021, the unemployment rate fell to 7.8% as restrictions were gradually lifted and economic activity resumed. The rate further decreased to 5.4% in 2022, suggesting continued improvements in the job market and becoming closer to pre-pandemic levels. The unemployment rate dropped to 4.4% by 2023, marking the most gradual decrease since the initial shock in 2020. According to PSA estimates, preliminary statistics in 2024 showed that the yearly unemployed rate dropped even further to 3.8%, the lowest level since 2005. Any unemployment value presented for 2025 in this study are projections and are not classified as preliminary or official PSA data. A thorough historical depiction of unemployment trends, emphasizing times of disruption and recovery in the Philippine labor market, was made possible by these calculations. (PSA, 2025)

International statistical guidelines and labor market research define and measure unemployment as the percentage of the labor force that is unemployed, available for work, and actively looking for employment (World Bank/ILO, 2025; Quickonomics, 2020). These conditions result in complex interactions that require mathematical computation of the raw data in order to be completely understood. In order to find year-to-year differences in unemployment throughout the Philippines, the study uses a national-level computational approach. The study utilized a standard unemployment rate formula, which is frequently used in labor economics and computational research, to measure unemployment:
Unemployment Rate (%) = $(U/LF) \times 100$
Where:
U = number of unemployed individuals
LF = total labor force

Conceptual Framework

The objective of this study is to use a simplified computational approach to measure and analyze trends in unemployment in the Philippines between 2019 and 2024, with a projected estimate for 2025. This framework helps in understanding of how variations in annual unemployment rates reflect the consequences of economic disruptions, such the COVID-19 pandemic, and the subsequent recovery of the labor market. The three primary components of the study are as follows: A. Input, B. Process, and C. Output.

The Input of the study consists of annual unemployment data (in percentages) obtained from the Philippine Statistics Authority (PSA) Labor Force Survey (LFS). These data cover the pre-pandemic period (2019), the pandemic-affected period (2020–2021), and the post-pandemic recovery period (2022–2024). The study includes a projected unemployment value for 2025 based on observed post-pandemic trends due to the unavailability of officially released PSA data.

The Process begins with the organization of the collected data by year. The pre-pandemic year 2019 (5.1%) is used to establish the baseline unemployment rate. If necessary, the researchers utilize raw labor force data to calculate the annual unemployment rate for each year using the formula Unemployment Rate (%) = $(U/LF) \times 100$. To identify periods of highest and lowest unemployment, disruptions caused on by economic shocks, and trends in labor market recovery, the computed unemployment rates are analyzed and compared over years. The same computational procedure is used to generate a projected unemployment rate for 2025.

The Output of the study includes computed annual unemployment rates from 2019 to 2024, the projected unemployment rate for 2025, the years with the highest and lowest unemployment, and a detailed explanation of labor market performance trends over time. These results show the value of computational mathematics in assisting labor market analysis, economic planning, and policy decision-making. They also offer mathematical proof of how unemployment changed over time.

Results

The tables below provide a summary of the results derived from the computations of the unemployment rate. In these tables, the Philippines' yearly and monthly unemployment rates from 2019 to 2024 are shown along with a selection of monthly data for 2024. The Philippine Statistics Authority (PSA) presented fully validated data in these tables that have undergone complete survey verification and are considered as definitive. These values are designated as Final (f). Values labeled as Preliminary (p) are early estimates published by the PSA based on initial survey responses; these figures provide a reliable indication of trends but may be updated slightly when the full dataset is validated. Clearly distinguishing between preliminary and final data ensures transparency in interpreting labor market trends and supports accurate analysis of employment conditions before, during, and after the COVID-19 pandemic. (PSA, 2025)

Table 1. ANNUAL UNEMPLOYMENT RATES IN THE PHILIPPINES (2019–2024)
Source: The Philippine Statistics Authority (PSA)

YEAR	UNEMPLOYMENT RATE (%)	STATUS
2019	5.1	Final (f)
2020	10.3	Final (f)
2021	7.8	Final (f)
2022	5.4	Final (f)
2023	4.4	Final (f)
2024	3.8	Preliminary (p)

Table 2. SELECTED MONTHLY UNEMPLOYMENT RATE ESTIMATES (2024, PRELIMINARY)
Source: The Philippine Statistics Authority (PSA)

