Vietnam’s AI Roadmap.
Leveraging AI in Vietnam’s most promising sectors.

Methodology Note

Polling

Polling claims derived from a survey of **1,077** online adults based in Vietnam in February 2025, conducted in English and Vietnamese. All results are weighted using Iterative Proportional Fitting, or 'Raking'. The results are weighted by age group, gender, education level, and region 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.

Potential economic impact of gen AI

Our headline estimate for the potential impact of AI is based on the Goldman Sachs methodology for calculating the growth and productivity impact of AI.

In order to estimate the economic impact of 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
- Based upon Goldman Sachs' identification of the types of tasks exposed to automation by generative AI, classify the proportions of tasks in each occupation that are susceptible to automation.

- Aggregate this into broader economic categories based on their overall share of US employment and average wage bill, and then create our own crosswalk to convert the results from each 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.

Proportion of workers likely to be augmented by, insulated from or at risk of displacement from AI

Based on our model for the potential economic impact of AI, we look at the modelled automability of each occupation and categorise them into one of three groups:

- **Augmented roles** are occupations which exceed a threshold level of automatability, and for which workers are likely to see significant productivity improvements from AI. However, automatability is not so high that AI is likely to be able to take over the whole role in the short to medium term.

- **Insulated roles** fall below our threshold for significant automatability, and are unlikely to be affected by AI in either a positive or negative manner.

- **Risk of displacement roles** exceed our higher threshold for automatability, and are at potential risk of complete replacement by AI. (Even here, however, this is just a measure of technical possibility, rather than a prediction that this will in practice take place.)

Potential from AI to save time in administrative tasks

We use our polling data to identify the number of hours the average worker spends on administrative tasks that could be automated by AI, calibrating the results against time use surveys of the labour force conducted in the APAC region and elsewhere.

We then apply to this an assumption of overall time that can be saved, based on a combination of our core AI model and a literature review of estimated potential time savings that have been found so far.

Potential from AI to boost worker productivity and wages

This is based on:

- Our overall estimate of average automability or labour productivity increases across the economy.
- Adjusting for average labour income share.

Potential from AI to boost worker skills

We estimate the potential impact of AI driven upskilling on human capital by combining:

- Data from the literature on AI's relative impact on worker productivity across the skills distribution.
- Our estimate of the human capital contribution to the growth gap between each country and the frontier leader, here taken as Singapore. We draw on data from Penn World Table (10.01) to perform our own growth accounting exercise, applying an augmented Cobb-Douglas framework to decompose output per worker difference

Impact of not overcoming AI divide

To quantify the economic impact of not overcoming the AI adoption divide we:

- **Quantify Adoption Differentials:** We leverage our polling data to estimate gender- and age-specific self-reported AI adoption rates within the workforce. These differentials represent the "adoption gap."

- **National Adoption Gap Estimation:** The identified adoption gaps are then applied to ILO statistics on national employment, disaggregated by gender and age cohorts. This allows for the calculation of an aggregate national reduction in AI adoption attributable to these demographic disparities.

- **Modeling GVA Impact under Differential Adoption Scenarios:** We employ a dynamic model projecting the trajectory of generative AI (gen AI) adoption in the workplace. This adoption model is integrated with our headline AI impact model, which quantifies the relationship between AI adoption and Gross Value Added (GVA). This integrated framework allows us to simulate two GVA trajectories:

    - A baseline scenario reflecting projected GVA uplift assuming the persistence of current gender and age-specific adoption gaps.

    - A counterfactual scenario projecting GVA uplift assuming the elimination of these adoption gaps (i.e., uniform adoption rates across demographic groups).

Potential impact of AI on cybersecurity

We estimate the cost savings from AI through:

- **Estimating total cost of data breaches:** We calculate the total cost of data breaches by country using existing third party cost-per-breach estimates, such as the Surfshark dataset on recorded breaches.

- **Faster responses to data fraud:** We then apply IBM's reported 33% cost reduction from AI-driven rapid response yields potential savings, adjusting for each country's cybersecurity readiness and AI adoption levels.

- **Preventing phishing:** We estimate national phishing costs using country-specific reports (e.g., Singapore's 2024 Cybercrime Brief) or, where unavailable, DMARC phishing data combined with regional averages. AI's effectiveness (95–99.5% accuracy versus 96% human accuracy) informs estimated savings from reduced phishing success rates. Results are adjusted by country-specific AI adoption and cybersecurity readiness.

Economic Impact of Google Products

Our headline estimate is the sum of our estimates for:

- **Google Ads:** We use third-party data to estimate the total size of the Google Ads market in each country, taking the most conservative estimate of the paid search advertising market from PWC's Global Entertainment, Media & Telecoms Outlook, Statista and eMarketer, and combining this with Statcounter's estimate of Google Search's market share per country. Following the methodology of the US Google Economic Impact Report, we then scale this revenue by an assumed Return on Investment (ROI) factor of 8.

- **AdSense:** Global AdSense revenue is estimated using Google's published Network Revenue, with an assumption for the proportion of Traffic Acquisition Costs going to publishers based on historical data. This is then apportioned to different markets based on each country's overall share of the global display advertising market.

