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Indonesia Economic Opportunity Report 2026

Methodology Note

AI's impact on innovation

In order to estimate the overall economic opportunity from AI, we:

- Draw on the US O*Net occupation database, which contains information on 51 different types of work activity for around ~800 types of occupations
- Use a series of LLM categorisations to classify the extent to which each work activity is exposed to automation or augmentation by generative AI. This allows us to estimate the proportion of tasks in each occupation that are susceptible to automation.
- Aggregate these results into broader economic categories based on each occupation's share of Singapore's employment and average wage bill, and create our own crosswalk to convert the results from each O*Net occupation to the corresponding occupation in ISCO-08.
- Aggregate by wagebill, occupation and sector to produce an estimate of the total possible improvement in labour productivity.
- Assume capital intensity remains constant, and convert this labour productivity improvement into an overall improvement in GVA.

We then use this model to estimate the ability of AI to augment R&D-relevant tasks and occupations in particular, aggregating up to a global and country-specific level by adjusting for the different R&D workforce composition in each country and existing levels of R&D activity.

For our global baseline, we draw on WIPO's Global Innovation Index estimate of total R&D spending and rebase it into constant 2025 USD using BLS CPI-U data, projecting it forward to 2040 at a 2.5% real CAGR. We apply a 60% labour share to isolate the wage-bill component of R&D expenditure that is susceptible to AI-driven productivity gains, anchored to OECD MSTI and NSF/NCSES estimates of the labour share of business and total R&D.

In order to convert R&D output, we accumulate additional R&D output into a knowledge stock with a five-year innovation lag and a 13.7% annual depreciation rate — both blended from separate values for business R&D (four-year lag, 15% depreciation) and public R&D (7.5-year lag, 10% depreciation) using

OECD GERD sector shares, drawing on Hall, Mairesse & Mohnen (2010) and Pakes & Schankerman (1984).

For the country decomposition, our modelled gains are re-weighted using each country's own R&D workforce composition, drawn from OECD MSTI for OECD members and UNESCO UIS for the rest, supplemented by national statistical sources for Taiwan, Hong Kong, Thailand and Malaysia. Each country's GDP-lens value is split into a domestic-return component, controlled by a retention rate tiered from 50% to 75% by trade openness (anchored to Coe & Helpman (1995), Eaton & Kortum (1999), and Myers & Lanahan (2022)), and an absorbed-spillover component.

Value from encouraging SMB adoption

We estimate the unrealised value from SMBs adopting AI at the same rate as large enterprises by starting with the total AI opportunity in each market from our AI opportunity model.

We allocate a share of this opportunity to SMBs using their structural share of GVA. We draw on national and regional sources for SMB value-added shares, including APEC data and national statistical or government sources.

We then estimate the current AI adoption gap between SMBs and large enterprises. Where available, we use country-level survey data on AI adoption by firm size from IMDA, IBM, and the OECD. For markets without direct country-level data, we apply peer-group benchmark gaps.

To reflect the greater potential upside in less digitally mature markets, we add a digital catch-up premium. This uses a digital intensity index built from country-level indicators including internet access, digital payments, e-commerce, small-firm digital operations, and mobile connectivity. The premium is calibrated using evidence from Brynjolfsson et al. (2025), which finds that lower-skilled workers gained disproportionately from AI adoption. We use this as indicative evidence that businesses and markets starting further behind may have greater catch-up potential from adopting AI, while bounding the premium to reflect institutional and infrastructural constraints.

Finally, we convert the unrealised economic value into labour equivalents by dividing by GVA per worker, drawing on ILO employment data and World Bank GDP data.

ROI from AI adoption

We estimate the return on AI investment for each sector by comparing the realisable productivity opportunity from AI with projected levels of AI spending.

On the opportunity side, we estimate the labour productivity uplift from our AI opportunity model, distributing these gains across sectors using a Eurostat staffing patterns crosswalk on the relationship between occupations and industries.

We convert this into a sector-level productivity opportunity by applying each sector’s GVA and labour share. We use national statistics, UN, and OECD data to estimate sector GVA, and draw on national statistics, OECD, and World KLEMS data to estimate sector-specific labour shares. We then allow adoption to rise over time in our modelling, drawn on observed adoption rates over time from Eurostat and BCG industry adoption data.