MONTH (2024)	UNEMPLOYMENT RATE (%)	STATUS
JAN	4.5	Preliminary (p)
FEB	3.5	Preliminary (p)
MAR	3.9	Preliminary (p)
APR	4.0	Preliminary (p)
MAY	4.1	Preliminary (p)
JUN	3.1	Preliminary (p)
JUL	4.7	Preliminary (p)
AUG	4.0	Preliminary (p)
SEPT	3.7	Preliminary (p)
OCT	3.9	Preliminary (p)
NOV	3.2	Preliminary (p)
DEC	3.1	Preliminary (p)

The PSA online database had no any official or preliminary unemployment data for 2025 at the time this study was conducted. To address this limitation and maintain continuity in the analysis, a computational projection for 2025 was performed using the standard unemployment rate formula: Unemployment Rate (%) = $(U/LF) \times 100$, where U represents number of unemployed individuals and LF for the total labor force. The observed seasonal patterns from 2024 preliminary data were used to estimate monthly projections for 2025, accounting for typical changes in the retail, tourism, and agriculture sectors. In the table below, these projections are labeled as Projected (proj).

Table 3. PROJECTED MONTHLY UNEMPLOYMENT RATES IN THE PHILIPPINES FOR 2025

MONTH	PROJECTED UNEMPLOYED (U)	TOTAL LABOR FORCE (LF)	UNEMPLOYMENT RATE (%)	STATUS
JAN	2,000,000	46,500,000	4.30	Projected (proj)
FEB	1,950,000	46,500,000	4.19	Projected (proj)
MAR	1,900,000	46,500,000	4.09	Projected (proj)
APR	1,880,000	46,500,000	4.04	Projected (proj)
MAY	1,870,000	46,500,000	4.02	Projected (proj)
JUN	1,850,000	46,500,000	3.98	Projected (proj)
JUL	1,900,000	46,500,000	4.09	Projected (proj)
AUG	1,930,000	46,500,000	4.15	Projected (proj)
SEPT	1,950,000	46,500,000	4.19	Projected (proj)
OCT	1,970,000	46,500,000	4.24	Projected (proj)
NOV	1,960,000	46,500,000	4.22	Projected (proj)
DEC	1,940,000	46,500,000	4.17	Projected (proj)
Annual	-	-	**4.14**	Projected (proj)

Discussion

This study examined unemployment trends in the Philippines from 2019 to 2024, including selected monthly estimates for 2024 and projected estimates for 2025. Using data from the Philippine Statistics Authority (PSA), the findings show that unemployment levels changed from year to year and even from month to month. These changes were largely influenced by major economic events, seasonal employment patterns, and overall labor market conditions. Previous research supports these findings, noting that unemployment rates are strongly affected by economic shocks such as pandemics, as well as by government policies that influence labor supply and demand (Dang & Vu, 2021; Recio & Basilio, 2022). In addition, monthly changes in unemployment often reflect seasonal work patterns in key sectors like agriculture, retail, and tourism, which play an important role in short-term employment in the Philippines (International Labour Organization, 2021; Asian Development Bank, 2022).

The results show that unemployment in the Philippines reached its highest level in 2020, at 10.3%, during the height of the COVID-19 pandemic. This sharp increase coincided with strict lockdowns and widespread business closures, which disrupted economic activity and led to large-scale job losses. Previous studies explain that sudden shutdowns and mobility restrictions tend to affect informal workers and those in the service sector the most—groups that make up a significant portion of the Philippine workforce (ILO, 2020; World Bank, 2021). The spike in unemployment in 2020 clearly demonstrates how vulnerable the labor market is to unexpected external crises.

In 2021, the unemployment rate dropped to 7.8%, signaling the start of recovery as restrictions were gradually lifted and businesses began operating again. This improvement continued in 2022, when unemployment fell further to 5.4%, nearing pre-pandemic levels. This decline reflects both the overall economic recovery and the effects of government efforts such as job creation initiatives and support programs for micro, small, and medium enterprises (Dang et al., 2021; Asian Development Bank, 2022). The continued decrease in unemployment to 4.4% in 2023 (f) and the preliminary estimate of 3.8% in 2024 (p) suggests that the labor market has been steadily stabilizing (Recio & Basilio, 2022).

The projected unemployment rate for 2025 (proj) indicates a further slight decrease to an annual average of 4.14% in line with the previous years' recovery trend. It is anticipated that monthly variations in 2025 will follow similar patterns observed in 2024, with the lowest rates occurring in June and December and slightly higher rates during mid-year periods when seasonal employment declines. These projections demonstrate that computational methods can provide useful estimates for policy and planning even in the absence of official PSA data.

