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# FORECASTING LABOUR FORCE TRENDS AMONG OLDER PERSONS IN MALAYSIA USING TIME SERIES ANALYSIS

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## ABSTRACT

Malaysia has transitioned into an ageing society faster than the previous demographic model suggested. The latest report from the Department of Statistics Malaysia (DOSM) confirms that as of 2025, individuals aged 65 and older already comprise 8% of the total population. To address the objectives of Sustainable Development Goal (SDG) 8.5 regarding productive employment, this study forecasts labour force participation trends among Malaysians aged 60 to 64 through the year 2030. This specific age group represents a critical segment for extending working lives and maintaining national productivity. The analysis utilises annual time series data from 1982 to 2021 for model estimation and evaluation, while actual observations from 2022 to 2024 serve as an ex-post benchmark to verify the forecast accuracy. This study applies four forecasting techniques, including double exponential smoothing (DES), Holt's exponential smoothing (HES), autoregressive integrated moving average (ARIMA), and time series regression (TSR). Following evaluation via mean absolute percentage error (MAPE), root mean square error (RMSE), and geometric root mean square error (GRMSE), the HES emerged as the most reliable, achieving a precision rate of 99.27% (0.73% error) against 2024 actuals. The final forecast trends indicate steady expansion, with the labour force participation expected to reach 533,020 older workers by 2030, which is a 10.47% cumulative increase from 2024. These findings confirm that prolonged workforce participation is no longer a temporary shift but a structural reality. Consequently, Malaysia requires immediate policy interventions focused on flexible retirement frameworks, targeted reskilling, and the creation of an age-inclusive workplace environment to sustain economic stability.

**Keywords:** Labour force participation, older persons, productive ageing, time series forecasting.

## INTRODUCTION

Malaysia is undergoing a demographic transition toward an ageing society. A recent report from the Department of Statistics Malaysia (DOSM, 2025) indicates that citizens aged 65 and above represented 8% of the total population in 2025, a proportion projected to rise steadily in the coming decade. This demographic shift suggests that Malaysia may reach the status of an aged nation earlier than initially anticipated. As the population ages, understanding labour force behaviour among older persons becomes essential for sustaining economic growth and ensuring social stability.

Labour participation among older Malaysians is both an economic and a social concern. The United Nations Sustainable Development Goal 8.5 aims to achieve full and productive employment and decent work for all women and men by 2030 (United Nations, 2025). Within this context, the engagement of older persons in the labour market supports national productivity while contributing to personal income security and active ageing. For Malaysia, keeping older persons engaged in the labour market serves a dual purpose, which is to bolster national productivity and provide individual income security. As highlighted in recent global economic assessments (World Bank, 2020; OECD, 2023), retaining the expertise of seasoned workers can strengthen a nation's economic resilience and alleviate the fiscal strain on public pension and social protection schemes.

Despite its significance, the ageing workforce faces challenges such as declining health, limited savings, and a shortage of flexible or age-friendly employment opportunities. As highlighted by Sulaiman (2024), the majority of older people remain physically and mentally capable of working, suggesting that current participation rates do not fully reflect their potential. While several Malaysian studies have examined ageing and labour market outcomes (Ramely, Ahmad, & Harith, 2022; Sulaiman, 2024), few have applied quantitative time series approaches to forecast labour force trends among older persons.

To address this gap, this study forecasts labour force trends among older persons in Malaysia up to 2030 using official data from the Department of Statistics Malaysia (DOSM). The analysis focuses on individuals aged 60 to 64 years, who form the upper tier of the national working-age population. The results aim to provide policymakers with empirical insights to design strategies that promote productive ageing, reskilling, and inclusive employment in Malaysia.

## LITERATURE REVIEW

Research on labour force trends among older persons has become increasingly important as Malaysia transitions into an ageing society. Understanding how older adults engage in the workforce is essential for economic sustainability, social inclusion, and policy planning. This focus aligns with SDG 8.5, which aims to achieve full and productive employment and decent work for all women and men by 2030 (United Nations, 2025). The definition of a working older person varies depending on study objectives and disciplinary context. Whiting (2005) described working older persons as those aged 60 years and above who remain in the labour force, while Bärnighausen et al. (2007) referred to individuals in the same age group who continue to work in either formal or informal sectors. In studies examining health and social outcomes, employment is often regarded as a component of overall well-being and social productivity (Siegrist et al., 2004). For this study, older persons are defined as individuals aged 60 to 64 years who are economically active, which means they are either employed or seeking employment. This aligns with the classification used by the Department of Statistics Malaysia (DOSM, 2025).