On the spend side, we start with IDC's forecasts for APAC AI spending up to 2028, allocating it across markets using GDP and the IMF AI Preparedness Index score, and then across sectors based on their share of national GVA. Spending beyond 2028 is projected using historical patterns from previous technology waves, such as ecommerce and cloud computing.

Finally, cumulative ROI is calculated as the cumulative realisable AI opportunity between 2025 and 2035 minus cumulative AI spend, divided by cumulative AI spend.

New jobs from AI

We combine estimates for three sources of potential AI related employment:

- The first is the **core AI industry (software and services).** For AI services and integration, we use Gartner's global AI Services market sizing, an APAC demand share calibrated to IDC's APAC AI spending track, and revenue-per-employee benchmarks of around $50–60K from major IT services firms (TCS, Infosys), with an adjustment for India. For AI software and platform companies, we use Gartner's parallel AI Software market and a higher revenue-per-employee benchmark calibrated to APAC AI product firms(SenseTime, iFlytek, 4Paradigm).

- The second is **AI-related infrastructure spending in data centres and chips**. We estimate this through a stock-flow capex model grounded in TSMC and Samsung Device Solutions capex disclosures, SEMI global semiconductor equipment billings, and jobs-per-$B benchmarks from TSMC's Arizona project and IMF Working Paper WP/21/131 on infrastructure employment multipliers.

- The third is **potential jobs at AI-enabled new businesses**. We extrapolate this from the ratio between core services / infrastructure jobs and product jobs in the mature internet economy, applying a multiplier to the core AI industry total drawn from the IAB/Harvard Digital Economy Study (2025), which reports both direct and indirect digital economy jobs in the US, cross-checking this against GSMA's APAC mobile economy and CompTIA's tech workforce figures.

Our estimate is deliberately conservative. It does not include wider induced demand for other occupations in the economy, which is likely to be orders of magnitude larger.

Economic Impact of Google Products

We estimate the economic impact of Google's products and services as the direct economic activity generated for businesses, publishers, creators and developers through Google Search, Ads, AdSense, YouTube, Play, Cloud and Workspace.

We estimate the total impact by summing the impact of the following products.

Search and Ads. We multiply the size of the paid search advertising market by Google's share of the search engine market and by an estimated return on advertising spend. We draw on third-party estimates of paid search advertising market size from PwC's Global Entertainment, Media & Telecoms Outlook, Statista Market Insights, and eMarketer, and use StatCounter data for Google's search market share. We apply an 8x return on advertising spend, based on Google's methodology.

Cloud and Workspace. We multiplied the total market size for cloud and workspace products by Google's share of the cloud market. We draw on Statista Market Insights for both the total cloud market size and Google Cloud's market share.

AdSense. We estimate publisher earnings from displaying Google-served ads on third-party websites and apps by taking Google Network revenues from Alphabet earnings reports and multiplying by the share paid to partner publishers through traffic acquisition costs. We then allocate this global publisher income to countries using each country's share of global display advertising spend, drawing on PwC's Global Entertainment, Media & Telecoms Outlook data.

YouTube. We estimate creator earnings from YouTube advertising by taking YouTube Ads revenue from Alphabet quarterly earnings reports and multiplying by YouTube's creator revenue share. We use a default creator share of 55%, based on YouTube's creator economy documentation. We then allocate global creator earnings to countries using each country's share of global video advertising spend, drawing on PwC's Global Entertainment, Media & Telecoms Outlook data.

Google Play. We draw on Sensor Tower data for the app revenue earned by developers through the Play ecosystem.

Economic Impact of Google Products for SMBs

We multiply the economic impact of Google products in each market by an SMB share estimated by combining the economic contribution of SMBs to a market's economy with their digital intensity.

We draw on official national statistics from government or regional economic institutions for SMB contribution to national GVA. These include APEC Policy Support Unit data and OECD SME Policy Index in addition to SMB value-added shares cited by national labour ministries.

We also construct a digital intensity index for each market. This combines five country-level indicators: internet connectivity, broadband access, small-firm digital operations, digital payments usage, and mobile connectivity quality or affordability. We draw on World Bank WDI indicators for internet and broadband access, World Bank Enterprise Surveys for small-firm digital behaviour, Global Findex for digital payments, and the GSMA Mobile Connectivity Index for mobile connectivity.

Jobs from Google Products

We multiply the economic impact of Google products in each market by its labour share of income, drawing on Penn World Tables data to estimate the labour-attributable portion of this activity.

We then estimate GVA per worker in each market, drawing on World Bank and IMF World Economic Outlook data on GVA and GDP as well as ILO data on labour force.

