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# Evaluating the risk of job displacement by transformative AI automation in developing countries: A case study on Brazil

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## Abstract

Transformative Artificial Intelligence (TAI) has the potential to cause large-scale displacement of jobs through automation, yet empirical evidence remains scarce. In this paper, we introduce an empirical and reproducible approach to monitoring job displacement by TAI. We first classify occupations based on current prompting behavior from a novel dataset from Anthropic, linking 4 million Claude Sonnet 3.7 prompts to tasks from the O\*NET occupation taxonomy. We then develop a seasonally-adjusted autoregressive model based on employment flow data from Brazil (CAGED<sup>1</sup>) between 2021 and 2024 to analyze the effects of diverging prompting behavior on employment trends per occupation. We conclude that there is no statistically significant difference in net-job dynamics between the occupations whose tasks feature the highest frequency in prompts and the ones with the lowest frequency, indicating that current AI technology has not initiated job displacement in Brazil.

*Keywords:* Transformative AI, job automation, job displacement, employment, Claude Sonnet 3.7, occupations

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<sup>1</sup> Cadastro Geral de Empregados e Desempregados

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## 1. Introduction

Transformative Artificial Intelligence (TAI) can provide many opportunities to enhance labor productivity by automating tasks, thus saving time and effort. However, the exact impact of TAI on labor markets is still uncertain. As we expect to witness further advancements in artificial intelligence, the way the world's economy functions will be disrupted with distributional implications in terms of employment. The World Economic Forum *Future of Jobs 2025* survey shows that 86% of employers ranked digital access and artificial intelligence as the top macrotrend transforming businesses by 2030<sup>2</sup>. Policy makers need to foresee potential challenges and be prepared to tackle them ahead of the curve.

This paper assesses the economic implications of TAI on job tasks to understand the risk of job displacement and job elimination through job automation in developing economies. This research falls under the distribution track of the Economics of Transformative AI research with BlueDot Impact & Apart Research. The research seeks to determine if occupations with higher levels of empirical use of Claude Sonnet 3.7 for automation tasks versus occupations with higher levels of empirical use of Claude Sonnet 3.7 for augmentation tasks, compared to occupations with low levels of Claude Sonnet 3.7, present different net job trends between 2021 and July 2024.

### Understanding the Anthropic Economic Index and Claude Sonnet 3.7

It is important to distinguish between AI and TAI. TAI refers to advanced AI systems capable of significantly altering how economic tasks are performed<sup>3</sup>. Unlike narrow AI which is designed for specific functions, TAI possesses broad capabilities that enable it to innovate across multiple industries, ranging from automation of routine tasks to augmenting human decision-making. TAI is expected to have profound impacts on both high- and low-income economies, particularly by disrupting existing labor markets, reconfiguring skill demands, and potentially creating new economic opportunities<sup>4</sup>. The rise of TAI presents a dual-edged sword: while it can drive efficiency and productivity, it also raises concerns regarding job displacement, wage inequality, and the reorganization of work itself.

In developing economies, the consequences of TAI adoption are particularly complex. Developing economies, typically characterized by lower income levels, emerging infrastructure, and higher rates of informal work, face unique challenges with advanced technologies. The potential for TAI to either replace or augment existing job functions in these contexts warrants further investigation, particularly in how countries like Brazil may experience these shifts. The effect of

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<sup>2</sup> The Future of Jobs Report. 2025. World Economic Forum. Accessed at: <https://www.weforum.org/publications/the-future-of-jobs-report-2025/>

<sup>3</sup> Gruetzemacher, Ross, and Jess Whittlestone. "The transformative potential of artificial intelligence." *Futures*, vol. 135, Jan. 2022, p. 102884, <https://doi.org/10.1016/j.futures.2021.102884>.

<sup>4</sup> Handa, Kunal, et al. "Which Economic Tasks Are Performed with Ai? Evidence from Millions of Claude Conversations." *arXiv.Org*, Anthropic, 11 Feb. 2025, [doi.org/10.48550/arXiv.2503.04761](https://doi.org/10.48550/arXiv.2503.04761).