In Malaysia, several studies have examined labour market dynamics using time series and econometric techniques. Lim, Abdul Rahman, and Arsad (2021) investigated gender-based determinants of the labour force participation rate and identified key socio-economic influences, though their focus was not on older age groups. Nor et al. (2018) compared Double Exponential Smoothing and Holt's Exponential Smoothing with the Box-Jenkins approach when forecasting unemployment and concluded that exponential smoothing models perform well for short-term forecasting. Similarly, Ismail, Ramzi, and Mah (2022) applied ARIMA and ARFIMA models, while Ramli et al. (2024) utilised stochastic mortality models to forecast retirement periods, demonstrating the usefulness of time series forecasting for Malaysian labour data. Other research, including Romzi and Hamdan (2022) and Ni et al. (2021), implemented multiple regression analysis to investigate the impact of inflation, urbanisation, unemployment, foreign direct investment, and GDP growth on labour force participation. These studies collectively highlight the applicability of time series and regression methods to Malaysia's labour data. However, most concentrate on overall participation or unemployment rather than specifically on older workers.

Internationally, various forecasting models have been used to study labour force participation. Frees (2003) developed stochastic and autoregressive models using longitudinal data to forecast participation rates in United States, while Kashkooli (2018) applied regional time series forecasting to labour force data in Maine. In the Philippines, Leynes (2021) employed multiple regression to identify the economic determinants of labour force participation, including employment rate, underemployment, gross national income, and GDP. Researchers have also adopted fuzzy time series approaches to address uncertainty and nonlinear patterns in labour data, which have shown promising results for social and economic forecasting. Complementing these quantitative efforts, Barusch, Luptak, and Hurtado (2009) reviewed international policy measures supporting older adults' continued participation in the labour market. It identified flexible work arrangements and retaining opportunities as effective interventions.

Overall, the literature demonstrates that time series forecasting models, such as exponential smoothing and ARIMA are widely applied in labour market analysis. However, there remains limited research that specifically forecasts the labour force of older persons. Existing Malaysian studies have primarily focused on aggregate youth unemployment rates, leaving a notable gap in understanding the trends and potential of the ageing workforce, specifically the 60 to 64 age cohort. Addressing this gap through empirical forecasting is crucial for informing evidence-based policymaking, particularly in areas of productive ageing, reskilling, and inclusive employment.

## METHODOLOGY

This study forecasts the labour force of older persons (aged 60 to 64) in Malaysia using official data obtained from the DOSM. This age group represents the upper segment of the working age population, a critical demographic for analysing extended working lives. The dataset spans from 1982 to 2024, offering a comprehensive historical record suitable for time series modelling. The data partitioning follows the robust forecasting framework established by Hyndman and Athanasopoulos (2021), where the training set (1982 to 2021) was used to estimate and select the best model. Specifically, the first 32 observations were used to set the model parameters and observations from 2014 to 2021 were used to compare different models for performance evaluation. The test set involving observations from 2022 to 2024 were served as a real world benchmark to verify the model's forecasting accuracy.

Four time series approaches were employed to forecast labour force trends, namely double exponential smoothing (DES), Holt's exponential smoothing (HES), autoregressive integrated moving average

(ARIMA), and time series regression (TSR). These methods were chosen for their proven performance in empirical forecasting, particularly for economic and demographic data that exhibit gradual upward trends. The DES techniques handle linear trends effectively as it uses a single smoothing parameter $\alpha$. The first ($S_t'$) and second ($S_t''$) smoothed values are used to find the level ($a_t$) as in Equation 1 and trend ($b_t$) as in Equation 2.

$$a_t = 2S_t' - S_t'' \tag{1}$$

$$b_t = \frac{\alpha}{1-\alpha}\left(S_t' - S_t''\right) \tag{2}$$

Where,

$$S_t' = \alpha Y_t + \left(1-\alpha\right) S_{t-1}' \tag{3}$$

$$S_t'' = \alpha S_t' + \left(1-\alpha\right) S_{t-1}'' \tag{4}$$

The forecast for $m$ periods ahead is calculated as in Equation 5.

$$\hat{Y}_{t+m} = a_t + mb_t \tag{5}$$

Meanwhile, HES applies two separate smoothing parameters for the level ($\alpha$) and the trend ($\beta$). This provides the model with greater flexibility to adapt to shifts in the labour force growth rate over time. The equation for level is given by Equation 6, and the trend is given by Equation 7.

$$L_t = \alpha Y_t + \left(1-\alpha\right)\left(L_{t-1} + T_{t-1}\right) \tag{6}$$

$$T_t = \beta\left(L_t - L_{t-1}\right) + \left(1-\beta\right) T_{t-1} \tag{7}$$

where $Y_t$ represents the actual labour force observation at time $t$. The forecast for $m$ periods ahead is given by Equation 8.

$$\hat{Y}_{t+m} = L_t + mT_t \tag{8}$$

The smoothing constants $\alpha$ and $\beta$ are constrained in the range of 0 and 1.

