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# QUANTIFYING THE ROLE OF LARGE LANGUAGE MODELS IN REBUILDING UKRAINE: LABOR AUTOMATION AND COST SAVINGS

# КІЛЬКІСНА ОЦІНКА РОЛІ ВЕЛИКИХ МОВНИХ МОДЕЛЕЙ У ВІДБУДОВІ УКРАЇНИ: АВТОМАТИЗАЦІЯ ПРАЦІ ТА ЕКОНОМІЯ ВИТРАТ

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This study examines the potential impact of Large Language Models (LLMs) on the Ukrainian labor market. For the first time, it attempts to estimate the share of employees that can be replaced by generative AI technology during the next five years. In addition, total cost savings were calculated based on forecasted wage and LLMs diffusion. Assuming no labor market frictions, the results indicate a modest but still significant potential for automation starting from 0.2% in 2026 based on pure LLM technology and reaching up to 2.6% of the labor force by 2030 with additional LLM-augmented software. Finally, net cost savings in 2026 are projected at approximately 7.9 billion UAH annually increasing to a maximum of 122.0 billion UAH by 2030. The results are relevant for government authorities and businesses supporting decision-making in human resource management, automation strategies, and the development of upskilling and reskilling programs.

**Keywords: Large** Language Models (LLMs); cost savings; labor shortages; economic efficiency; labor automation; reconstruction of Ukraine.

Метою статті є аналіз потенційного впливу великих мовних моделей (ВММ) на дефіцит робочої сили та оцінка економічної вигоди від їх впровадження під час відбудови України. Актуальність дослідження зумовлена двома паралельними тенденціями: швидким поширенням технологій штучного інтелекту та серйозними обмеженнями на ринку праці, з якими стикається Україна через втрати, які пов'язані з російською агресією, міграцією та демографічним спадом. Замість того, щоб покладатися на складні макроекономічні моделі з багатьма припущеннями, які важко калібрувати, у статті застосовується більш прозорий підхід. Аналіз охоплює 35 секторів та підсекторів української економіки та виокремлює два основні канали впливу. Перший відображає завдання, які можна суттєво пришвидшити лише за допомогою ВММ. Другий охоплює ширший потенціал для автоматизації, коли ВММ поєднуються з додатковим програмним забезпеченням, включаючи технології машинного зору. Модель оцінює автоматизований еквівалент зайнятості як функцію поширення технологій, рівня автоматизації, експозиції до ВММ, економії часу, прибутковості та кількості працівників, зайнятих у кожному секторі. Результати свідчать про те, що ВММ можуть частково зменшити дефіцит робочої сили, але навряд чи вони здатні повністю його усунути в середньостроковій перспективі. За більш консервативним сценарієм автоматизований еквівалент робочих місць залишається помірним і становить від 0,2% до 1,2% протягом 2026-2030 років. За ширшим сценарієм ефект стає більш помітним, але все ще обмеженим відносно загальних потреб у реконструкції, досягаючи максимуму автоматизації на рівні 2,6% робочої сили у 2030 році. Більшість секторів продовжують стикатися з дефіцитом працівників навіть після врахування впровадження ВММ. Незважаючи на це, чисті заощадження від автоматизації коливаються від 7,9 до 122,0 млрд. грн на рік залежно від сценарію та періоду. Отримані результати можуть бути використані органами державної влади, бізнесом і дослідниками для планування кадрової політики, цифровізації, створення програм підвищення кваліфікації та перекваліфікації працівників.

**Ключові слова:** великі мовні моделі (ВММ); економія витрат; дефіцит робочої сили; економічна ефективність; автоматизація праці; відбудова України.

**Statement of the problem.** Due to Russia's full-scale aggression, the Ukrainian economy has been facing a significant outflow of population. More than 5.6 million refugees have left the country and 4.6 million individuals are registered as internally displaced persons. At the same time, hundreds of thousands of men and women have been conscripted into the Defense Forces of Ukraine. As a result, the civilian labor market exhibits a substantial labor shortage, which negatively affects rapid reconstruction, economic support of the armed forces, and the sustainability of statehood [1; 2].