- **Play:** The Android app economy's impact is estimated using total app revenue data from SensorTower.

- **YouTube:** Total YouTube ad spend is estimated by applying the country's share of global video display spending to YouTube's published global ad revenue. This is then adjusted based on an assumed revenue share going to creators.

- **Google Cloud:** The total economic activity is estimated by multiplying Google's cloud market share by the total public cloud market size in each country, drawing on data from Statista.

We then convert this into an equivalent number of jobs supported by dividing our estimate by GVA per worker per country.

Consumer surplus from Google's products

Following the methodology of 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. 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. Finally, we scaled this estimate by third party estimates of Internet prevalence and polling information on product usage by country.

Potential impact of AI on manufacturing

We estimate the potential impact of AI on the manufacturing sector through its impact on three channels: (a) supply chain optimisation, (b) downtime reduction, and (c) defect minimisation. For each channel, we apply a per firm efficiency gain from AI from the relevant literature and apply it to the total spending in that area across the sector. We sum efficiency gains across channels to estimate the total potential increase in manufacturing output from AI.

Potential impact of AI on education

To estimate the potential impact of AI-powered digital tutors on access to education, we multiply the following together:

- **The number of people who did not complete secondary education**. This represents the total addressable market for AI-powered digital tutors supporting formal education. We estimate this by multiplying a country's population by the proportion of citizens who did not complete secondary school. We draw on United Nations data for population and Our World in Data analysis on the completion rate for secondary education.
- **Propensity to use AI-powered digital tutors**. We draw on Public First consumer polling on the percentage of citizens willing to use AI-powered digital tutors to further their formal education, adjusting for the online nature of sample collection with smartphone and Internet penetration rates from the International Telecommunications Union (ITU).

Potential from AI to boost digital trade

We run a trade gravity model to estimate current levels of bilateral trade for countries in APAC, applying the WTO's index of trade costs and export costs as a 'distance' parameter representing barriers to trade.

We then estimate a reduction in language and regulatory barriers due to AI automating translation and simplifying regulatory complexity, using existing pilots of AI tools and academic analysis to guide the size of this reduction.

We apply this estimated reduction to the coefficient estimate associated with our distance parameter from our gravity model to identify the value of the additional exports enabled by AI.

Potential impact of AI on agriculture

We combine estimates based on:

- **Optimising yields.** We collect data on total agricultural output, including crop and livestock production, using national datasets where available and USDA data for countries without detailed yield information. We then apply an estimated yield increase, based on a literature review of existing studies,to project the impact of AI on agricultural output. These estimates are then adjusted for country-specific factors, particularly farm size and capital intensity, as larger farms are more likely to adopt AI technologies. Finally, the projected increase in agricultural output is combined with international market price data from FPMA to estimate the total market value of AI-driven productivity gains.

- **Reducing costs.** We start by estimating the key inputs in the agriculture sector, including fertiliser, water, and labour, using World Bank data on fertiliser use, agricultural water consumption, and national employment statistics. The cost of these inputs is then calculated by combining input quantity estimates with price data, sourced from the World Bank Commodity Prices dataset for fertiliser costs, commercial water prices by country, and wage data from national accounts or ILO estimates where necessary. To assess the potential impact of AI, a literature review is conducted to obtain estimates of cost reductions, split by reduction in fertiliser use, water use and labour costs. As above, we then adjust for country-specific factors, before aggregating into our final estimate.

Potential impact of AI on tourism

We estimate the potential impact of AI on tourism for smaller businesses by multiplying the following together:

- **Total market size for tourism**. We derive this from World Bank data on a country's total receipts from tourism
- **AI-driven productivity gain for tourism**. We draw on Public First's headline model for the **potential economic impact of gen AI**, identifying the labour productivity gain from AI in key sectors for tourism. We then calculate an average for the overall increase in productivity, weighting by each sector's relative contribution to tourism. We draw on data from the National Statistical Office of Vietnam for the contribution of different sectors, adjusting this for other markets using I-O tables and price ratios.
- **SME share of GDP**. We draw on OECD data and policy reporting for this.

AI and Digital Infrastructure supporting FDI

First, we assemble a dataset of existing data centre facilities, including delivery year and power capacity in megawatts (MW), using publicly available commercial datasets on data centre footprints in the region and facility-level information from industry directories and operator disclosures. We then estimate future capacity by applying compound annual growth rates (CAGR) derived from this historical build-out and validate against industry forecasts for APAC hyperscale and colocation expansion.

We convert projected MW growth into investment using case studies from data centre developers and industry analysts on construction costs. Multiplying these cost-per-MW estimates by each country's projected MW growth gives the direct investment requirement, which we treat as inward FDI under the assumption that foreign providers dominate hyperscale investment across APAC.

We then estimate knock-on investment effects by applying an economic multiplier for the indirect and induced economic activity generated from direct data centre investment. To convert this additional activity into an FDI estimate, we draw on World Bank data on the ratio of FDI inflows to GDP for each country. This allows us to estimate the share of the indirect economic activity that would plausibly materialise as further inward investment.

We sum direct investment from new data centre capacity and indirect investment from spillover effects to estimate the total downstream FDI effects of AI investment.