Unlike exponential smoothing, the ARIMA ($p$, $d$, $q$) model is designed to describe the autocorrelations within the time series. This technique is highly effective for data where the current observation depends on previous observations and past errors. It relies on three main components, the autoregressive order

($p$), the degree of differencing ($d$) to achieve stationarity, and the moving average order ($q$). The general equation is given by Equation 9.

$$Y_t' = c + \phi_1 Y_{t-1}' + \cdots + \phi_p Y_{t-p}' + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{9}$$

where $Y_t'$ is the differenced labour force observation at time $t$, $c$ is a constant term, $\phi_1, \ldots, \phi_p$ are the autoregressive parameters, $\theta_1, \ldots, \theta_q$ are the moving average parameters, and $\varepsilon_t$ is the random error at time $t$.

The fourth technique is TSR, which models the labour force as a deterministic function of time. This model is used to identify a steady trend line throughout the historical period. The equation is expressed as in Equation 10.

$$Y_t = \beta_0 + \beta_1 T_t + \varepsilon_t \tag{10}$$

where $Y_t$ is the labour force at time $t$, $T_t$ represents the time index ($t$ = 1, 2, …, $n$), $\beta_0$ is the intercept, $\beta_1$ is the slope coefficient representing the average annual increase in the labour force, and $\varepsilon_t$ is the error term.

The forecasting model performance was assessed using three common error measures, which are mean absolute percentage error (MAPE), root mean square error (RMSE), and geometric root mean square error (GRMSE). These measures were calculated by comparing the actual labour force observations $Y_t$ with the forecasted values $\hat{Y}_t$ over $n$ periods. Each measure reflects a different aspect of model accuracy. MAPE provides a percentage-based interpretation of the average forecasting error, allowing results to be compared across datasets of different scales. It is defined as in Equation 11.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \tag{11}$$

RMSE is the most common error measure for assessing the performance of forecasting models. The formula is given by Equation 12.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \tag{12}$$

It is particularly sensitive to outliers and extreme deviations. Hence, the GRMSE is included since it is able to mitigate the influence of outliers. It is calculated using Equation 13.

$$GRMSE = \left(\prod_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2\right)^{\frac{1}{2n}} \tag{13}$$

The models were estimated and analyzed using SAS and Microsoft Excel. A series of diagnostic checking including residual analysis and stability tests were performed to verify that the assumptions of each model were satisfied. After identifying the best performing models, forecasts of the labour force of older persons were generated for the period 2022 to 2030. A key step in the validation process involved comparing these forecasted values against actual observations from 2022 to 2024. This out-of-sample comparison allowed us to empirically verify the reliability of the chosen model.

## RESULTS AND DISCUSSION

Table 1 summarises the demographic characteristics of older persons aged 60 to 64 who were active in Malaysia's labour force in 2024. The participation among older persons was largely concentrated in urban areas, where 349,100 individuals or 72.4%, as compared to rural locations, which accounted only 27.7% of older workers who were economically active. This pattern reflects where employment opportunities are more accessible, especially for older workers. Labour force participation in both areas was dominated by male with 236,900 individuals in the urban area and 98,100 individuals in the rural area. Older women workers were found more located in urban area (23.3%), while only 7.3% participated in rural area. These figures highlight differences in participation of older women in urban area were likely to be more economically active than those in rural areas. Looking at the ethnic composition, half of the older workers were Bumiputera (50.6%), followed by Chinese workers (38.9%), while approximately 50,000 individuals were Indians, non-Malaysian citizens, together with other ethnics group. In the employment status category, nearly half of older persons in the labour force were employees, totalling 230,700 individuals. A substantial proportion worked as own account workers with 38%, highlighting the importance of self-employment and informal economic activity at old ages. Small numbers were recorded for employers (40,100 persons) and unpaid family workers (17,900 persons). Taken together, the figures show that older Malaysians remain economically active through a range of employment arrangements, shaped by location areas, ethnicity, and work type.