According to the European Business Association (EBA) survey, 74% of companies reported that their primary challenge is the shortage of skilled workers. In addition to production constraints, companies are raising real wages to retain talent, which is contributing to demand-side inflationary pressure. Overall, it impacts the macroeconomic environment including fiscal and defense financing, reduces long-term economic potential, and contributes to the expansion of the shadow economy [3].

Firms adopt various adaptation strategies. Among them are remote work, increased participation of women in occupations traditionally dominated by men, and greater inclusion of people with disabilities and older individuals to the labor force. The most affected sectors are construction, critical infrastructure and utilities, energy, as well as small- and medium-sized enterprises (SMEs) [4].

With the rapid advancement of artificial intelligence (AI) technologies in recent years, another potential way to alleviate labor shortages is the integration of Large Language Models (LLMs) into business processes. This type of automation and technological augmentation can significantly increase productivity and partially reallocate human resources, making them available for sectors that are less exposed to AI. In addition to its benefits, automation may also represent a relatively safe option for regions close to the front line, which are among the most vulnerable and where the labor market may not function properly.

**Analysis of recent research and publications.** The emerging literature on LLMs and financial and economic effects on the labor market can be divided into three main strands. The first one focuses on measuring potential exposure of individual occupations to the introduction of LLMs. It is based on detailed task descriptions and then humans or LLMs themselves assess what percentage of tasks can be completed significantly faster with the application of new technologies. The second strand of literature analyzes the potential macro-level impact of AI and automation on productivity, labor market dynamics, and GDP growth. Finally, the third strand examines already realized labor market effects such as changes in employment, wages, vacancies, and so on.

Potential for automation based on LLMs is high. T. Eloundou et al. [5] found that for the United States, at least 80% of the workforce faces the possibility to automate 10% of their tasks. Half of the tasks can be automated for 19% of workers. Similar results were obtained for the Chinese labor market by Q. Chen et al. [6], who assigned to each occupation a score that falls into one of four categories each describing the level of LLM exposure. Even though the authors aggregated LLM exposure to the industry level, these results were not further propagated to the macroeconomic output level.

D. Acemoglu [7] built a static macroeconomic model where country's output is an aggregate of a continuum of $N$ tasks, each produced either with capital or labor inputs. The author combined tasks into occupations and then aggregated them to GDP level using wages as weights. The resulting country-level GDP exposure was estimated at 20%. However, not all these tasks are profitable for the businesses to automate. M. Svanberg et al. [8] estimated for computer vision tasks that only 23% of the tasks with AI exposure will be chosen by businesses to automate with the current wage levels. It results in only 20% * 23% = 4.6% share of GDP tasks that are actually impacted by AI (through automation or augmentation). Estimated cost savings from AI are 14.4%. The resulting TFP gains from AI over the next 10 years are only 0.66%. The impact on GDP is also small and amounts to 1.16%. Similar moderate effects of AI chatbots on the labor market were found by A. Humlum and E. Vestergaard [9] for the Danish economy. The majority of workers have implemented innovative technologies into their daily routines reporting productivity growth and the emergence of new tasks; however, no significant impact on employment or wages in general was reported.

Abovementioned macroeconomic models are well-suited to assess the potential impact of AI on the whole economy. However, they rely on many structural assumptions and require calculating numerous parameters which are difficult to calibrate in wartime and post-war Ukraine. Instead, we will use a more transparent exposure-based approach and will aggregate

T. Eloundou et al. [5] shares to estimate potential reduction in labor requirements and related cost-benefit analysis. This approach is more portable and empirically operational than a highly parameterized macro model.

In terms of Ukrainian labor market, local scientists usually conduct descriptive analysis of LLMs impact on automation without any relevant quantitative measures.

**Highlighting previously unresolved parts of the overall problem.** To the best of our knowledge, it is the first attempt to examine potential employment needs reduction and net wage savings due to LLMs usage in the Ukrainian economy. Namely, we will simulate expected benefits and costs for the medium-term horizon assuming gradual adoption of LLM-based technologies across sectors rather than their immediate full-scale implementation.

**Formation of the objectives of the article.** The goal of the paper is to quantify what percentage of the labor force can be automated with the help of LLMs and software built on them (including computer vision) and the net monetary benefits resulting from the implementation of this technology.