Finally, we divide the labour-attributable impact by GVA per worker to estimate the number of jobs supported.

Exports from Google Products

We estimate the value of exports enabled by Google products by estimating the following export shares to multiply with the economic impact of the relevant Google products:

Search and Ads, Cloud and Workspace, AdSense. We define export share as commercial service exports divided by services GVA, drawn from World Bank data on service exports and services value added. This captures the share of a country's service economy that is outward-facing, and is used as a proxy for the share of Google-enabled activity likely to generate revenue from overseas customers.

We use this same service export ratio for Search and Ads, AdSense and Cloud because all three products primarily support digitally enabled service exporters, including e-commerce sellers, digital marketers, SaaS firms, IT outsourcers, publishers and cloud-enabled platforms. The products differ in the size of their activity base, but use the same export-intensity proxy.

YouTube. We draw on data from the YouTube API to estimate the share of a country's YouTube activity attributable to overseas viewers of domestically produced content, using this as a proxy for export share.

Play. We draw on Sensor Tower data for the proportion of app revenue earned by developers from consumers in other countries.

Consumer Surplus from Google Products

Following Brynjolfsson et al (2019), we used a 'willingness to accept' framing to model the current default hypothetical consumers face. As part of our polling, we asked participants a single discrete binary choice question of "Would you prefer to keep access to [product] or go without access to [product] for one month and get paid [price]" with the price offered randomised between set levels per country.

We regressed the results of this poll to derive a demand curve and used this to calculate total consumer surplus per user. We also scaled this estimate by third party estimates of Internet prevalence and polling information on product usage by country. **To be implemented:** In order to reduce noise, we regressed our country estimates against GDP per capita, and used this to produce our final smoothed per country estimate.

Economic value of generative media for the creative sector

We use our AI opportunity model to estimate the productivity impact of generative media tools, drawing on O*NET task data across 26 core creative occupations as well as creative tasks performed throughout the wider economy. We use a series of LLM classifications to assess both the potential for AI augmentation and constraining factors such as sensitivity, creativity requirements, or intrinsic human value, then aggregate up to sectors and occupations weighted by wagebill, mapping across to international ISCO-08 codes and applying an S-curve adoption model through to 2035. In the second stage, we layer in potential demand effects from new forms, improved distribution and wider economic growth, accounting for price effects, income elasticity, and viability effects as lower costs make marginal creative projects more feasible. We triangulate between historical analogues such as UGC and mobile gaming and a bottom-up estimate of new forms to give a conservative overall figure.

Acceleration of product development

We estimate how much faster start-ups could release new product features by modelling AI's impact across the software development lifecycle.

We first divide the lifecycle into development, QA and testing, design, and project management, using effort-allocation benchmarks from Hypersense Software. We then assign AI speedup assumptions to each stage. For development and QA, we use the AI coding agents methodology, which draws on developer task-share evidence from Atlassian and TideLift / New Stack, with lower-bound adjustments informed by METR. For design, we draw on evidence from Cieden, IDEO / Parallel and Startup House on AI-assisted prototyping and design workflows, while reflecting Nielsen Norman Group's caution that AI-generated designs are not always production-ready. For project management and requirements work, we draw on Noy and Zhang (2023), Dell'Acqua et al. (2026), and Startup House evidence on AI-assisted drafting, synthesis and discovery workflows.

We combine these stage-level effects using Amdahl's Law, so the overall speedup reflects both the size of each stage and the AI speedup within it.

Finally, we adjust the base speedup by country using projected AI adoption in 2035 from the Public First AI adoption model, which combines Google Patents data on AI innovation, Sensor Tower data on consumer AI app usage, and data from various AI model-builders on the use of their consumer and enterprise AI tools. This reflects the extent to which firms in each market are likely to realise the potential speedup from AI tools.

Saving time for teachers

We draw on our AI opportunity model to estimate the country-specific productivity uplift for primary and secondary school teachers from AI.

We then draw on Ministry of Manpower and ILO data on hours worked and employment in the education sector, isolating primary and secondary teacher hours using the share of education-sector employment accounted for by these professions.

We multiply these together and adjust by labour share of income using ILO data so the estimate captures the share of AI-enabled productivity gains that accrue as worker-side benefit rather than being captured as reduced costs or other capital-side gains. Finally, we convert aggregate freed hours into two outputs: total annual hours saved across teachers, and hours saved per teacher per week.