**Table 1**

*Demographic Characteristics of Labour Force Participation among of Older Persons (Aged 60-64) in Malaysia, 2024*

| Characteristic | Category | | Labour Force (Persons) | Percentage (%) |
|---|---|---|---|---|
| Strata | Urban | Male | 236,900 | 49.1 |
| | | Female | 112,200 | 23.3 |
| | Rural | Male | 98,100 | 20.3 |
| | | Female | 35,300 | 7.3 |
| Ethnics | Bumiputera | | 244,200 | 50.6 |
| | Chinese | | 187,800 | 38.9 |
| | Indians | | 27,200 | 5.6 |
| | Others | | 2,600 | 0.5 |
| | Non-Malaysian citizens | | 20,700 | 4.3 |
| Employment Status | Employee | | 230,700 | 49.6 |
| | Employer | | 40,100 | 8.6 |
| | Own account worker | | 176,900 | 38.0 |
| | Unpaid family worker | | 17,900 | 3.8 |

**Figure 1**

*Labour Force Trend of Older Persons (1982-2024)*

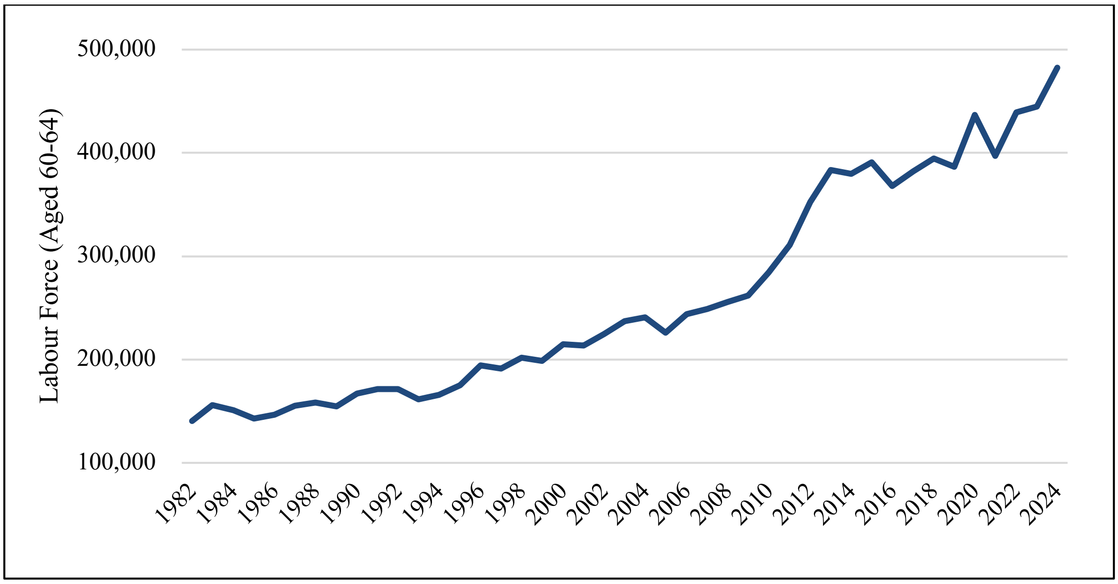


Figure 1 illustrates the number of older persons aged 60 to 64 years in Malaysia's labour force from 1982 to 2024. The overall trend shows a sustained and substantial increase over the past four decades. In the early 1980s, the labour force in this age group stood at slightly above 150,000 persons. The figure then rose gradually throughout the 1990s and early 2000s before accelerating sharply after 2008. By 2024, the labour force in this age group had reached nearly 500,000 individuals, marking a more than threefold increase since 1982. Although the growth trend is generally upward, some short-term fluctuations are visible between 2015 and 2020, reflecting temporary changes in economic conditions and demographic composition. The notable rise after 2020 suggests a renewed interest in labour market participation among older Malaysians, possibly driven by the need for income security and the desire for longer working lives. This continuous increase highlights the growing significance of older workers in Malaysia's labour market and sets the foundation for examining the demographic and employment characteristics of these older persons.