TAI in such settings depends on several factors, including the nature of AI adoption, the type of labor market in place, and the strategies adopted by both local governments and employers.

This research builds on recent empirical work by Handa et al. (2025)<sup>5</sup>, who analyzed millions of Claude Sonnet 3.7 conversations to study AI's role across economic tasks. This database offers one of the first large-scale empirical assessments of how AI is used across economic tasks. They find that AI use is more often augmentative (57%) than automative (43%), with higher usage concentrated in mid-to-high wage occupations like programmers and data scientists, and lower adoption in both the lowest- and highest-paid roles.

This study extends their framework to a developing economy, using Brazil as a case study. Our hypothesis posits that: a) job trends for different levels of exposure to automation and augmentation will differ, and b) jobs with high exposure to automation are at a higher risk of being eliminated or experiencing slower job creation than those with low exposure to automation or high exposure to augmentation. By analyzing job trends between 2021 and 2024, we explore how subscription-based foreign AI services might reshape labor markets in developing countries under varying AI adoption scenarios.

## 2. Methods

### Conceptual Framework

We base our analysis on the task-based conceptual framework, following Acemoglu and Restrepo (2019, 2018a and 2018b)<sup>6</sup>. In this framework, the production process depends on tasks that can either be done through labor or capital. Technology can enhance the productivity of the factors of production (labor and capital) in performing these tasks, and it can affect how tasks are allocated between factors of production. This is what is referred to as the *task content of production*. A new technology or automation affects the *task content of production* and as such affects labor demand as follows:

$$\text{labor demand (automation impact)} = \text{Productivity effect} + \text{Displacement effect}$$

The equation shows that the use of automation can increase productivity and value added, but at the cost of labour displacement. Depending on the strength of each factor on the right-hand side of the equation, the labor demand is determined. Also, it is worth mentioning that technologies that have low quality compared to human performance, such as automated customer service, can threaten employment as they do not result in high productivity effects. Therefore, automation net effect depends on the magnitude of productivity and displacement. Following Acemoglu and Restrepo (2019), we prefer a task-based framework as it is superior to a canonical production function in our context. A canonical production function takes the form of  $Y = F(A^K K, A^L L)$  does not provide a realistic description of the problem as it does not examine tasks in the production process.

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<sup>5</sup> Ibid.

<sup>6</sup> Acemoglu D. and P. Restrepo. (2018b). Robots and Jobs: Evidence from US Labor Markets NBER WP No. 23285.

## Data sources and economic indicators analyzed

Three datasets were primarily used for this research. They are the O\*NET<sup>7</sup>-SOC taxonomy<sup>8</sup> from the O\*NET Resource Center, Brazil's official data on hirings and terminations between August 2023 and July 2024 from the Cadastro Geral de Empregados e Desempregados (CAGE, or CAGED)<sup>9</sup>, and Anthropic's Economic Index: Insights from Claude 3.7 Sonnet released on March 2025<sup>10</sup>.

Due to the differences in the taxonomies of the datasets, we did a crosswalk of all three using ChatGPT to establish the uniformity, similarities and relationships between them. Given the short timeframe for the development of the project (3 days), further revision on the output of the crosswalk is required. ChatGPT also provided a level of confidence and a justification for each item in the crosswalk. 41% of the linkages were classified as high confidence (either direct translation or based on previous open-access attempts to link the two datasets), 41% medium confidence (descriptions and scopes are sufficiently similar to make the linkage with confidence), and 10% low confidence (descriptions and scope don't match precisely or are vague, requiring discretion to choose a particular mapping).

CAGE's dataset uses the Classification of Occupation or CBO as its taxonomy for occupation categories. It presents information on hirings and terminations using the Year, Month, Job, Occupation category (CBO) and Net jobs. The CBO has 45 subgroups.

On the other hand, O\*NET dataset adopts "Minor Group" as its taxonomy for occupations in the United States that is occupations such as "pharmacist" and "elementary English teacher" are Minor Groups. ONET has 121 subgroups.