Saving time for doctors

We draw on our AI opportunity model to estimate the country-specific productivity uplift for medical doctors from AI. We take the automatability of doctors' tasks at the occupation level (ISCO-08 group 221, generalist and specialist medical practitioners), wage-bill-weighted using Indonesian employment and wages, focusing on the administrative and documentation tasks that AI can take on rather than direct clinical care.

We then draw on ILO data on hours worked and employment in the health sector, isolating doctors' hours using the share of health-sector employment accounted for by medical practitioners.

We multiply these together and adjust by the health-sector labour share of income (ILO), so the estimate captures the share of AI-enabled productivity gains that accrue as freed clinician time rather than being captured as reduced costs. Finally, we convert the aggregate into hours saved per doctor per week. We cross-check the scale of the administrative burden against time-and-motion evidence on physician documentation load from Sinsky et al. (2016) and Woolhandler & Himmelstein (2014).

Impact of AI education on growth

We estimate how AI-enabled learning could raise student skills and, through a more skilled workforce, Indonesia's long-run growth. We start from an AI learning effect size of around 0.6 standard deviations, the conservative midpoint of six 2025 meta-analyses of AI and generative-AI tutoring (Letourneau et al. 2025, Kestin et al. 2025, Han et al. 2025, Ma and Zhong 2025, Dong et al. 2025, Liu et al. 2025). We convert this into a skills uplift by benchmarking against Indonesia's World Bank Harmonised Test Scores, so the same effect size translates into a larger percentage gain where baseline scores are lower.

We map the resulting skills gain to growth using the Hanushek and Woessmann (2012) framework, in which a one-standard-deviation rise in test scores is associated with around two percentage points of additional annual GDP-per-capita growth.

We then phase the effect over time, combining an AI-adoption path in schools (calibrated to UNESCO and OECD TALIS 2024 teacher-adoption data) with the gradual entry of AI-taught cohorts into the workforce over a 40-year working life. Compounding the annual uplift to 2050 gives the cumulative addition to GDP, which we express using World Bank / IMF GDP projections.

Improving educational outcomes

We estimate how AI-powered educational agents that help teachers tailor lessons to each student's needs could improve learning outcomes in Indonesia. We take an AI-tutoring effect size anchored in Muralidharan, Singh & Ganimian (2019)'s randomised evaluation of personalised adaptive learning and corroborated by a meta-analysis of tutoring trials (Nickow, Oreopoulos & Quan 2024) and a generative-AI classroom trial (World Bank 2024).

We convert this effect size into score points using the standard deviation of Indonesian PISA maths scores, and apply it to every currently below-proficiency student in the OECD PISA 2022 Indonesia student microdata. We then count the share of below-proficiency students whose improved score would cross the PISA Level 2 minimum-proficiency threshold, using OECD and UNESCO / BPS enrolment data to express this as students reaching proficiency each year. The figure is a potential improvement conditional on AI tutoring being available to all lagging students, not an adoption-adjusted forecast.

Enabling digital healthcare

We estimate the downstream cost savings from AI-enabled telemedicine delivering personalised care plans in Indonesia by modelling how a shift toward earlier detection and prevention-focused management could reduce complication costs for three priority chronic conditions: type 2 diabetes, cardiovascular disease, and chronic kidney disease.

We first estimate the avoidable late-stage cost pool for each condition within the national BPJS Kesehatan (JKN) system, drawing on the Indonesian Health Survey (SKI) 2023 and BPJS cost data for diabetes and hypertension, Databoks / Katadata figures on the most expensive chronic diseases, and the Indonesian Renal Registry for kidney failure, with the hypertension- and diabetes-attributable share of cardiovascular and renal costs drawn from INTERHEART and INTERSTROKE.

We then apply an AI-enabled shift rate, representing the share of priority cases that could be moved into earlier-stage detection and management under full adoption. This is based on a conservative reading of evidence from AI clinical decision support and earlier-intervention studies, including Romero-Brufau et al (2020). on AI-enabled readmission reduction, Lin et al. (2024) on AI-enabled ECG alerts, and clinical trial evidence from Steno-2 and UKPDS on the impact of intensive early management.

For each condition we estimate the saving from earlier detection as the difference between late-stage and early-stage management costs, apply this to the avoidable pool, and sum across the three conditions. This should be read as a gross annual saving under full adoption, before netting AI deployment or data-infrastructure costs.