**Table 2**

*Summary of Model Estimation and Evaluation Error Measures*

| Model | Estimation (1982 – 2013) | | | Evaluation (2014 – 2021) | | |
|---|---|---|---|---|---|---|
| | **MAPE (%)** | **RMSE** | **GRMSE** | **MAPE (%)** | **RMSE** | **GRMSE** |
| DES ($\alpha = 0.5$) | 5.07 | 17,113 | 6,885 | 5.07 | 32,085 | 8,914 |
| HES ($\alpha = 0.7$, $\beta = 0.2$) | 4.41 | 13,593 | 6,310 | **4.79** | **30,471** | **13,291** |
| ARIMA (0,2,1) | 4.27 | 10,226 | 7,066 | 6.69 | 34,796 | 18,474 |
| TSR (Cubic) | 7.74 | 22,972 | 11,256 | 5.07 | 21,584 | 19,534 |

This study examined two variations of exponential smoothing to capture the upward momentum of the older labour force participation, as shown in Figure 1. Table 2 summarises the specific parameters for each estimated model and the corresponding error measures calculated from both the estimation (1982-2013) and evaluation (2014-2021) datasets. The first two models are the variations of exponential smoothing aimed to capture the upward trend of the older labour force participation as shown in Figure 1. The estimated smoothing constant of $\alpha = 0.5$ in DES model indicates a balanced approach by giving equal weight to produce a stable forecasting trend. The model maintained a consistent error rate with a MAPE of 5.07% in both estimation and evaluation phases. Unlike DES, HES model was optimised with a level parameter of $\alpha = 0.7$ and a trend parameter of $\beta = 0.2$. The higher value of $\alpha$ suggests that the labour force size is sensitive to recent socio-economic shifts, while the lower $\beta$ value ensures the long-term trend remains steady without being distracted by short-term noise. This flexibility allowed HES to outperform DES by achieving a lower MAPE of 4.79% and the lowest RMSE (30,471) among these two smoothing models in the evaluation phase. This stability makes HES a reliable candidate to forecast ageing workforce trends until 2030.

Preliminary testing of various ARIMA configurations identified (0, 2, 1) as the best performing specification. This model utilises second-order differencing ($d = 2$) to achieve stationarity in the data and a first-order moving average term ($q = 1$) to account for shocks in the series. In the estimation phase, the model appeared promising by yielding the lowest MAPE (4.27%) and RMSE (10,226) among all candidate models. However, its reliability diminished during the evaluation phase, where the MAPE increased to 6.69%. This suggests that while the (0, 2, 1) parameters could closely mimic historical patterns, they may have been too rigid to adapt to the shifting labour market dynamics observed between 2014 and 2021.

Among the various curve estimations tested under the TSR approach, the cubic was found to be the best in explaining 83.6% of the total variation in the data. Even though it had a rough start with the highest error rate (7.74%) in the estimation phase, the rate dropped to 5.07% in the evaluation years. While the model achieved the lowest RMSE (21,584), its highest GRMSE (19,534) indicates that its errors were less consistent and more spread out than those of the HES model.

With the comparison results of all estimated models, HES is chosen as the best performing model for forecasting older labour force trends until 2030. The HES is more consistent across both phases of estimation and evaluation, while the ARIMA was only accurate in the estimation. HES achieved the best balance with a 4.79% error rate in the evaluation phase, making it the most reliable model for predicting the future trend of Malaysia's older labour force.

**Figure 2**

*Forecasting of Labour Force Trends among Older Persons with 95% Confidence Interval up to 2030*

