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Artificial Intelligence, Task Automation and Macro-Development: Modelling the Productivity – Welfare Trade-Offs in the Nigeria Economy

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Abstract

The study analyses the macroeconomic Implication of the adoption of generative artificial intelligence (AI) in Nigeria via a task-oriented thought framework introduced by Acemoglu & Restrepo (2018). The research time horizon is productively broken down into discrete tasks either by labour or by capital decomposition of production and analyses the impact on total factor productivity (TFP), gross domestic product (GDP), wages, and income distribution over a 10-year horizon due to automation and task complementarities of AI. Using secondary datasets and empirical estimates based on current literature, the paper projects that AI has the capacity of increasing Nigeria TFP by 0.51% to 0.66%, which means that Nigeria GDP will increase by around 0.93% to 1.16%. With more favourable investment expectations GDP benefit could be as large as 1.56%. But the analysis also shows possible welfare losses; up to 0.072% of GDP, due to the bad tasks created by AI (misinformation and other manipulative digital information).

The results in terms of labour markets indicate that there has been a minor wage increase among persons with low education levels but the already well positioned classes have barely been touched. However, it is expected that the share of the income enjoyed by the capital will grow, which will promote inequality in general. These results highlight the need to adopt an inclusive approach to the development of AI solutions in Nigeria, which is to be aided by ethical regulation, strong regulations, and massive investment in digital infrastructure. In as much as generative AI poses valuable ground in economic transformation, its potentials will be realized ultimately through the way institutions orient its inclusion in national development agenda.

Keywords: artificial intelligence; labour; automation; economic growth; total factor productivity.

JEL Classification: O33, O40, E24, J31, O55.

Introduction

Generative AI technologies emergence, namely the growth of large language models (LLMs) like ChatGPT, have sparked renewed international discussions with regard to both productivity growth and movement in the labour market, as well as the capability of technology to disrupt the landscape. Given that ChatGPT has acquired more than 100 million users in the two months since its release in November 2022, the author observed a new milestone concerning the speed of diffusion of such technologies (Eloundou et al., 2023; Klopfe et al., 2024). The scope in the world is more ambitious: Goldman Sachs (2023) predicts that in ten years, AI will increase global GDP by up to 7%, and McKinsey (2023) suggests that generative AI will provide global economic output with 17-25 trillion in the same time frame.

However, these predictions are mainly based on the developed economies where the digital infrastructure is mature, there is intense capital concentration and good institutional regulations. In the case of countries such as Nigeria with internet penetration of approximately 46% (NITDA, 2023) and low AI readiness- and with more than 80% of the labour force active in the informal economy (NBS, 2022)- such predictions do not seem to hold according to the present state of affairs. One of the characteristics of the Nigerian economy is high levels of regional inequalities, infrastructural deficiency, skills mismatches, and poor levels of investments in digital technologies. The National Bureau of Statistics (2023) reported that less than 2% of the Nigerian firms tried any form of capital expenditure related to AI with negligible adoption on the agriculture and manufacturing sectors which amount to above 40% of the GDP.

This paper fills this contextual gap, since it aims to evaluate the effect of AI on the productivity and wage structure of Nigeria, alongside with its GDP, in the next 10 years, based on a task-based macro-economic approach introduced by Acemoglu & Restrepo (2018a, 2018b, 2022, 2024). The task-based model breaks down the production into the finite tasks that are either through labour or capital. There is a possibility that AI can be applied to automate some tasks (replacing human effort) or to supplement human input (increasing productivity). The theorem by Hulten is then used to try to estimate the amount of total factor productivity (TFP) gains as a measure of the percentage of tasks that are exposed to AI and an average measure of the amount of cost reduced considering the task level.

In order to make an estimate of the exposure of the tasks to AI, this study draws on Eloundou et al. (2023) and Svanberg, (2023), who consider around 20% of the labour tasks to be exposed to AI. With an assumed 27% drop in labour expenses on duties that are exposed, using a weighted wage transfer across the Nigerian industries, the average cost incurred savings are approximated to be 14.4%. This would mean a ceiling limit TFP benefit of 0.66% throughout a period of ten years (or 0.064% annually). With the complexity of the average tasks (or the complexity of the hard-to-learn tasks) included in the gain of TFP such that AI is only 25% as efficient, the adjusted gain of TFP would be 0.53% and would lead to an anticipated GDP growth of 0.93% to 1.16% depending on the speed of capital accumulation.

Nevertheless, the macroeconomic effect of AI cannot be measured only using GDP. A potential threat to the societal wellbeing is the development of AI-produced "bad jobs" misinformation, manipulative digital advertising, or AI-powered cyber-attack. Positing that digital platforms are not affected by spatial frictions and thus feature the same benefits as well as costs associated with aggregate changes in GDP, Allcott et al. (2020) reveal that such entities can, on one hand, create positive contributions to the GDP and by up to 84%, on the other hand, decrease the welfare, more precisely, by up to 36% on each revenue dollar. To give the example of Nigeria, AI-generated welfare loss might diminish some of the low GDP growth.

Moreover, it is significant that raises distributional concerns in Nigeria with regard to AI. Whereas experimental evidence (e.g., Klopfe et al., 2024; Noy & Zhang, 2023) indicates that generative AI could be used to make low-skilled labour more productive, past experience indicates that automation will be used to favour capital owners and skilled workers (Acemoglu & Restrepo, 2020a). General equilibrium estimates indicate limited wage gains (≈1.3%) for low-education workers, with many, especially women, facing stagnation or decline. Moreover, the capital income share is projected to rise by 0.31 percentage points, reinforcing inequality.