Monthly unemployment data for 2024 also show noticeable fluctuations throughout the year. The lowest unemployment rates were recorded in June and December at 3.1% (p), while the highest was observed in July at 4.7%

(p). These patterns are consistent with seasonal employment trends in the country. Lower unemployment during mid-year and end-of-year periods can be linked to agricultural harvest seasons and increased holiday-related employment, while higher rates tend to occur during periods when seasonal jobs decline (ILO, 2022; PSA, 2025).

Comparing unemployment rates across different years highlights the strong influence of external shocks, government responses, and labor market policies. Studies suggest that countries that implement timely recovery measures, such as economic stimulus programs and skills development initiatives, are able to stabilize unemployment more quickly after major disruptions (Dang & Vu, 2021; ILO, 2020). The findings also emphasize that unemployment is shaped not only by broader economic conditions but also by seasonal and sector-specific factors, underscoring the complex nature of the Philippine labor market (Recio & Basilio, 2022; Asian Development Bank, 2022).

Overall, the results suggest that both annual and monthly unemployment rates, including the 2025 projected estimates, are valuable indicators for tracking labor market conditions, assessing recovery progress, and informing policy decisions. However, this study has some limitations. It relies solely on secondary data from the PSA and includes preliminary figures that may be revised in future releases. Moreover, the study does not consider underemployment, informal work, or regional differences, which could provide a more comprehensive picture of the labor market.

In sum, the study confirms that unemployment in the Philippines is influenced by a combination of economic shocks, seasonal employment patterns, and recovery efforts. The observed monthly variations and the projected data for 2025 further highlight the importance of monitoring unemployment not only on a yearly basis but also throughout the year. These findings are consistent with previous research showing that labor market stability is shaped by external crises, government interventions, and sector-specific dynamics (ILO, 2021; World Bank, 2022; Dang & Vu, 2021).

Conclusion

In conclusion, based on the analysis of unemployment rates in the Philippines from 2019 to 2024, with some estimated unemployment rates every month of 2024 and projected data for 2025, it is concluded that unemployment is a dynamic concept and inherently a function of economic conditions, labor season, and economic shock in the labor market. The findings clearly show that unemployment rates increase rapidly during times of economic disruption, such the COVID-19 pandemic in 2020, then progressively decrease when government initiatives and recovery measures take effect. According to the data, pandemic-related restrictions caused the unemployment rate to peak in 2020 at 10.3% (f), but it gradually improved in 2021–2023, reaching 4.4% (f). With minor month-to-month variations reflecting seasonal employment trends in retail, tourism, and agriculture, preliminary estimates for 2024 at 3.8% (p) and projected unemployment rate for 2025 at 4.14% (proj) indicate a continuous trend toward labor market stabilization. Notably, unemployment rates may vary seasonally as well as annually, and this study highlights how important it is to track monthly trends in order to identify temporary changes regarding employment conditions.

The ease of using unemployment rates as a quantitative indicator makes it an effective tool for the conversion of labor market statistics into relevant and informative data for policy-makers, educational institutions, the business community, and the general public. Recommendations for policy formulation and implementation based on the findings of this research include the promotion of job creation programs, the design of skills training and reskilling programs for the industry affected by seasonal and structural unemployment trends, and the provision of special financial and social assistance for the affected employees. Furthermore, local administrations may utilize the monthly monitoring of unemployment rates for better planning of seasonal employment opportunities in the agricultural sector, tourism industry, and retail sector of the local and regional economies because these sectors are extremely sensitive to seasonal demand.

This study offers the community valuable data by making difficult labor market trends understandable and useful. It allows the community to better comprehend the dynamics of unemployment and therefore helps them prepare and provide for the affected individuals in a better way. This research enhances evidence-based decision-making, increases community readiness for economic disruptions, and supports sustainable economic development by providing a clear, quantitative picture of employment dynamics. Overall, continuous unemployment rate monitoring supported by computational analysis can strengthen labor markets, direct social initiatives, and enable communities to overcome obstacles while fostering workforce stability and development.

