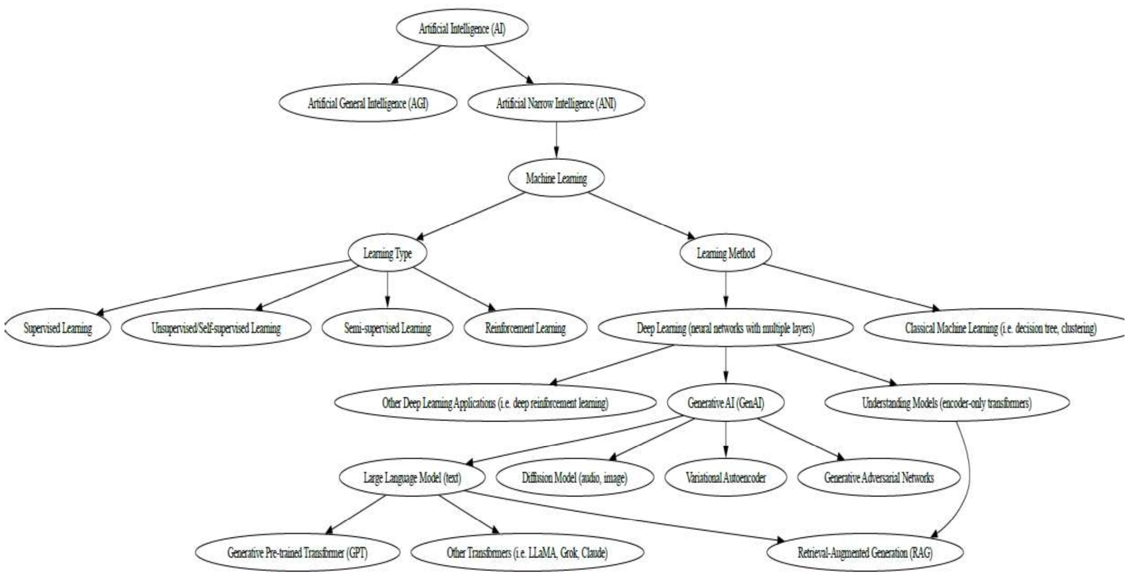
2. Labor Market Exposure to GenAI—The Case of Brunei [55]

1. Recent advancements in GenAI are pushing the boundaries of technological capability and redefining the very nature of work. With increasingly multimodal capabilities and a rapidly expanding range of applications, GenAI distinguishes itself in both scope and speed of diffusion. Early studies have produced highly divergent estimates of AI's automation potential, driven by differences in methodologies and underlying assumptions. More recently, a growing body of research has assessed GenAI-driven automation risks using novel approaches that leverage Large Language Models (LLMs) as domain-specific evaluators. LLMs—a class of GenAI models built on neural network architectures, particularly transformers (Figure A2.1) [56]—are trained on vast amounts of text to understand and generate human-like language. Their applications as analytical tools have expanded rapidly across disciplines, although ongoing scrutiny remains over their reliability, validity, and suitability for structured evaluation tasks. [57] Against such backdrop, this Selected Issue adopts and extends a task-based framework, utilizing LLMs in combination with detailed labor force employment data, to assess occupational exposure to Generative AI in Brunei.

Figure A2.1: AI Diagram



Source: AMRO staff compilation

Data and Methodology

2. To assess labor market exposure at the job task level for each occupation, this study relies on the latest International Labor Organization (ILO) occupation classification and task descriptions. Specifically, the ILO's ISCO-08 four-digit classification

[55] Prepared by Xianguo Huang, Senior Economist.
[56] This research stream, initiated by Eloundou et al. (2023), has since expanded with global analysis by Gmyrek et al. (2023) and a China-focused study by Chen et al. (2023). Colombo et al. (2024) applied internal LLM evaluations to estimate AI exposure in the U.S. labour market, while Gmyrek et al. (2024) compared GPT-4 with human assessments in the UK.
[57] Examples include AI-generated responses in healthcare (Tan et al., 2024), e-commerce reviews (Roumeliotis et al., 2024), climate assessments (Joe et al., 2024), and financial analysis, as in Bybee (2023), which compares AI outputs with human expert judgments.