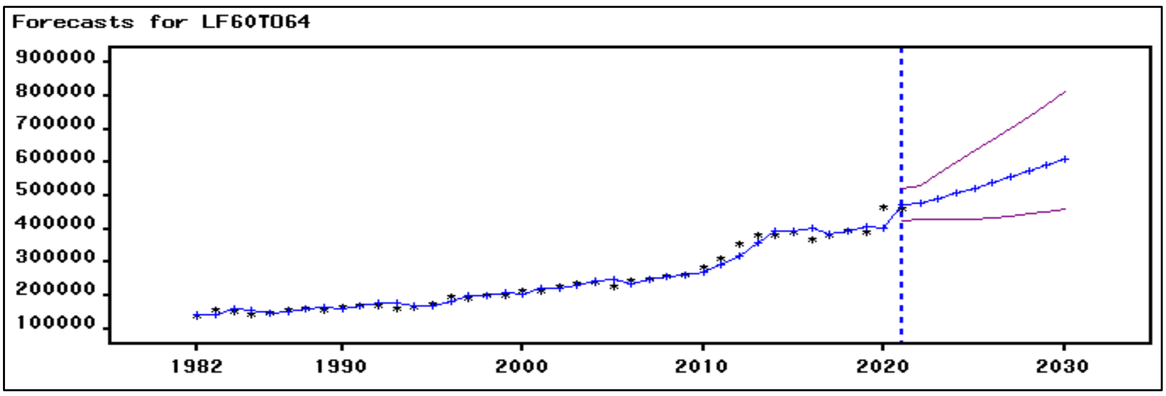

Figure 2 visualizes the trend in the labour force participation of older persons from 1982 to 2030. The forecast trend after 2021 is generated by Holt's Exponential Smoothing (HES) model with a 95% confidence interval indicated by the red line. The forecast for the labour force in the aged group of 60 to 64 anticipates a gradual but consistent increase over the next decade. It shows a clear and steady rise, suggesting that the number of workers aged 60 to 64 will continue to climb, potentially reaching more than 500,000 by 2030. The graph also shows that the 95% confidence interval starts quite narrow and gradually widens as it moves toward 2030. This visual serves as a reminder that while the growth is certain, the specific outcome in 2030 remains subject to the evolving dynamic of the labour market.

**Table 3**

*Comparison of Actual and Forecasted Labour Force of Older Persons*

| Year | Actual | Forecast | Absolute % Error |
|---|---|---|---|
| 2022 | 439,400 | 470,340 | 7.04 |
| 2023 | 444,900 | 478,175 | 7.48 |
| 2024 | 482,500 | 486,010 | 0.73 |

Table 3 shows the results of an ex-post benchmark used to verify the HES forecast accuracy by comparing it against the most recent actual data. This 'reality check' allows us to see how the model's predictions align with the real-world recovery of the labour market between 2022 and 2024. Across the three-year period, the HES model maintained a strong performance with an average error of 5.08%. While the forecast was slightly higher than the actual figures in 2022 and 2023, the gap narrowed significantly by 2024. In that year, the absolute error dropped to 0.73%, showing that the model and reality have almost perfectly converged.

**Table 4**

*Forecasted Labour Force of Older Persons*

| Year | Forecasted Value (persons) | Annual Growth Rate (%) | Cumulative Growth (%) |
|---|---|---|---|
| 2025 | 493,846 | 1.61 | 2.35 |
| 2026 | 501,681 | 1.59 | 3.98 |
| 2027 | 509,516 | 1.56 | 5.60 |
| 2028 | 517,352 | 1.54 | 7.22 |
| 2029 | 525,187 | 1.51 | 8.85 |
| 2030 | 533,020 | 1.49 | 10.47 |

Note: Cumulative growth is calculated using the 2024 actual data as the base year.

Table 4 presents the forecast values for the labour force participation of older persons in Malaysia from 2025 through 2030 with the expected annual and cumulative growth rates. The results reveal a significant trend where by 2030, Malaysia's older labour force is expected to reach 533,020 individuals. This represents a total expansion of 10.47% over six years starting from 2024. Interestingly, while the total number of older workers is rising, the annual growth rate shows a slight decrease from 1.61% in 2025 to 1.49% by 2030. This deceleration in the growth rate suggests that while the 'silvering' of the workforce is a permanent shift, the pace of entry for this age group is beginning to stabilise. However, the cumulative increase of over 10% underscores the importance of preparing for a future where older individuals play an increasingly vital role in the national economy.

## CONCLUSION

The findings of this study have significant implications for Malaysia's labour and social policies as the nation advances under the Thirteenth Malaysia Plan (13MP) for 2026-2030. By utilising the Holt's exponential smoothing (HES) model, which demonstrated high reliability with a 2024 precision rate of 0.73%, this study offers a credible roadmap for the decade ahead. The forecasted upward trend in the labour force participation of older persons aged 60 to 64, reaching 533,020 individuals by 2030, underscores a cumulative expansion of 10.47% from the 2024 base year. This trajectory reflects potential shifts in retirement patterns and extended career engagement, highlighting the evolving dynamics of a maturing workforce.

To address these shifts, policymakers should strengthen initiatives that extend employability through flexible retirement schemes, reskilling programmes, and age-friendly workplace conditions that safeguard the dignity of older employees. Such directions are consistent with the 13MP's focus on inclusive living and contribute to Sustainable Development Goal 8.5 regarding productive employment for all. Future studies could incorporate qualitative factors such as health status and financial literacy, or apply hybrid machine learning models to further refine forecast accuracy across different demographic subgroups. By integrating these measures, Malaysia can better harness the experience of its ageing workforce while sustaining social inclusion and economic stability.

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## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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