Handa et Al. (2025) uses the CLIO privacy-preserving methodology [Tamkin et al.]<sup>11</sup> to link over 4 million prompts to O\*NET's Taxonomy at the level of tasks. Each prompt was also categorised in terms of whether the exhibited prompting behavior between feedback loop, directives, validation,

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<sup>7</sup> The O\*NET Program is the United State's primary source of occupational information.

<https://www.onetcenter.org/overview.html>

<sup>8</sup> <https://www.onetcenter.org/taxonomy.html>

<sup>9</sup> CAGED is the Brazilian Ministry of Labor's General Register of Employed and Unemployed Workers. <https://www.gov.br/trabalho-e-emprego/pt-br/assuntos/estatisticas-trabalho/novo-caged/2025/fevereiro/pagina-inicial>

<sup>10</sup> Anthropic Economic Index: Insights from Claude 3.7 Sonnet. 2025.

<https://www.anthropic.com/news/anthropic-economic-index-insights-from-claude-sonnet-3-7> Accessed April 2025

<sup>11</sup> Tamkin, M. McCain, K. Handa, E. Durmus, L. Lovitt, A. Rathi, S. Huang, A. Mountfield, J. Hong, S. Ritchie, M. Stern, B. Clarke, L. Goldberg, T. R. Sumers, J. Mueller, W. McEachen, W. Mitchell, S. Carter, J. Clark, J. Kaplan, and D. Ganguli. Clio: Privacy-preserving insights into real-world ai use, 2024. URL <https://arxiv.org/abs/2412.13678>

task iteration, learning and filtered<sup>12</sup> prompts. Tasks with higher ratios of prompts that are feedback loops and directives as automation tasks, while those with validation, task iteration, learning and filtered prompts are augmentation tasks.

The crosswalk is then used to link the CAGE dataset (CBO taxonomy, at the level of subgroup) with the Anthropic dataset (O\*NET taxonomy, at the level of Minor Groups).

The Anthropic datasets provide two quantities that we use: the frequency of the task as a percentage of the total interactions in the dataset, and, for each task, the frequency distribution across the 6 behavior categories mentioned above. By multiplying the first by the latter and grouping between augmentative behavior (validation, task iteration, and learning) and automation behavior (feedback loops and directives), we obtain the frequency of these behaviors as a percentage of total interactions. These values were used to create 4 categories of jobs. The categories are

- a. T10: 10 occupations in Brazil with the highest share of total interactions with Claude Sonnet 3.7
- b. B10: 10 occupations in Brazil with the lowest share of total interactions with Claude Sonnet 3.7
- c. T10aug: 10 occupations in Brazil with the highest share of interactions with Claude Sonnet 3.7 demonstrating augmentative behavior
- d. T10aut: 10 occupations in Brazil with the highest share of interactions with Claude Sonnet 3.7 demonstrating automation behavior

The table with the occupations per category can be found in the appendix.

The CAGED dataset contains monthly net jobs microdata at the level of occupation. The data was aggregated to the subgroup level, using the sum of net jobs as the aggregation method. We used the customized crosswalks to link the data with the O\*NET taxonomy and the Anthropic dataset, including the four categories described above, which were then used for aggregation. The final dataset contains the net jobs per month per category, the percentage of total (global) interactions, the percentage of total (global) augmentative interactions, and the percentage of total (global) automation interactions. During aggregation, we can simply sum the net jobs and the percentage of total (global) interactions.

Given the wide range of net jobs per occupation (from a few hundred to hundreds of thousands per month), we scaled using the mean.