covers 427 occupations (excluding armed forces occupations), with 3,265 individual tasks evaluated based on their detailed text descriptions of job tasks.[58]

3. **The model was selected to ensure access to the latest knowledge and was instructed to produce more calibrated and structured responses.** Grok-2 by AI was chosen for its up-to-date knowledge base, real-time data integration capabilities, large context window, and ability to deliver calibrated and deterministic outputs. A system prompt was used to guide the model to act as a skills specialist with expertise in AI technologies, while user prompts instructed it to assess all tasks associated with each occupation in a single API call. This batch-processing approach optimized efficiency and minimized latency. The prompts directed the model to generate automation scores and estimate the proportion of time allocated to each task. Meanwhile, by leveraging recent advancements in reasoning models and the availability of larger context windows, additional instructions were incorporated to enhance consistency and strengthen the rigor of the justification process, while employing various prompt techniques to minimize hallucination. [59]

4. **Exposure to GenAI is assessed at a task level and key statistics are used to evaluate associated occupation exposure.** This follows the classification framework proposed by Gmyrek, Berg, and Bescond (2023) and the defined categorization of task and occupation exposure. At the task level, a score of 0.5 as indicative of 'medium exposure' while a score of 0.75 is indicative of 'high exposure' to AI automation. At the occupation level, based on the disaggregated task results, the mean and standard deviation are used to characterize the Occupation Exposure to GenAI with groups such as 'augmentation potential' and 'automation potential', according to the rules defined in Table A2.1.

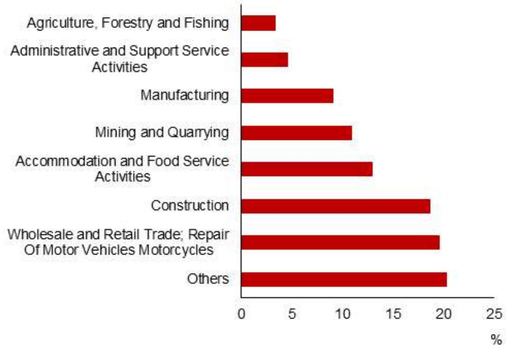
Table A2.1: Occupation Classification Criteria

Category	Criterion 1	Criterion 2
'Augmentation potential'	< 0.4	$\mu + \sigma \geq 0.5$
'Automation potential	>0.6	$\mu - \sigma \geq 0.5$
'Not affected'	< 0.4	$\mu + \sigma \leq 0.5$
'Big unknown'	> 0.6	$\mu - \sigma \leq 0.5$
'Others'	Other unspecified	

Source: Gmyrek, Berg, and Bescond (2023)
Note: μ and σ refer to mean and standard deviation.

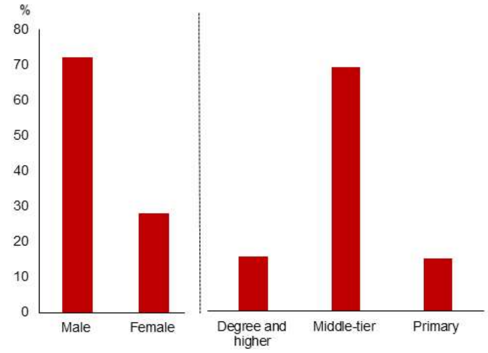
[58] The numbers exclude three occupations categorized under Code 0 (military) and six occupation titles labeled as "not elsewhere classified" across various groups.
[59] It adopted the Chain of Thought (CoT) prompting technique (Chen et al. 2023) to encourage structured and sequential reasoning. Furthermore, the paper applied the "tip and penalize" principle—an incentive-based strategy that explicitly defines rewards for well-reasoned responses and penalties for inadequate ones—as demonstrated by Bsharat, Myrzakhan, and Shen (2023) and Chen and Zhao (2024). Few-shot prompting with a small number of examples also help guide its response to query.