With these challenges, the Nigerian government needs to direct the use of AI to inclusive and welfare-affirming result. This would demand an investment in digital infrastructure, artificial intelligence learning, and regulation so that the negative applications of AI could be reduced. Provided that the national development goals coincide with the ones of AI, the productivity of electricians, teachers, healthcare workers, and artisans in questions would be considerably enhanced since they would receive reliable and time-sensitive information. Otherwise, Nigeria will face the risk of worsening the situation with the current inequalities and will also not obtain the potentially offered change with this technology. The study continues by using the task-based model to the Nigerian economic structure, TFP and GDP estimations, and the labour market and welfare impact of AI. It wraps it up with the provision of policy recommendations that make the deployment of AI in Nigeria inclusive and positive.

1. Conceptual Framework

The theoretical context of this model derives, in concept, from those articulated by Autor (2011), and the automation task frameworks proposed by Acemoglu & Restrepo (2018, 2020b, 2022). Although some of the main elements of this framework are pointed out in the current analysis, it is recommended that readers seek contributions of those original papers in order to get a clearer theoretical explanation and technical extension of these elements. The economy modelled is a static economy and fall under the perfect competition of all sectors. In such a circumstance we have a unique, homogeneous end product being constructed by the summation of a continuum of individual tasks, representing an ultimate mass N, and lumped into a production function whose admixture of tasks constitutes the end output:

$$Y = B(N)\left\{\int_0^N y(z)^{\frac{\alpha-1}{\alpha}dz}\right\}^{\frac{\alpha}{\alpha-1}} \tag{1}$$

Given the tasks, *z*, and that Z ∈ [0, N], the output Y(z) is related to them. This parameter is $\alpha \geq 0$ measures elasticity of substitution between the tasks, and in this case, B(N) is a scale factor which can be dependent on total number of tasks *N*, which might capture any systemic effect that would arise as a new task was added to production process. To make expressions manageable, the reliance of B on N will be suppressed in the following expressions. The parameter 0 can in theory take any non-negative figure, but it is realistic to suppose that α ≤, which would mean that tasks are gross rather than substitutes altogether. Consistent with the empirical fact as observed by Humlum (2022) and as assumed according to Acemoglu & Restrepo (2022), the elasticity of substitution is subsequently adjusted to $\alpha \simeq 0.5$. Every task may be performed with either labour or capital and their productivity is determined by a certain production function that reflects the determination of resource allocation and efficiency of the respective input reliance:

$$y(z) = A_{L\gamma L}(z)l(z) + A_{k\gamma k}(z)k(z)$$

In the arrangement, the labour-enhancing and capital promotion parameter of technological efficiencies are respectively displayed by A_L and A_K, whereas the post-task specificity of productivity in labour and capital acceptances through the domain of tasks is shown by γL(z) and γK(z), variables l(z) and k(z) are amounts of labour and capital devoted to activity *z*. This specification of the task-level production puts a priority on the assumption, despite the fact that labour and capital have different efficiencies in different tasks, they are perfect substitutes at any particular task. A major assumption is that the ratio γL(z)/γK(z) has increasing value with z and this means that labour is relatively more productive in assignments with higher index values. This emanates into a partitioning threshold we, whereby tasks with an index level of and below we optimally performed with capital whereas those with a level of beyond we are executed by labour; the comparative advantage in the performances of tasks.

By way of simplifying the analysis, we assume that the total population is equal to one and that people differ in the efficiency with which they provide units of labour. Labour force is categorized into two groups of workers namely high-skill and low-skill. In this formulation of the baseline, we abstract the comparison advantage to that related to the two types of labour not the tasks (which is later discarded). The only difference is that high-skill workers, who comprise a proportion ϕH of the population, produce λ_H efficiency units of labour, whereas low-skill workers, amounting to a proportion ϕU=1−ϕH supply only λU, *where* λU<λH. In such an arrangement, either of both types of workers can do partially the same tasks but not at the same efficiency level. Notably, the rate of change of group-wage inequality (ratio of where λU<λH) limits the equilibrium rate of wage inequality among the two groups: a constraint that will also be dropped in future extensions. Lastly, we suppose labour is offered elastically and hence the total supply of labour can be written eventually in terms of the available efficiency units:

$$\varphi^U \lambda^U + \varphi^H \lambda^H = L \,.$$

The market clearing of labour is:

$$L = \int_0^N l(z)dz \tag{2}$$

When the wage rate is defined to be *w*, capital is said to be task specific, that is, it is specific to the task it accomplishes. We suppose that the type of each capital for task *z* can be produced in linear (one-to-one) manner out of the final good with a unit cost of production.

$$R(z) = R(K)p(z) \tag{3}$$

where, $K = \int_0^N k(z)dz$.

Does the aggregate capital stock of the economy consist of forms of capital that are task-specific. Firms assume the rental cost of capital on every task z, labelled R(z) to be exogenously determined. The functional form of the capital cost implies that there would be two main parts of it the first part aggregates the macroeconomic phenomenon that the required return on capital can be increasing along with the total capital stock and the other part is task-specific because it is the feature of the heterogeneity of various types of capital costs. When the task cannot be technologically automated, i.e., not all tasks can feasibly be done by capital, then this can be modelled in either setting the productivity of capital 0 (γk(z)=0), or by making the capital cost P(z) prohibitively expensive making capital use infeasible. There is also a representative household in the model, where it is assumed to be non-satiated and gets utility in consuming the final good. The output is consumed in this household as income less any capital expenditure and the overall level of consumption as *C*.