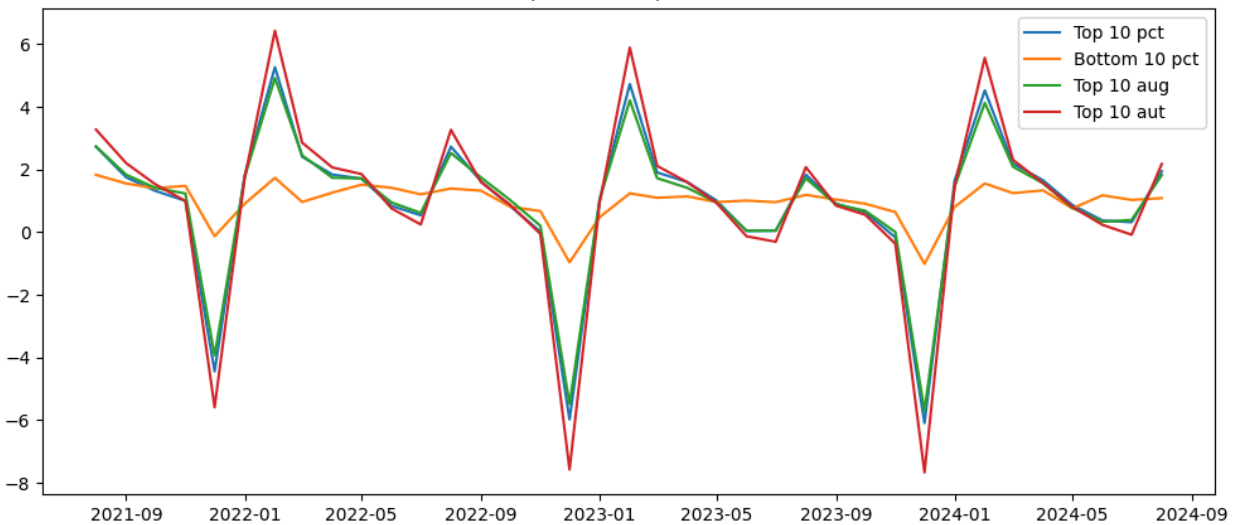
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<sup>12</sup> Feedback Loop Prompts: Prompts that create a cycle of continuous improvement by incorporating evaluation and refinement of previous outputs. Directives Prompts: Clear instructions that explicitly guide the AI toward producing a specific type of response or outcome. Validation Prompts: Prompts designed to verify the accuracy, appropriateness, or quality of AI-generated content against defined criteria. Task Iteration Prompts: Prompts that break complex requests into sequential steps that build upon each other for more manageable problem-solving. Learning Prompts: Prompts that use examples or corrections to help the AI better understand user needs and improve responses within a conversation. Filtered Prompts: Prompts that impose specific constraints or parameters to narrow the scope of possible responses and focus on particular aspects of a question or task. Source: Claude AI (Prompt: Provide one sentence definitions of the feedback loop, directives, validation, task iteration, learning and filtered prompts)

### 3. Results

The charts below show the plot of the scaled data of our findings.<sup>13</sup>

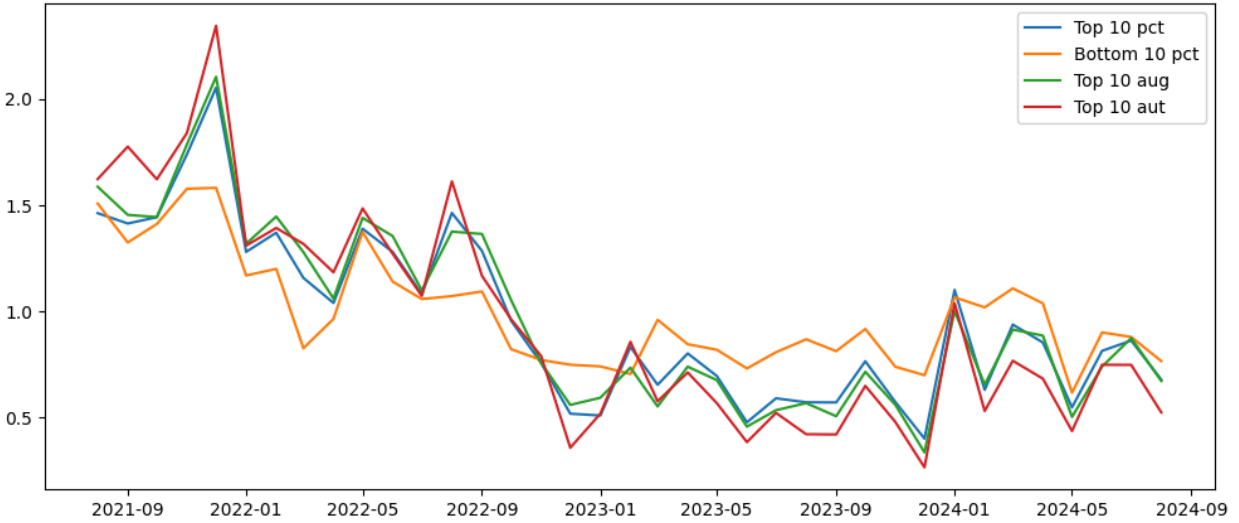
**Chart 1:** Normalized net jobs per occupation category, from August 2021 to July 2024 (category mean = 1).