Figure A2.2. Employment by Sector



Source: Employer and Employee Census 2023

Figure A2.3. Employment by Gender and Education



Source: Employer and Employee Census 2023

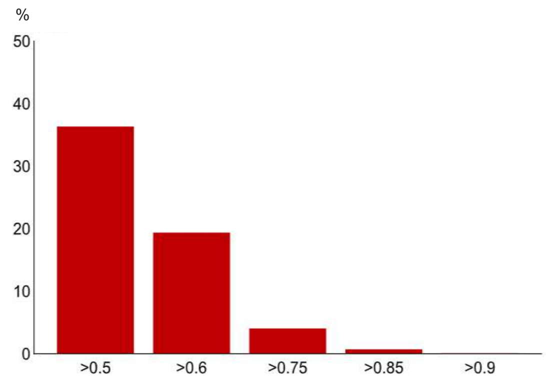
5. A detailed breakdown of Brunei's private sector employment reveals key sectoral, educational, and gender patterns shaping the labor market. Detailed data by economic sector, gender, education level, and ISCO-08 4-digit occupation codes, cover private sector employment, excluding private household services (e.g., domestic helpers), and provide a comprehensive snapshot of Brunei's labor market.[60] As shown in Figure A2.2, wholesale and retail trade, construction, accommodation and food services, mining and quarrying, and manufacturing—collectively account for 71.6 percent of total employment. Male workers, workers with primary education, or with degree and higher qualifications accounted for 72.1 percent, 14.9 percent and 15.6 percent respectively (Figure A2.3).

Key Findings

6. A bottom-up approach analyzing task exposure suggests there is a small share of tasks that is highly exposed to GenAI automation potential. At the task level, associated with 3265 task descriptions, one-third of tasks are found to exhibit medium exposure and only about 3 percent of tasks are evaluated to be at a high exposure to GenAI automation potential (Figure A2.4 and Figure A2.5). For example, those tasks with the highest score of automation potential include i) recording notes for follow-up actions, updating marketing databases, and maintaining call statistics by contact center salespersons in high-income and middle-income countries; and ii) issuing tickets, passes and vouchers by travel consultants and clerks in middle-income countries. Tasks with the lowest score (0.00) are consistently associated with athletes and sports players across all country groups, reflecting the nature of physical, real-time decision-making tasks that remain beyond GenAI capabilities.

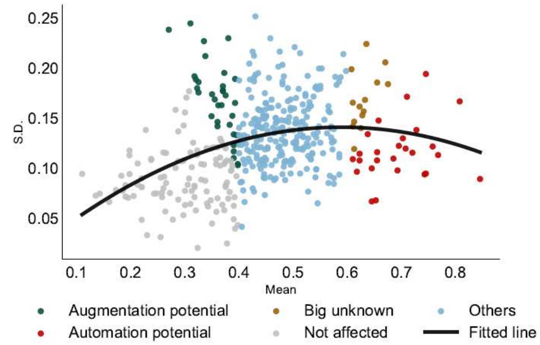
[60] Brunei labor market data of employment by occupation is based on the Employer and Employee Census 2023.

Figure A2.4. GenAI Exposure Score at Task level (Share, Above threshold)



Source: AMRO staff estimates

Figure A2.5. GenAI Exposure Score Mean and Standard Deviation (Occupation level)