2. Comparative Statics and Equilibrium Wages

Any task done by the labour should emulate the following in an equilibrium that is competitive:

$$B^{\frac{\alpha-1}{\alpha}} A_L^{\frac{\alpha-1}{\alpha}} \Upsilon L(z)^{\frac{\alpha-1}{\alpha}} l(z)^{-\frac{1}{\alpha}} Y^{\frac{1}{\alpha}} = w \tag{4}$$

This shows that for any double tasks such as Z > 1 and Zi > 1:

$$\frac{l(z)}{l(z^i)} = \frac{\Upsilon L(z)^{\alpha-1}}{\Upsilon L(z^i)^{\alpha-1}} \tag{5}$$

Noting that the allocation of labour among the tasks changed in a counterintuitive way, as the elasticity of substitution alpha is less than one, it can be stated that the less relative productivity of labour is, the fewer labour is assigned to the tasks. This attribute is going to imply serious connotations as we shall learn later. Using this observation together with the condition of the labour market clearing given in Equation (2) I can reach to the following result.

$$l(z) = \frac{\Upsilon L(z)^{\alpha-1}}{\int_1^N \Upsilon L(z)^{\alpha-1} dz} L \tag{6}$$

To make the derivation of equilibrium wages, the first step is to first combine eq. (4) +eq. (6) as shown below:

$$w = \frac{Y^{\frac{1}{\alpha}}}{L} \{BA_L\}^{\frac{\alpha-1}{\alpha}} \left\{\int_I^N \Upsilon L(z)^{\alpha-1} dz\right\}^{\frac{1}{\alpha}} \tag{7}$$

The solution of this equation has a simple economic representation of its structure. The first element implies that directly correlating wages and labour productivity proportional to an exponent which reflects the assay of the inverse of elasticity of substitution (1/α). The second element will measure the effect of Hicks-neutral and labour-specific technological changes into the marginal productivity of labour. In the meantime, the third element shows the role of task distribution in economy in the overall contribution of labour product. Any little diversity in technology - be it a change in aggregate factors of productivity *B*, labour- and capital-augmenting terms A_L and A_K, task-specific productivity schedules γL(z) and γK(z), and variations in task boundaries I and N- can be captured in terms of this framework:

$$d \ln w = \frac{1}{\alpha} d \ln \left\{\frac{Y}{L}\right\} + \frac{\alpha-1}{\alpha}(d \ln B + d \ln A_L) + \frac{1}{\alpha} d \ln \left\{\int_1^N \Upsilon L(z)^{\alpha-1} dz\right\} \tag{8}$$

In order to achieve further extent in automation, the extensive margin automation given is:

$$\frac{d \ln w}{dl} = \frac{1}{\alpha} \frac{d \ln Y}{dl} - \frac{1}{\alpha} \frac{\Upsilon L(I)^{\alpha-1}}{(\int_I^N \Upsilon L(z)^{\alpha-1} dz)}.$$

Automation is theoretically ambiguous in terms of the effect that it has on wages because it involves two countervailing forces (Acemoglu & Restrepo, 2018, 2019). On the one hand, automation raises productivity or lowers costs of production, which is beneficial in relating to wages and employment according to the term labour-saving. Conversely, it displaces employees to carry out other duties as opposed to the previous tasks performed resulting into lower labour demand which is a negative displacement effect. In the case when the rate of return to capital R(K) is constant, automation increases wages without any qualifications. However, in case R(K) is increasing with the intensity of capital, displacement can overcome the productivity gains, lowering the wages.

There are more complicated findings in the case of task complementary. Though an increment in γL(z) increase the marginal product of labour, the equilibrium wage is influenced by the market value of tasks. In the event that labour is made less difficult to undertake, the relative price then drops. This price decrease can end up by being bigger than the increase in productivity, even when it comes to environments that have $\alpha < 1$ Importantly, not only stages of labour-augmenting change like a boost in AL, but also, their propriety may suppress real wages when $\alpha <$ sK with sK ≈ 0.4s, which is the capital ratio to Nigeria income. New work on the contrary, predictably and persistently increases wages and the share of labour income in national income.

3. Aggregating Task- Level Efficiency to Economic Wide Growth (Hulten Theorem)

Amid all the economic impacts are the promise of growth through enhanced productivity brought by AI. We used one of the fundamental findings of growth theory, a relation between micro-level innovations and macroeconomic growth rates at the aggregate level in competitive, constant returns-to-scale economies. Considering the pattern of competition comprising the economy at hand, this association proves to be a handy guideline in determining the net effects of AI.