The chart evidences strong seasonal data over a period of 12 months. We then apply a Loess seasonal trend decomposition (STL) to each class using the statsmodel package and subtract the seasonal factor from the normalized data. The chart below shows the normalized, de-seasonalized net jobs:

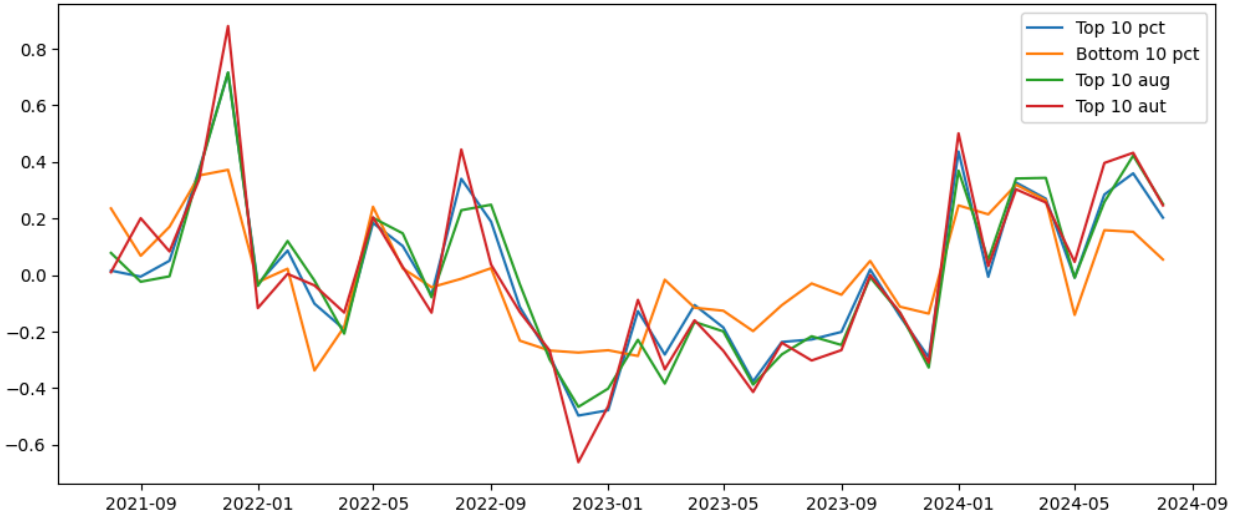
**Chart 2:** Normalized, de-seasonalized net jobs per occupation category, from August 2021 to July 2024 (category mean = 1, period = 12, method = STL).

<sup>13</sup> All code used, as well as the crosswalks and prompts to LLM used in the analysis can be found in [https://github.com/vitorgtomaz/caged\\_onet\\_anthropic](https://github.com/vitorgtomaz/caged_onet_anthropic)



Because the CAGED dataset provides employment flows, the dataset is already differenced, so we choose to apply a linear fit to de-trend the results. After removing the linear trend, the chart below was obtained:

**Chart 3:** Normalized, de-seasonalized and de-trended net jobs per occupation category, from August 2021 to July 2024 (category mean = 1, period = 12, method = STL).



Finally, we apply an autoregressive model to the residuals using the `statsmodels.tsa.ar_model.AutoReg` and calculate the Augmented Dickey-Fuller (ADF) test for stationarity, the lag, and the Akaike Information Criterion (AIC).

