AI VS. HUMAN LABOR: ASSESSING ENERGY-RELATED INTERNAL AND EXTERNAL OPERATIONAL COSTS IN A TRANSFORMING WORKFORCE

Fehmi Gorkem Uctug, Izmir University of Economics, +90 232 4888354, gorkem.uctug@ieu.edu.tr
Kardelen Afrodit Adsal, Trinomics, +90 535 6434858, afrodit.adsal@trinomics.eu

Overview

The rapid advancement of artificial intelligence (AI) is reshaping the global workforce, offering unprecedented efficiency gains while raising significant concerns about energy consumption and environmental impacts. This study investigates the operational costs of replacing human labor with AI systems across three representative case studies: autonomous driving, call center services, and data analysis tasks. By comparing the labor cost of human workers under business-as-usual scenarios with the energy cost (including internalized CO_2 emissions) of AI-driven systems, the study quantifies the economic trade-offs associated with AI adoption. Regional variations in labor wages, carbon emission intensities, and CO2 prices are incorporated to provide a robust comparison framework..

Methods

The main purpose of our approach is to develop a universally applicable model, and the case studies below merely function to show how the model works. Our model focuses exclusively on operational costs and develops a region-sensitive economic model to compare human labor costs with AI energy-related costs. The cost difference is expressed as follows, with the timeframe for each task being 1 hour:

$$\Delta C = (C_{AI,energy} + C_{AI,CO2}) - C_{human}$$

where:

ΔC: Cost difference between AI and human labor (per hour)

$C_{AI,energy}$: Energy cost of AI operation, calculated as $C_{AI,energy} = E_{AI} \times P_E$, where E_{AI} is the net energy consumed by AI systems (kWh) compared to energy consumed during manual labor per hour, whereas P_E is the regional energy price per kWh. If the energy consumption by AI and by human labor are equal for a given task, E_{AI} will be taken as zero. If human-labor requires more energy input than AI, then E_{AI} will also be taken as zero.

$C_{AI,CO2}$: Internalized CO_2 emission cost of AI energy consumption, given by $C_{AI,CO2} = E_{AI} \times EF_{AI} \times P_{CO2}$, where EF_{AI} is the emission factor (kg CO_2e/kWh) and P_{CO2} is the shadow price of CO_2 per ($/kg)

C_{human}: Labor cost of human workers ($/hour)

The case studies and the scope of the analysis can be found below:

1. Case Studies:
   - <u>Autonomous Driving (AD)</u>: Replacement of human-driven transportation fleets with AI-based autonomous vehicles. Energy costs include on-board computing systems, sensors (e.g., LiDAR), and back-end data processing in data centers [1].
   - <u>AI-Driven Farming (AF)</u>: Autonomous tractors, drones for crop monitoring, and AI-based irrigation systems increase energy usage compared to traditional human-driven farming practices. Manual labor generally uses no energy beyond human effort [2].
   - <u>AI-Based Security Surveillance (ASSU)</u>: Shifting from human security guards to AI-powered systems (e.g., automated cameras with facial recognition) demands constant energy input for running cameras, processing video feeds, and storing large volumes of data [3].
2. Economic Variables:
   - Regional energy price per kWh
   - Shadow CO_2 price per ton [4]
   - CO_2 emission factor for regional electricity grids (kg CO_2/kWh)
   - Regional labor cost per hour (assuming a weekly working load of 40 hours)
3. Analysis Framework: The economic model is applied to three regions with distinct labor costs, energy prices, and CO_2 prices. These regions are i) Türkiye, where this study was conducted, ii) EU average, iii) US average

Results

The results of our analysis can be found in Table 1 below.

Table 1. Detailed parameter analysis for the energy related operational costs of AI vs. human labor

Parameter	Turkish value	EU average value	US average value	Unit
ΔC	**AD: -2.33**	**AD: -8.07**	**AD: -6.78**	USD/hour
	AF: -2.52	**AF: -8.30**	**AF: -7.25**	
	AF: -2.52	**AF: -8.30**	**AF: -7.25**	
$C_{AI,energy}$	AD: 0.12	AD: 0.19	AD: 0.168	USD/hour
	AF: 0	AF: 0	AF: 0	
	ASSU: 0	ASSU: 0	ASSU: 0	
$C_{AI,CO2}$	AD: 0.0745	AD: 0.036	AD: 0.305	USD/hour
	AF: 0	AF: 0	AF: 0	
	ASSU: 0	ASSU: 0	ASSU: 0	
C_{human}	2.52	8.30	7.25	USD/hour
$\boldsymbol{E_{AI}}$	AD: 1	AD: 1	AD: 1	kWh/task
	AF: 0	AF: 0	AF: 0	
	ASSU: 0	ASSU: 0	ASSU: 0	
$\boldsymbol{P_E}$	0.120	0.190	0.168	USD/kWh
$\boldsymbol{EF_{AI}}$	0.434	0.21	1.78	kg CO_2e/kWh
$\boldsymbol{P_{CO2}}$	0.1716	0.1716	0.1716	USD/kg CO_2e

Conclusions

The results suggest that as AI-based services demonstrate lower operational costs, even with the internalization of external CO_2 emission costs, the global adoption of AI to replace human labor in various sectors could accelerate significantly in the near future. This transition has the potential to reshape labor markets on a massive scale, leading to widespread automation of routine and semi-skilled tasks. To address the social implications of this shift, governments should proactively invest in reskilling and upskilling programs to help displaced workers transition into emerging job roles, implement policies to ensure equitable distribution of the economic benefits of AI, and consider measures such as universal basic income or tax incentives to cushion the socioeconomic impact of automation.

References

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