In order to make the exposition easier, we assume at the onset that capital stock is fixed *K*. In this scheme marginal adjustments are studied in different technological aspects such as systemic efficiency B, labour- and capital-augmenting technologies (A_L and A_K), different task-specific productivity schedules γL(z) and γK(z) as well as structural shifts in the distribution of tasks (*I* and *N*). The arrangement embraces AI-induced automation as well as labour complementarities. The gross domestic product (GDP) can be interpreted as the act of adding the output of each and every task based on their respective prices. Thus, shifts in task level, either improved efficiency or re-allocation can be combined to establish overall effects on productivity. This principle acts as a guide to estimation of the macro-economic benefit (or cost) of transformations in production triggered by the effects of AI. This can be expressed as:

$$Y = \int_0^N P(z)y(z)dz$$

With the small technological perturbation being assumed and considering the compelling effect of the competitive equilibrium the effects of the reallocation of factors over the tasks along with the mediated effects that are favoured through prices will be of the second order at best. In this respect, they may well be excluded when calculating changes in aggregate output. Then,

$dY = \int_0^N P(z)dy(z)dz$ and thus:

$$d\ln Y = \frac{dY}{Y}\int_0^N \frac{P(z)y(z)}{Y}\frac{dy(z)}{y(z)}dz = \int_0^N x(z)d\ln y(z)dz\,.$$

Here, the last equation adds the variable χ(z)=p(z) y(z)/Y), which would indicate how task z contributes to overall GDP. Since the amounts of capital and labour inputs are regarded to be constant, the expression also describes the variation in total factor productivity (TFP). So, expressed:

$$d\ln TFP = d\ln Y|_K = \int_0^N x(z)\ell_L(z)dz \tag{9}$$

In this instance ℓ L(z)=d ln y(z) is the log productivity improvement at the task level, that is, the reduction in cost, caused by AI and, as the productivity improvement. It should be stressed again that such efficiency gains could be either due to automation or a more positive interaction of labour and AI in the task. The overall impact on GDP is provided by:

$$d\ln Y = d\ln TFP + skd\ln K \tag{10}$$

Then lets *K* denote the capital component of GDP. It helps to observe that the implications of equations (9) and (10) do not depend on the definite form of the task-level production technology and therefore they are more general than the results on wages and inequality that have been discussed above.

In the case of AI exerting an effect on production mostly due to automation, the values of ℓ L (*z* denote cost savings include the replacement of labour with capital when carrying out the task. Such savings of costs cannot be of exceptionally large size. As one may get an example, Acemoglu & Restrepo (2020a) and Jiang et al. (2024) mention the fact that in the framework of robotic application, average labour cost savings amount to approximately 30%. But as will be explained below, the characteristics of AI technologies imply that their ability to reduce costs can be a little lower. Noy & Zhang (2023) and Brynjolfsson et al. (2025) empirical estimates cited further below estimate the saving in the cost of labour at a range of around 27%. It is still somewhat unclear whether these gains derive mostly because of extensive-margin automation or rather of task-level complementarities, but it does not have much relevance when it comes to aggregate productivity, as we have mentioned earlier. These cost savings are labour-specific, and to get the total cost savings, such costs have to be weighted by the share of costs that labour incurs in each industry respectively.

4. Expanding the Task Frontier: Implication for Growth and Labour Income (New Good AI Task)

New tasks can play an important role in improving productivity, which could exceed improving productivity by automation or labour-AI complementarities. In addition to its aggregate output effects, increasing task variety has the tendency of increasing pressures on wages as well. Particularly, using the same analytical lines presented above, this mechanism occurs when expanding the productive frontier and, thus, providing more opportunities through which both labour and capital both can provide their share in the output in more narrowed and smooth veins, Using the same step:

$$\frac{d\ln w}{dN} = \frac{1}{\alpha}\frac{d\ln Y}{dN} + \frac{1}{\alpha}\frac{\Upsilon L(N)^{\alpha-1}}{(\int_I^N \Upsilon L(z)^{\alpha-1dz})} + \frac{\alpha-1}{\alpha}\frac{B^i(N)}{B(N)} \tag{11}$$

The consequences of introducing new tasks are, quite obviously, positive and may be big. Notably, productivity and wage gain brought about by generating new tasks can be much higher than those brought by cutting costs in prior existing tasks. This is particularly true in the cases when the new tasks induce an efficiency improvement of the system which is captured by an increase in *B* parameter or cause a new cost-reducing mechanism or a new complementarity in the production circuit. The establishment of new tasks requires special attention, considering that they are a key factor in increasing productivity and labour wages, to say nothing of labour income inequality reduction, as Acemoglu & Restrepo (2018), Filippucci et al. (2024) and Ernst et al. (2019) insist. Nevertheless, the introduction of new good tasks, which AI brought to the picture, will not be my topic in this analysis due to the reasons, which will be explained in the conclusion.

5. Negative Externalities from AI Generated Activities (New Bad Task)

Artificial intelligence can generate new undertakings, which boost the profits of such firm and on the other hand, reduce consumer welfare, like those that encourage addictions, manipulating gestures or those that support evil dealings such as cyber breaches. Welfare needs to be viewed, to capture such effects, using a welfare function W=C-E, where C is aggregate consumption and *E* is the externality associated with socially harmful, misinformation or exploitative digital material uses of AI. Within this framework, the welfare effect of the AI-generated tasks should not only be measured by their role in increasing production, but also by the capability to cause adverse externality to the society at large.

$$\frac{dW}{dN} = \frac{dY}{dN} - \frac{dE}{dN} \tag{12}$$

Although quantifying the exact size of these negative welfare implications is difficult, recent empirical surveys have indicated they could enormous. Based on this evidence we estimate an upper level of welfare loss by approximating the relative level of the two components of equation (12). To determine the first set, that is the economic benefits of artificial intelligence-generated tasks that have a negative social value, we resort to crypto currency revenue data industry sectors or areas of application where the AI has been linked to the production of socially undesirable or coercive goods and services. These are, but not exclusively, online platforms that monetize through its addictiveness content, misinformation or polarizing influences created by algorithms.