Table 1 contains the results of the analysis:

Category	ADF	AR(i)	AIC
T10	p=0.518	i =6	-0.712
B10	p=0.013	i = 1	-22.87
T10aug	p=0.021	i = 6	-1.61
T10aut	p=0.666	i = 6	7.25

### 4. Discussion

Our analysis concluded that there is no significant difference or divergence between the four categories of net jobs examined in our graph. The results do not support our initial hypotheses. There are several possible reasons for this, in addition to the limitations of the research:

- a. The AI technology may not be advanced enough yet to cause jobs displacements in most job sectors, but it is important to monitor it as AI tools evolve over time. It may also suggest the early days of initial adoption and integration of AI tools for work automation.
- b. Low AI adoption in Brazil due to resistance by Brazilians. Although AI tools are accessible to some strata in Brazil, the proportion of workers actively using these tools is low. In a recent survey in Brazil, 83% expressed their fear of losing their jobs to automation, while 80% expressed fear of inequality<sup>14</sup>. Such a significant percentage indicates the reluctance to adopt AI tools to automate or augment work.
- c. Inadequate access to AI training. In instances where Brazilians are keen to adopt AI tools to automate their tasks, workers in Brazil lack access to capacity-building initiatives to aid the adoption of AI tools. “A LinkedIn study reveals that 62% of Brazilian workers desire to learn more about AI, but 38% stated they are unable to do so due to a lack of training from their employers.”<sup>15</sup>
- d. AI automation may have more impact on job tasks and not always the jobs they make up. Workers may tend to adopt AI tools to automate or augment a proportion of tasks in their jobs, and not necessarily all the tasks in their jobs. Therefore, there might be negligible implications for job displacement, especially when the tasks being automated are low-productivity tasks.

These results are not static and can change in the future, subject to change in different factors. As such, policymakers in Brazil and other developing countries need to update these analyses and be well prepared for any disruption in the labor market.

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<sup>14</sup> Richter, F-J. 2024. The Future of Work in Brazil. Accessed at <https://horasis.org/the-future-of-work-in-brazil/>

<sup>15</sup> Ibid.

## Limitations

Empirical analysis of job displacement by TAI is challenging, especially because, as proposed by Acemoglu and Restrepo (2019), analysis at the occupation level is not granular enough to provide the level of insight required to capture how TAI is and will be employed. Linking task data to actual usage of LLMs and creation and displacement of jobs is a promising approach to monitor trends in the effects of TAI.

Despite the expected advantages of the approach, we still face several hurdles to deploying fine-grained analysis of the use of AI for automation and augmentation of labor. In the subsequent paragraphs, we discuss several of the limitations in our analysis and suggest ways to develop our model in the future to have a more fine-grained “microscope” to analyze the econometrics of TAI. Some of these limitations have been discussed by Kunal et al. (2025).

The first key limitation of the current analysis is the Anthropic dataset. The dataset was generated from one week of prompts to Claude Sonnet 3.7. With such a short timeframe, the data does not capture seasonality and might be anomalous in many different ways. The data is also heavily biased towards certain applications due to the specificities of Claude. Claude is unable to generate images and videos, which means that occupations that rely on graphic generation (such as graphic designers, video editors, etc) ought to be subrepresented; moreover, Claude is popular among software developers, having even pioneered desktop clients that run on the command line with Claude Code. In the future, obtaining data from multiple relevant models and longer timeframes could significantly increase the quality of the data. In particular, data from image and video-generating models (such as Sora, Midjourney, or Dall-e) would at least partially solve the bias in occupations.

The second key limitation is classification itself. That limitation has two facets. Firstly, Kunal et al. (2025) offer very limited insight into the classification methodology, which also limits our ability to understand the output of their analysis and exercise critical judgment. The authors also recognize that it is often not possible to neatly classify a prompt into one task or one type of behavior; besides, the authors also have to trust the LLM in the classification task, given the privacy-preserving nature of the CLIO method. The second face of this limitation has to do with our crosswalk. We also had to rely on LLM and did not have effective time to thoroughly revise the quality of the output. Future iterations of our model should pursue a higher diversity of data sources and request transparency in the data generation processes.