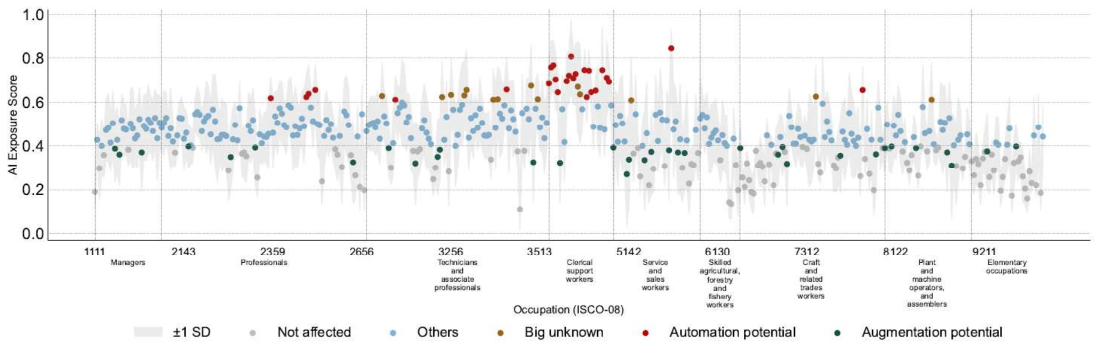
Source: AMRO staff estimates

7. **Most occupations highly susceptible to GenAI automation risk are characterized by repetitive and rule-based tasks.** Aggregating tasks under each occupation leads to exposure scores at the occupation level, of which key statistics are used to differentiate occupations in terms and automation and augmentation potential.

- Occupations with high automation potential—characterized by a high mean task score and low variance across tasks—comprise 5.6 percent of the occupation list. In contrast, occupations with high augmentation potential—marked by a low mean task score and significant variance across tasks—represent 8.2 percent (see Figure A2.6).

- These findings highlight the dual role of GenAI in potentially displacing certain job functions while enhancing others, reflecting the nuanced interplay between automation and human capability in work execution. Of the 24 occupations identified as having high automation potential, 20 are clerical support-related roles, characterized by repetitive and rule-based tasks, while the remaining four encompass professionals, technicians, and associate professionals, such as those in technical or academic fields. In contrast, occupations with high augmentation potential—where GenAI enhances rather than replaces human effort—span a more diverse range of job types. These include managers, who may leverage AI for decision-making support; professionals, such as professors, who could integrate AI into research or teaching; and elementary occupations, where routine tasks might be complemented by AI-driven tools. This diversity underscores the varied impact of GenAI across the occupational spectrum, reflecting its capacity to both streamline efficiency and amplify human capabilities.

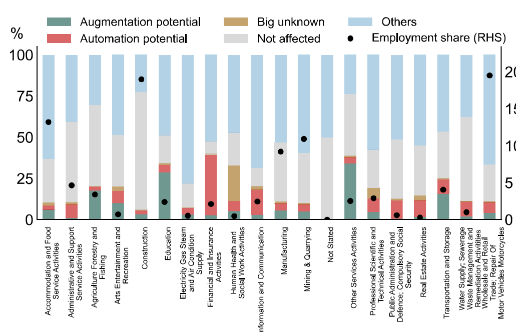
Figure A2.6. GenAI Automation Exposure across Occupation



Source: AMRO staff estimates

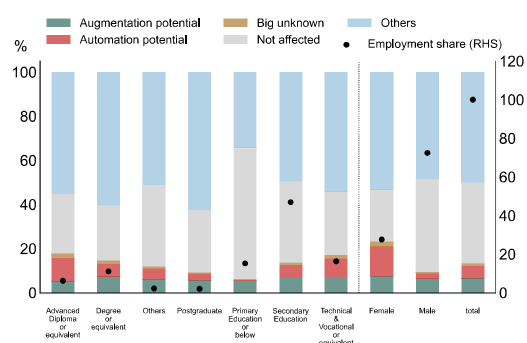
8. The financial and insurance sectors are most exposed to GenAI risks but they have a limited share in total employment. Combining occupation classification with detailed employment information in Brunei's labor market, GenAI exposure for each economic sector could be assessed. As depicted in Figure A2.7 (dots aligned with the right-hand axis), sectors with elevated automation potential include financial and insurance activities, followed by some government-related domains and professional, scientific, and technical activities. By contrast, sectors with pronounced augmentation potential—where GenAI amplifies human capabilities rather than supplants them—span education, other service activities, and transport and storage.