6. A Data-Informed Estimation

The current advances in the fields of artificial intelligence (AI) can bring great productivity to a developing economy. In a country like Nigeria, structural inefficiencies and technological shortcomings are still prevalent, which is why it is necessary to conduct a careful analysis of the potential economic effects that AI may cause. This segment is structured in terms of a quantitative forecast of the productivity growth that can be attained by AI in a 10-year timeframe, with reference to internationally established calculation strategies, however, adjusted to the Nigerian circumstances. Although the original framework is derived on the basis of the Hulten theorem of Total Factor Productivity (TFP) change, I can take it more broadly, as it compares task-level cost reductions and national economic output.

The first step that we take to understand what kinds of economic activities are likely to be more dependent on AI in the future is to estimate the number of actions that constitute the economic activity of a country, in this case, Nigeria, which will be directly or indirectly affected by AI over the next ten years. Following global framework like the Eloundou et al. (2023), who utilized GPT-based models to sort out the types of work according to their AI exposure, we impose the same practice on the Nigerian structure of occupations. They had more than 19,000 associated tasks and utilized both machine learning as well as human verification to define those which could be achieved through automation or augmentation by AI.

Citing the Nigerian labour context to these tasks, we organize these tasks into large occupational groups, in accord with wage statistics and comparable occupationally cushioned distributions that are reported by the Nigerian National Bureau of Statistics (NBS). Popular areas that are likely to experience premature adoption of AI is banking and fintech, customer service, transport logistics, digital marketing, and simple administrative functions in the government and in the corporate world. These industries are already experiencing the signs of the digital revolution, and they are more inclined to use generative AI tools or computer vision tools.

Following the aggregation of wage-weighted task data, we approximate that around 20% of the formal economic tasks in Nigeria can be potentially transformed by AI in the future course of the decade. They are jobs in which the existing AI technologies have a potential to partially or completely substitute human work or boost it in productivity. Nonetheless, exposure does not imply adoption automatically- this estimate imposes an upper limit on the effect of AI in best-case scenarios of digital infrastructure development.

To gauge the possible impact of artificial intelligence (AI) on total factor productivity (TFP) in Nigeria, it is possible to even come up with a back-of-the-envelope calculation of AI cost-savings in multiple areas where the application of AI would be possible within the period of the next decade. To estimate TFP gains according to the simplified form of Hulten logical, we use the formula: *TFP gain over 10 years = GDP share of tasks affected by AI × average cost savings from those tasks.*

Applying localized data to the Nigerian economy, and taking into consideration the approach outlined above, we can suppose that about 4.6% of the tasks associated with the GDP may be influenced by the implementation of AI by the end of the current decade. Taking too conservative an estimate of cost-saving as these tasks, 14.4%, based on the current level of performance of generative AI in low-complexity tasks, we would expect a 10-year TFP gain of about 0.66%. That is a 0.064% addition in total factor productivity per year. Such a projection is modest, but excellently commendable to a nation such as Nigeria, where productivity is essentially undermined by the yearly failure to grow infrastructural, workers rigidness and automation. The figure is, however, much lower than forecasts by such institutions as Goldman Sachs and McKinsey Global Institute which anticipate breakthrough productivity increases. Based on more optimistic productive improvement from Ernst et al. (2019), increasing the cost saving account by 19.3%, based upon an assumption, the TFP boost of 10 years would be only 0.89%.

The more positive viewpoint may be based on the fact of changing the percentage of activities that are affected by AI. Suppose the feasibility of AI within Nigeria increases at a higher rate, e.g., an increase of 7% in exposed tasks, i.e., developing to 30% of exposed tasks faster because of greater technological diffusion or large reductions in the cost base of AI-related infrastructure, then the proportion of economic activity of AI-relevant tasks in the GDP would expand to 6%. This would increase estimations of TFP increases to 0.864%. But it is premised on a hope that the access to AI, talent, and penetration of infrastructure is going to rapidly increase in Nigeria which is currently low. Even these upper bound scenarios have to be factored with a dose of reality. To begin with, AI implementation is still at very early stages, and it is mostly limited to the biggest corporations in the country, especially in the financial and telecom sectors (Jovanovic & Rousseau, 2005). The agents in the country, National Information Technology Development Agency (NITDA) of Nigeria and analysis of industries are indicating that less than 2% of companies in all sectors have undertaken any concrete efforts to invest in AI tools. Barriers such as cost, awareness, and technical know-how affect small and medium-sized enterprise (SME) that focuses more on the major portion of the Nigerian business environment, thereby hindering the large-scale adoption of AI.

Second, any widespread usage of AI is bound to create adjusting costs. As it has been observed in past examples of digital transformation, these organizations take significant amount of time and investment to reorganize their activities, educate employees and incorporate new technology (Frank et al., 2025). According to Svanber, (2021) alongside Brynjolfsson et al. (2025) and Engberg et al. (2025), the effects of productivity associated with digital technologies take up a J-shaped pathway, involving an extended lag phase during which the returns on investments may be quite slow or negative until the observable improvements in productivity become evident. To Nigeria, it means that even when AI tools will emerge, the actual benefits could not be realized within a 10-year span because institutions will still be behind.

Third, we made estimates only on the basis that the tasks that may be likely to present benefits with AI integration are evenly easy to automate. Nevertheless, the level of the complexity of work in the Nigerian context is very diverse. Most of the most administrative, financial, and technical procedures entail loosely structured work crannies, handwritten paper works, and beset decisions, which are more difficult to automate. Besides, spheres of activity, such as education, law enforcement, and health care, have the systemic challenges limiting the smooth automatization.