Boosting equitable access to healthcare

We estimate the share of the healthy-life-expectancy (HALE) gap between Eastern Indonesia (Kawasan Timur Indonesia) and the rest of the country that AI-enabled care navigation, referral coordination and follow-up could close.

We first construct the gap by taking provincial HALE from the GBD 2019 Indonesia study (Mboi et al. 2022), population-weighted using the BPS 2020 census into an Eastern-Indonesia average and a rest-of-country average, and converting life expectancy to healthy life expectancy using Indonesia's WHO HALE-to-life-expectancy ratio.

We then estimate the per-resident HALE gain AI could deliver across six independent disease channels: maternal mortality, neonatal and under-5 mortality, tuberculosis, hypertension, type 2 diabetes and mental health. For the mortality channels we combine deaths per capita, the share avertable under full-coverage care (Bhutta et al. 2014), and the coverage improvement AI-enabled navigation could achieve, using meta-analytic effect sizes for mobile-health and digital-health interventions (Gayesa et al. 2023, Cheng et al. 2025, Boima et al. 2024, Moschonis et al. 2022, Cuijpers et al. 2022). For the chronic channels we combine at-risk prevalence, the life-years gained from optimal management, and the same digital-health effectiveness evidence.

We sum the channels into a per-resident HALE uplift and express it as a share of the Eastern-versus-Western gap, alongside the aggregate additional healthy life-years across the Eastern Indonesian population. Disease baselines are drawn from Indonesian national surveys (SKI 2023, Riskesdas 2018, SDKI 2017) and WHO disease data.

AI and creative exports

We estimate the additional creative-services exports that AI-enabled creation and localisation could unlock for Indonesia. We start from Indonesia's formal creative-services export base from UNCTAD STAT, and adjust it upward for platform-mediated freelance activity that official trade data under-counts, using an informal-economy multiplier derived from banking penetration in the World Bank Global Findex.

We then apply two AI uplift channels. A creation channel captures production-side productivity gains from generative AI using an uplift from McKinsey (2023). A localisation channel captures wider overseas market access when AI translation lowers language barriers, using the trade uplift from Brynjolfsson, Hui & Liu (2019)'s study of machine translation on a large digital marketplace; to avoid double-counting with the informal adjustment, we apply the localisation uplift only to the formal export base.

Improving paediatric health outcomes

We estimate AI's impact on paediatric health in Indonesia through two mechanisms.

For health outcomes, we build an in-scope paediatric disease burden in disability-adjusted life years (DALYs) across the conditions with direct AI outcome evidence: low-birth-weight neonatal mortality, childhood cancer and congenital anomalies, using global disease burden data with Indonesian child-mortality and low-birth-weight figures from the UN and World Bank. We credit AI only where published outcome evidence exists, principally the HeRO heart-rate-monitoring trial (Moorman et al. 2011) showing a 22% reduction in low-birth-weight neonatal mortality, plus AI-accelerated drug discovery reaching childhood cancer and rare disease. Summing the DALYs averted and dividing by the in-scope burden gives the percentage improvement in outcomes.

For drug development, we take a drug-mix-weighted paediatric development timeline, built from adult cycle times (Paul et al. 2010) plus the additional paediatric and orphan-drug stages, and apply the share of the development lifecycle AI can compress (Agarwal et al. 2026) to estimate the years saved. We convert additional treatments into lives and life-years using Lichtenberg (2019)'s estimate of life-years gained per new drug.

Polling claims

Polling claims are derived from a survey of 1,026 online adults based in Indonesia in March 2026, conducted in English and Indonesian. All results are weighted using Iterative Proportional Fitting, or 'Raking'. The results are weighted by age group, gender, and education level to nationally representative proportions.

We used a range of different panel providers who contacted respondents on our behalf. In return for their participation in our survey, respondents were provided with a financial incentive.

Like all polling data, market research is susceptible to poor memory or consumers not answering truthfully. In order to reduce the risk of this, we completed a number of standard quality checks on the polling data to help ensure that respondents are paying attention:

- Excluding respondents who take too long to answer;
- Excluding respondents who 'straight-line', eg. always picking the top or left most option to every question;
- Excluding respondents who fail an attention check, eg in the middle of a longer question, we ask them to pick a particular option if they are reading;
- Excluding respondents whose answers all perfectly match another;
- Excluding respondents whose open text answers are incoherent or look like they have been generated by a computer bot.