The third key limitation is that the key metric we use (percentage of total Claude interactions) does not offer insight into what percentage of the total work of an occupation is represented by it and how much time is actually saved. Translation, for example, represents the majority of work of a Translator, and can be almost entirely replaced by AI; paralegals, on the other hand, also generate high volumes of interactions, however drafting is only part of their job, and obtaining the final version of a document might require several iterations, leading to an inflation of task frequency. Future iterations of our model could be extended to incorporate data on time distribution across tasks per occupation.

Our model shows that the four categories drawn from the Anthropic Data - T10, B10, T10aug, T10aut - do not exhibit statistically distinguishable employment flow signals over the timeframe.

The ADF p-values for the T10 and T10aut categories ( $p=52$  and  $0.67$ , respectively) mean that we fail to reject stationarity of the data, and visual inspection of Chart 3 does not seem to indicate any strong divergent tendencies not captured by the model.

## Policy recommendations

We propose policy recommendations that can mitigate the negative economic impact in Brazil and other developing countries as AI adoption rate accelerates. The implementation of these strategies should be done by governments and technology corporations individually and collaboratively, as necessary. The Brazilian and other developing countries' governments should:

- a. Conduct additional research to ensure that the right insights are generated. Policy makers and technology companies should collaboratively conduct further assessments to ensure that the right insights to inform policy making that mitigates AI-driven job displacement and replacement are being generated. The government of Brazil and other developing countries should progress research in this area to better identify trends and observe the key insights needed to inform their decision-making in this regard.
- b. Retrain their workforce to drive AI-complemented productivity and develop digital infrastructure. The Brazilian government needs to act in advance to build digital infrastructure that enables its citizens to benefit from AI automation and augmentation. The government should also collaborate with private technology companies to reskill its labor force on the use of digital platforms. It is important to note that the introduction of digital tools should be proposed to workers as a supporting tool rather than a replacement. This is to avoid potential cases of jobs displacements and the socioeconomic challenges it may bring in its wake.
- c. Incentivize employers to adopt AI tools and policies that prioritize job augmentation rather than job replacement
- d. Prepare for scenarios where safety nets would need to be deployed in scenarios where AI adoption leads to job displacements. Examples of initiatives that can be adopted include:
  - i. Social safety nets: The Brazilian government can work on smoothing the transition period of unemployment for those displaced from their jobs through providing unemployment benefits. Also, the Brazilian government needs to sponsor the displaced laborers to be retrained in using AI tools so they can compete again in the job market.
  - ii. Windfall Clause: In the windfall clause paper<sup>16</sup>, the authors proposed that corporations need to donate a percentage of extreme profits generated by AI. Although donations are primarily thought of as cash donations, the Brazilian government can work with international corporations to make their services available for free or at least affordable. Providing access to the latest technologies for free or at an affordable price to Brazilians can help in continuously upgrading

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<sup>16</sup> O'Keefe, C., et al. (2020). The Windfall Clause: Distributing the Benefits of AI. Policy proposal for distributing extreme AI gains across society. <https://arxiv.org/pdf/1912.11595>

talents and, hence, improving productivity. For example, if a corporation releases software that can diagnose skin diseases using AI by scanning a patient's skin, this can enable many patients in Brazil to be quickly diagnosed, saving time and financial costs. As such, it enables medical doctors to cure and handle more patients where medical doctors are scarce due to the brain drain phenomenon.<sup>17</sup>

## 5. Conclusion

In this paper, we have proposed a new empirical approach to monitoring workforce displacement by AI by combining analysis of prompts to link with task-occupation taxonomies - more specifically, O\*NET and CBO (Classificação Brasileira de Ocupações) - with employment flows data - the Brazilian CAGED dataset. This approach allows a more fine-grained and real-time analysis of displacement trends than previous empirical methods by associating AI Usage for direct augmentation or automation of tasks with effects in employment flows.

Our analysis has demonstrated that there are still no statistically significant signs of job displacement by AI in Brazil during the period of analysis (Aug. 2021-Jul 2024), as measured by differential employment flow trends for jobs with varying frequencies of prompts relating to automation of tasks, even after differencing, correcting for seasonality, linear trends and autocorrelation.