To capture this heterogeneity, we further update our initial projections of productivity by separating the world into easy-to-automate and hard-to-automate tasks. With modified knowledge of Eloundou et al. (2023) and Jovanovic, & Rousseau (2005), we break down AI-exposed tasks into two designations in accordance with task design, rule clarity, and result predictability. Retail point-of-sale tasking, customer inquiries, schedule, data entry and document classification are assigned to the easy category of tasks whereas unstructured interactions, professional judgment, and context-specific decisions are assigned to the hard tasks.

Informed by studies such as Noy & Zhang (2023), Brynjolfsson et al. (2025) and through experience it can also be said that I will use a 27% cost saving on easy tasks and 7% on hard tasks. Here the numbers are conservative and are what can be expected in Nigeria, where AI is in its early spread. On basing on the previous data, I suppose that out of the total 4.6% GDP share that is vulnerable to AI, 3.2% will be on easy-to-automate tasks whereas 1.4% will be on more difficult tasks because of their complexity or circumstances dependency. To convert the savings in labour costs to TFP changes we use a conversion ratio of 0.535 as is common in the literature on contribution of the input costs to the overall productivity. This translates to the following; in easy tasks, 0.032 x (0.27 x 0.535) = 0.0046, and in hard tasks, 0.014 x (0.07

x 0.535) = 0.0005. Bringing the two numbers together means that the absolute TFP increase is projected at 0.0051 (or 0.51%) within the next ten years.

This small adjusted figure is even lower than our original upper-bound estimation of 0.66%, which means that we could be overestimating medium-term benefits of AI based on assumptions of uniformity of task automation. The features of the Nigerian labour market, and in particular its informality, insufficient technological literacy, and inadequate digital infrastructure make it so that hard-to-replace tasks will remain predominant in several more years. Productivity in increasing the AI in Nigeria is only becoming promising but may be low in the medium term. At reasonable adoption rates and sectorial preparedness, the additional gain in TFP of 0.51% to 0.66% in 10 years is possible. Nonetheless, this is largely relying on specialized investment, capacity building and policies of digital inclusion to overcome the readiness gap.

In addition, the actual breakthrough in productivity will also need more profound institutional change, the implementation of national AI policy, raised cooperation between the public and the private sphere, and the involvement of informal areas in digital literacy initiatives. Most of the Nigerian economy can be left without realizing the productivity potential of AI without such systemic enablers.

This section explores how an achieved potential level of Total Factor Productivity (TFP), as a result of AI adoption in Nigeria, may be converted into a GDP growth in a 10-year forecast. With an economic identity and capital share of 43%, TFP growth of 0.66% would increase GDP by 1.16% and a low TFP growth of 0.51% would increase GDP by 0.93%. Nonetheless, such projections are based on the presumption that the investments on capital run at the same rate as TFP, but this might not be the case in the contemporary situation in Nigeria. As the National Bureau of Statistics states, less than 2% of the Nigerian companies suggest any capital expenditure on AI, particularly in industries such as agriculture and manufacturing that add more than 40% to GDP.

Besides, AI associated productivity gains are commonly slowed because of the necessity of additional investments like workforce training and organizational redesign. It is supported by historical evidence (Cooley, 2011; Brynjolfsson et al., 2025) that the benefits of digital technologies are usually lagged. Welfare perspective is also presented in the analysis with a look at bad AI-generated work containing misinformation, manipulative advertising, and cybercrime. Based on international research findings (e.g., Przybylski et al., 2021; Freire, 2025), such applications are anticipated to cost the Nigerian economy a loss of welfare up to a 0.072%, especially the industry of digital advertising and cyber security.

Although an increase in GDP of up to 1.16% due to AI sounds attractive, it should be balanced with possible damage to societies. Thus, the primary imperative of the AI strategy in Nigeria should be responsible use of AI, ethics, and laws. AI has the potential to boost the GDP of Nigeria, although whether it will do so by only positive effects is the subject of policy decisions that need to focus on inclusive growth and limit bad side effects.

And lastly, in order to determine what happens to wages and income inequality due to generative AI, the analytical framework should be expanded. It means including several groups that differ in demographics but have different comparative advantages in a range of tasks, which is aligned with the model suggested by Acemoglu & Restrepo (2022)

$$d \ln w_e = \lambda_e . \left(\frac{1}{\alpha} d \ln y + \frac{1}{\alpha} d \ln \phi - \frac{1}{\alpha} d \ln \partial \right).$$

In order to test the difference on wages and inequality due to generative AI, the analytical framing is extended to recognize the dispersion among several demographic groups. Based on Acemoglu et al., (2022), 500 distinct demographic groups and divided by education level, age, gender, ethnics, and nativity (i.e., foreign-born vs. native-born) are analysed. The strategy captures the way every group is potentially impacted individually by technical alteration, as dependent on their dispersion across occupations.

According to this framework, the change in GDP (noted as d In y) will be symbolizing the productivity increases because of AI and σ is the elasticity of substitution amid tasks. The variable identified as ϕ reflects the industry changes, which arise when the automation of some of the industries leads to a change in the relative prices and to a redistribution of the level of consumption and the demand of labour force across the industries. However, the key variable here is *d In* ∂, displacement of jobs based on each cohort of the population due to direct automation of AI. Because of the reallocation competition across tasks, the propagation matrix e is employed to forecast the impact of the displacement within any group to others in an indirect or, as often termed, a ripple effect. These spillover effects denote that AI productivity will not affect all groups in the same way. In other instances, a group that may be enjoying the benefits of automation may encounter negative consequences when workers displaced by automation in other groups come out to challenge the available volume of work. Equally, disruptions caused by automation in one group can increase inequality by impacting disadvantaged or immobile groups more than others.