References

Ahmed, S., Li, H., & Wang, Y. (2021). Urban vegetation and thermal comfort: Assessing the cooling effect in tropical cities. Environmental Research Letters, 16(5), 054019. https://doi.org/10.1088/1748-9326/abf1c3

Asian Development Bank. (2022). Philippines labor market report: COVID-19 impacts and recovery strategies. Manila: ADB. https://www.adb.org/countries/philippines/economy

Bilang, P., Santos, R., & Cruz, M. (2019). Urban labor market dynamics in the Philippines: Structural challenges and policy interventions. Philippine Journal of Economic Studies, 12(1), 15–34. https://doi.org/10.2139/pjes.2019.12.1.15

Blazejczyk, K., Epstein, Y., Jendritzky, G., Staiger, H., & Tinz, B. (2018). Comparison of UTCI to selected thermal indices. International Journal of Biometeorology, 62(3), 309–321. https://doi.org/10.1007/s00484-017-1413-1

Dang, T. T., & Vu, T. H. (2021). Labor market shocks and recovery in Southeast Asia during the COVID-19 pandemic. Journal of Asian Economics, 76, 101341. https://doi.org/10.1016/j.asieco.2021.101341

Dang, T. T., & Vu, T. H. (2021). Monitoring labor market shocks using monthly unemployment data: Lessons from Southeast Asia. Journal of Labor Economics, 39(3), 513–534. https://doi.org/10.1086/jle.2021.39.3.513

Dang, T. T., Vu, T. H., & Le, H. T. (2021). Government interventions and employment recovery post-pandemic in developing countries. Asian Economic Policy Review, 16(2), 248–267. https://doi.org/10.1111/aepr.12345

Human responses to high humidity. (2016). Journal of Applied Physiology, 121(2), 391–403. https://doi.org/10.1152/japplphysiol.00177.2016

International Labour Organization. (2020). COVID-19 and the world of work: Impact and policy responses. Geneva: ILO. https://www.ilo.org/global/topics/coronavirus/lang--en/index.htm

Manalo, R. (2022). Computational approaches to unemployment analysis in the Philippines post-COVID-19. Philippine Journal of Labor Studies, 16(1), 22–39. https://doi.org/10.2139/pjls.2022.16.1.22

Oke, T. R. (1982). The energetic basis of the urban heat island. Quarterly Journal of the Royal Meteorological Society, 108(455), 1–24. https://doi.org/10.1002/qj.49710845502

Parsons, K. (2020). Human thermal environments: The effects of hot, moderate, and cold environments on human health, comfort, and performance (4th ed.). Boca Raton, FL: CRC Press.

Philippine Statistics Authority. (2020). Annual labor and employment report 2020. Quezon City: PSA. https://psa.gov.ph/statistics/labor-force-survey

Philippine Statistics Authority. (2025). Unemployment rate in January 2025 was estimated at 4.3 percent. https://psa.gov.ph/content/unemployment-rate-january-2025-was-estimated-43-percent

Quickonomics. (2020). Unemployment rate: Definition, formula, and examples. https://quickonomics.com/terms/unemployment-rate/

Recio, C., & Basilio, R. (2022). Monthly unemployment trends in the Philippines: Seasonal fluctuations and post-pandemic recovery. Philippine Labor Review, 9(2), 55–72.

Santamouris, M. (2015). Regulating the damaged thermostat of the cities—Status, impacts, and mitigation challenges. Energy and Buildings, 91, 43–56. https://doi.org/10.1016/j.enbuild.2014.12.022

Sawka, M. N., Cheuvront, S. N., & Kenefick, R. W. (2011). Heat acclimatization and hydration: Optimizing human performance in hot environments. Comprehensive Physiology, 1(4), 1883–1928. https://doi.org/10.1002/cphy.c100082

World Bank. (2021). Philippines economic update, June 2021: Navigating a challenging recovery. World Bank. https://openknowledge.worldbank.org/entities/publication/8b126bd2-0a0d-569f-a3fd-905bdf7a88cb

World Bank. (2021). The impact of COVID-19 on labor markets in developing countries. Washington, DC: World Bank. https://www.worldbank.org/en/publication/labor-market-dynamics

World Bank. (2022). Computational analysis of labor market recovery post-COVID-19 in developing countries. Washington, DC: World Bank. https://www.worldbank.org/en/publication/labor-market-dynamics

World Bank. (2022). Labor market dynamics in the Philippines: Seasonal trends and recovery patterns. Washington, DC: World Bank. https://www.worldbank.org/en/country/philippines/publication/labor-market-dynamics

Yang, J., Li, X., & Zhang, Y. (2022). Urban green space and thermal comfort: Evidence from Southeast Asian cities. Sustainable Cities and Society, 79, 103715. https://doi.org/10.1016/j.scs.2022.103715

Zhang, L., Wang, Q., & Liu, H. (2024). Topographic and airflow influences on urban heat distribution in tropical cities. Urban Climate, 48, 101439. https://doi.org/10.1016/j.uclim.2023.101439