Figure A2.7. AI Exposure by Sector



Source: AMRO staff estimates
Note: Economic sectors are categorized based on the primary activity of companies.

Figure A2.8. AI Exposure by Education and Gender



Source: AMRO staff estimates
Note: "Others" in education category is dropped.

9. Workers with low and high levels of education have relatively lower exposure to automation potential, compared to those with middle-tier education qualifications. Individuals with lower qualifications (e.g., primary education) or advanced credentials (e.g., postgraduate degrees) experience lower exposure, likely reflecting some non-standardized demands of higher-tier roles or labor-intensive ones. Middle-tier qualifications—including secondary education, advanced diplomas, undergraduate degrees, and technical or vocational training—show a higher exposure not only to automation, but also augmentation.

10. Looked by gender, females encounter greater automation risk than males—a pattern echoing global findings—while augmentation potential remains broadly

equivalent across genders. Quantitatively, Brunei's labor market shows 5.4 percent of employment at risk of automation and 7.9 percent poised for augmentation (Figure A2.8). Comparatively, Gmyrek et al. (2023) estimate that in high-income economies globally, 5.1 percent of jobs are automation-prone and 13.4 percent augmentation-prone, with female employment facing double the automation risk of male employment.[61]

Discussions

11. Given Brunei's labor market structure, overall exposure to GenAI remains relatively limited for now. On balance, augmentation potential tends to outweigh automation risk, reflecting a labor market where GenAI is more likely to complement rather than replace human work. Nonetheless, specific occupations—particularly clerical and support roles—face elevated exposure due to the nature of their tasks, such as data entry, document processing, and routine correspondence, which are highly amenable to automation or enhancement through GenAI. High-exposure sectors, including financial and insurance services as well as administrative and support service activities, are especially vulnerable given their reliance on structured, rule-based processes. In such roles—for example, insurance underwriters or paralegals—GenAI may either displace workers or significantly alter workflows toward AI-assisted models.

12. However, the impact could be amplified via indirect channels which have not been captured in this study, and become more prominent with continued AI progress. The current measurement approaches typically overlook second-order effects and general equilibrium dynamics. For instance, within a single occupation, workers whose productivity is significantly enhanced through AI augmentation may outcompete peers with lower productivity gains, especially if labor demand does not expand proportionally in the short term. This dynamic could lead to a paradox where even occupations with high augmentation potential face displacement pressures—not through direct automation, but via intensified intra-occupational competition. In addition, as pointed out by Acemoglu and Restrepo (2022), the general equilibrium effect with changes in industry composition and due to task reallocation, could lead to profound second-round effects and is beyond the scope of the current study. Looking ahead, AI exposure is likely to intensify as technology progresses where GenAI-driven augmentation evolves.

13. Policy makers are encouraged to enhance data adequacy to effectively monitor the development of AI use and understand the potential impact of AI. Addressing existing data gaps is a critical starting step and multiple existing survey channels could be utilized to serve this purpose. These include the annual Labour Force Survey conducted by Department of Economic Planning and Statistics (Ministry of Finance and Economy), Annual Employer and Employee Census by Department of Labour (Ministry of Home Affairs), or monthly survey to construct Business Sentiment Index by the Brunei Darussalam Central Bank. A new standalone survey could also be considered to allow greater flexibility. Strengthening mechanisms such as targeted workforce development, re-skilling initiatives, and adaptive

[61] A distinct 'big unknown' category emerges across specific sectors and education levels, encompassing occupations that exhibit both high average task scores and significant task-level variability. This group spans diverse fields, including healthcare and social work, arts and entertainment, financial services, professional sectors, and real estate. The pronounced heterogeneity within this category amplifies uncertainty regarding GenAI's ultimate net and realized impact.

social protection policies would also be critical to ensuring that the gains from AI are inclusive and aligned with national development goals.

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