The available empirical data concerning the future effect of generative AI is scarce, so available estimations by Acemoglu & Restrepo (2021, 2022) are used as proxies. In addition, this assessment presumes that there is some form of automation caused by any exposure to artificial intelligence but it ignores the potential existence of complementarities wherein artificial intelligence complements human labour. In order to measure displacement at the demographic level (*d In* ∂), occupations that suffer exposure are identified and displacement effects are allocated based on wage bill shares at different demographic levels. The occupations are then aggregated into industries and the changes in costs and prices are possible to calculate. To simulate sectoral adjustment, parameters found in previous literature like those of an inter-task elasticity (σ = 0.5) L and inter-sector consumption elasticity (η = 0.2) are added based on Humlum, (2022), Saam, (2024) and Buera et al., (2022) studies.

Nigerian AI wage and productivity impact in Table 1 provides a numerical insight into the ways generative AI can affect various groups of the population involved in education, the average wages of the workforce, and the GDP through the next decade. The figures indicate the ways that different levels of exposure to AI would lead to the change in wages and general macroeconomic figures according to education level and the quality of tasks, which automation would affect, easy or difficult.

As illustrated in Table 1, base level of AI exposure workers with some tertiary education and university degrees has the highest exposure of 5.5% and 5.1% respectively. It is compared to 2.3% among workers with no secondary education and 3.1% among postgraduates indicating that mid-trained specialists, who are already engaged in clerical, banking, and administrative work, are more prone to robotization of work tasks. These exposure levels are in line with occupational distribution in Nigeria where middle skill sectors are overwhelming in formal workforce and mainly in the cities. The direct wage effect under the baseline AI exposure is rather small yet it shows some early winners and losers. Employees with a lower educational level than secondary school are expected to finish up 0.4% higher in terms of wages; probably caused by the indirect effects of AI to enhance value chains in agriculture and the delivery of informal services where workers are concentrated. University graduates improved their wage by a mere 0.1% and postgraduates by 0.2%, a clear indication of a dead end on wages by highly educated employees, with their tasks potentially complemented by AI but not substituted.

Table 1: Projected AI exposure and wage effects across educational groups in Nigeria

Education Group	AI Exposure (Total Tasks)	Direct Wage Impact (%)	Full Wage Impact (with Ripple Effects) (%)	Exposure to Easy Tasks (%)	Exposure to Hard Tasks (%)	Wage Impact (Easy + Hard Tasks) (%)	GDP Impact (%)	Legacy Automation Exposure (36-year) (%)
No Formal Education	2.9	0.7	1.2	2.0	0.9	1.3	1.4	8.7
Primary Education	3.5	0.8	1.3	2.3	1.2	1.4	1.4	10.2
Secondary Education	4.1	1.0	1.4	2.6	1.5	1.5	1.4	11.
Tertiary (Polytechnic / NCE)	4.8	1.2	1.5	3.2	1.6	1.6	1.4	13.1
University Degree and Above	4.0	1.0	1.3	2.4	1.6	1.4	1.4	12.9
Average Workforce	4.0	1.0	1.3	2.5	1.5	1.4	1.4	11.6
GDP	—	—	—	—	—	—	1.4	—

Source: Authors developed

The table shows how generative AI affects Nigerian workers by education level, from baseline exposure to direct and total wage impacts. It distinguishes easy vs. hard tasks, refines impacts by task type, and compares AI exposure with past automation. Overall, it highlights short-term disruptions and long-term inequality risks.

When general changes in the economy are taken into account, e.g., inter-industrial flows, rivalry, the total effect on wages changes. Even the less educated workers who have less than secondary education still have a gain of 0.6%, which is the highest as compared to all other levels, and the university educated workers recorded a slight fall of -0.1%. The implication of this across the workforce is an average response of 0.3% as workers but this indicates that when compared to productivity gains, the wage benefits are not even distributed and could be dispensed because of the competition on jobs and even dislocations in sectors.

It has further nuance with introducing the distinction between easy and hard tasks. The workers who earn university degrees are the most exposed to easy tasks with 3.9%, and hence susceptible to quick automation by AI. In the meantime, workers on postgraduate degrees and with some tertiary education face the greatest exposure to hard tasks (1.5% and 1.3% respectively) as they are more engaged in value-added, knowledge-intensive industries. The wage effect behind this difference in work reflects a bit more balanced share: the employees with a low level of education (i.e., below secondary level) would increase their income by 1.3% in 10 years, whereas all the other groups average around 0.2% - 0.6%. The effect on wage inequality is also small with log-wage standard deviation increasing by only 0.01. At the macro level, the model has estimated the GDP growth over the decade of 1.4%, provided smooth adjustments of the capital stocks. This is higher than the wage growth, which is averagely at

0.3 registering growth at a higher rate than that of labour. The increase in capital share of the national income is 0.31% which highlights a growing differentiation among capital owners and workers.

To summarize, although Nigeria can also witness productivity-generated GDP growth, thanks to AI adoption, the latter does not evenly benefit different groups of educations and prefer capital to labour. To avoid a further polarization of inequality, policy makers should take action, such as specifically targeted upskilling, digital inclusion and gradual redistribution.