It is important, however, to take the findings with caution, as the data used has at least three significant limitations: using only data from prompts to Claude Sonnet 3.7, a monomodal model; using data from a short time window (1 week); the lack of transparency as to how the classification of the prompts was executed. We propose that future iterations of this model should pursue data from other important providers of AI as a service (in particular multimodal and image and video-generating models, such as Sora, Midjourney and Leonardo.AI), wider timeframes and more diverse geographies.

While we find no significant differences in patterns in job creation or elimination trends across different categories of AI adoption in Brazil, this doesn't mean it won't happen in the future. Therefore, continued monitoring of how different job groups evolve is recommended, especially as AI technology advances and adoption increases in Brazil. Additionally, alternative job categorisation strategies should be explored beyond the current four categories of analysis. Finally, it is also recommended that data beyond Claude be explored for a better picture of job trends in Brazil and other developing countries. These should take place vis-à-vis the implementation of displacement mitigating strategies by policymakers.

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<sup>17</sup> The Economist. 2021. Brazil's brain drain is getting worse. Accessed at <https://www.economist.com/the-americas/2021/07/24/brazils-brain-drain-is-getting-worse>

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## 7. Appendix

Occupations (CBO) per classification and net jobs

class	cbo_subgroup_en	net_jobs
Bottom 10 pct	Assemblers of Precision and Musical Instruments	215,00
Bottom 10 pct	Cross-Functional Support Workers	1.347.629,00
Bottom 10 pct	Managers	-313.588,00
Bottom 10 pct	Mid-Level Technicians in Cultural, Communications and Sports Services	61.848,00
Bottom 10 pct	Mid-Level Technicians in Transport Services	17.308,00
Bottom 10 pct	Service Workers	4.864.155,00
Bottom 10 pct	Workers in Continuous-Process and Other Industries	16.618,00

Bottom 10 pct	Workers in Extractive Industry and Civil Construction	805.345,00
Top 10 aug	Biological and Health Sciences Professionals	168.380,00
Top 10 aug	Exact, Physical Sciences and Engineering Professionals	155.753,00
Top 10 aug	Jewelers, Glassmakers, Ceramists and Related Craftspeople	3.279,00
Top 10 aug	Lay and Mid-Level Teachers	172.138,00
Top 10 aug	Mid-Level Technicians in Physical & Chemical Sciences, Engineering and Related Fields	338.290,00
Top 10 aug	Multidisciplinary Researchers and Professionals	16.076,00
Top 10 aug	Social and Human Sciences Professionals	135.938,00
Top 10 aug	Teaching Professionals	73.473,00
Top 10 aut	Communicators, Artists and Religious Professionals	34.742,00
Top 10 aut	Craft Workers	685,00
Top 10 aut	Lay and Mid-Level Teachers	172.138,00
Top 10 aut	Mid-Level Technicians in Cultural, Communications and Sports Services	61.848,00
Top 10 aut	Mid-Level Technicians in Physical & Chemical Sciences, Engineering and Related Fields	169.145,00
Top 10 aut	Social and Human Sciences Professionals	135.938,00
Top 10 aut	Teaching Professionals	73.473,00
Top 10 pct	Biological and Health Sciences Professionals	168.380,00
Top 10 pct	Jewelers, Glassmakers, Ceramists and Related Craftspeople	3.279,00
Top 10 pct	Lay and Mid-Level Teachers	172.138,00
Top 10 pct	Mid-Level Technicians in Cultural, Communications and Sports Services	61.848,00
Top 10 pct	Mid-Level Technicians in Physical & Chemical Sciences, Engineering and Related Fields	338.290,00
Top 10 pct	Multidisciplinary Researchers and Professionals	8.038,00

Top 10 pct	Social and Human Sciences Professionals	135.938,00
Top 10 pct	Teaching Professionals	73.473,00

**Additional Materials and Prompts Used**

All code used, as well as the crosswalks and prompts to LLM used in the analysis can be found in [https://github.com/vitorgtomaz/caged\\_onet\\_anthropic](https://github.com/vitorgtomaz/caged_onet_anthropic).