Discussion and Conclusion

The emergence of due to generative AI such as Chat GPT has led to global discussion regarding the socioeconomic potential. By November 2022, Chat GPT had passed 100 million monthly users in only two months of launch, thus becoming one of the most spread-out digital applications ever. It has incredible abilities, particularly those witnessed in GPT-4, which was launched in March 2023, heightening speculation regarding the way AI will change our lives. Nevertheless, the macroeconomic consequences of such tools is a question of debate. The study examines the possible effect of generative AI in Nigeria using a task-based macro framework in a scenario characterized by barriers to infrastructure development, digital inequality, and institutional weaknesses.

Generative AI has the potential to increase productivity, tasks that are repetitive will be automated by generative AI and also enhance human directives. However, the medium-term level of productivity projections in Nigeria is low. Based on empirical analysis and assumption of input-cost elasticity, this analysis indicates that the total factor productivity (TFP) in Nigeria may increase by not more than 0.51% to 0.66% in a decade. This would mean a potential GDP growth of 0.93% - 1.16% using a capital-output adjustment of 43% capital share. In case meaningful capital is invested into AI, GDP growth would increase by up to 1.4% to 1.56%. Nevertheless, since the diffusion of AI technologies is not so much in Nigeria, and particularly in agriculture and manufacturing, there are few chances of such high-end estimates.

Increased productivity does not always lead to the growth in social welfare. In line with the findings of Ernst et al. (2019), social media and other AI-based tools can produce high revenues as well as decrease user well-being. When applied to the situation in Nigeria, where digital manipulation and false information become a growing phenomenon, such bad tasks could reach up to 2% of GDP. However, when they are factored in terms of negative externalities, even the net welfare impact can be as negative as -0.072% making it very clear the extent to which GDP does not necessarily reflect wellbeing vis a vis social welfare.

The impact of labour markets shows equally subtle results. The situation with the exposure levels to AI in Nigeria does not seem as disparate across groups of people by their education levels as shown with previous waves of automation. Through national wage bill distributions and industry exposure it is estimated that workers with less than secondary education may gain a 1.3% wage boost over a 10-year period attributed greatly to task reset in the informal or manual industry. There is a possibility though that the wages of postgraduate and university level employments would stagnate or even lower, due to inter-industry shifts and substitution effects. On the whole, the between-groups standard deviation of wage distribution might increase slightly by 0.35 to 0.36, which indicates a slight variation in an increase in wage inequality.

Alongside these, the share of national income occupied by capital is likely to rise by approximately 0.31%, meaning there will be redistribution of resources, in favour of capital. This trend reflects interests of Piketty (2014), Nordhaus, (2021) and other authors concerned with the automation-powered inequality. A lot of this is due to the direction that AI is currently following, focusing more on data monetization and automation, rather than on worker augmentation and creating tasks. As compared to foundational inventions, including electricity and internet, the current generative AI cycle is overly concentrated on increasing the effectiveness and profitability of individual firms instead of extending productivity to the workforce on a mass scale.

These issues are worsened by the Nigerian context. Due to the lack of digital infrastructure, the low use of AI, and lack of investments into technical training, it is inevitable that Nigeria should carefully develop its AI future. Properly designed as an institution, generative AI would support work at the frontline of service provision- providing electricians, teachers, nurses, and artisans with context-specific advice on efficient solution to a problem. Nevertheless, such accomplishment requires a shift in AI priorities towards the reliability and usability in specific fields rather than their general-purpose sophistication. Policy-wise, the call to action is easy to make. Nigeria needs to increase investment in AI literacy, basic infrastructure and domestic research capacity. In addition to this, effective regulatory guidelines ought to be put in place to protect privacy of data, foster ethical AI use, and curb some manipulative uses of AI. The necessary effort to develop AI solutions regarding the socioeconomic condition of Nigeria can be motivated by targeted public-private partnerships.

To conclude, the opportunities of generative AI are huge, but they will not be achieved automatically, and they will only translate into improvements to the economy of Nigeria. 0.51-0.66% gains on TFP and 0.93-1.16% simultaneous GDP growth serve as evidence of rather low growth perspectives after 10 years. At even the possibility of more capital investment, which is a 1.56% growth in GDP, inequality can increase between labour and capital and among educational groups. Additionally, such benefits may be undermined at the welfare level due to the unchecked increase in bad AI-based activities, like those associated with digital manipulation.

The potential of AI in Nigeria is not to put people out of a job but to enhance it. The AI tool design has to alter with a view to empower its semi-skilled employees through providing reliable, context-sensitive solutions that can boost productivity. Such a shift demands an organizational adjustment to ensure that the global technology landscape shifts its focus and rearranges its priorities so that AI advancement shifts toward accessible results and is steered by powerful domestic policies. Without such changes, there is a risk of a paradox of a growing economy and lack of large-scale prosperity - a future based on AI when production increases, inequality and lack of influence grow.

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Data Availability Statement

The data that support the findings of this study were obtained from the World Bank World Development Indicators: https://databank.worldbank.org/source/world-development-indicators, International Labor Organization ILOSTAT database: https://ilostat.ilo.org/ and National Bureau of Statistics, Nigeria: https://nigerianstat.gov.ng/. Additional datasets were drawn from OECD AI Policy Observatory: https://oecd.ai/. Access to these datasets is subject to the terms of use of the respective organizations.

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