**Summary of the main research material.** Since we use estimates of LLM exposure from T. Eloundou et al. [5], originally defined for occupations in the United States, we aggregate these measures to the industry level and subsequently align them with Ukrainian economic sectors. Data on wages and employment across key sectors (reported by State Statistics Service of Ukraine) largely corresponds to U.S. sectoral classification with three notable exceptions. At a high level, the U.S. classification distinguishes wholesale and retail trade, separately reports natural gas supply, and treats management of companies and enterprises as distinct from professional services. Each U.S. sector is represented by a dedicated dataset containing detailed occupational employment for 2024, which is used to aggregate LLM exposure estimates to the industry level [10].

When considering manufacturing subsector, Ukrainian and U.S. Bureau of Labor Statistics (BLS) classification largely coincide with some differences due to higher granularity in U.S. data. Specifically, textile mills, apparel manufacturing, leather production and allied product manufacturing are combined into a single Ukrainian subsector: textiles, wearing apparel, leather, and other materials. Similarly, the Ukrainian category wood, paper and printing corresponds to U.S. wood product manufacturing, paper manufacturing, and printing activities. The Ukrainian category rubber and plastic products with other non-metallic mineral products is constructed by aggregating corresponding U.S. subsectors. Primary and fabricated metals are also merged into a unified Ukrainian category. It is important to note that the U.S. classification includes separate subsector miscellaneous manufacturing which has no direct Ukrainian equivalent. Given its small share of less than 5%, it is excluded from analysis. Transportation and warehousing classifications are largely compatible across countries with U.S. providing more detailed breakdowns (e.g., for land transport and pipelines) [11].

In summary, 51 BLS sectors and subsectors are mapped to corresponding Ukrainian classifications. Each sector is associated with a dataset of underlying occupations and employment levels, which are matched to occupations with defined LLM exposure from T. Eloundou et al. [5].

Using the O*NET 27.2 database [12], which serves the primary source of occupational information in the United States, T. Eloundou et al. [5] assign to each occupation the share of tasks that can be completed faster using LLMs. In the resulting table, there are 923 occupational codes with detailed task descriptions. The authors distinguish three types of exposure. At E0, tasks cannot be automated using LLM (GPT-4). At E1, tasks can be automated using LLMs alone. At E2, automation requires LLMs in combination with additional software including computer vision technologies. Automation itself is defined as a reduction of task completion time by at least 50%. Since E1 and E2 are mutually exclusive, three aggregate indicators are defined: α-exposure (E1), β-exposure (E1 plus a half of E2), and γ-exposure (E1 plus E2). Tasks classification is conducted both by human experts and GPT-4 LLM and we use the average of them.

O*NET occupations are largely consistent with BLS classifications. However, there are minor discrepancies in timing and granularity. Specifically, O*NET is based on 2023 data, while BLS reflects 2024 leading to minor changes such as splits or redefinitions of occupations. Additionally, differences in aggregation levels may arise. Nevertheless, only 10 occupations required reconciliation, which was performed by aggregating O*NET categories to match BLS definitions. This improves coverage of occupations with defined LLM exposure.

Using Python, we matched all 51 sectors and subsectors with the LLM productivity gains. The lowest matching shares are observed in apparel manufacturing (89.8%), leather and allied product manufacturing (89.8%), and government (89.2%). All other sectors and subsectors exceed 91% coverage with the highest (more than 99%) in accommodation and food services, as well as couriers and messengers. The median matching rate is 96.4%. The inability to achieve total coverage is explained by the fact that BLS occupations contain residual items capturing all other work types not identified separately. For example, all other business operations specialists or all other agricultural workers. Naturally, these types of occupations are heterogeneous and consist of diverse activities which cannot be uniformly described in terms of their underlying tasks. Consequently, no LLM exposure can be provided for them. They are conservatively assumed to have zero LLM exposure.

To determine the exposure for LLM automation at sector and subsector levels, the results are further aggregated using weighted-average formula:

$$LLM = \frac{\sum_{j=1}^{N} O_j^{LLM} * O_j^{E}}{\sum_{j=1}^{N} O_j^{E}}, \qquad (1)$$

where $O_j^{LLM}$ is the exposure of occupation $j$ to LLM automation, $O_j^{E}$ is the number of employees, and $N$ is the number of distinct occupations in sector or subsector.

Table 1

**Sector-level LLM exposure, employment, and wages as of 2025**

| Sector | Growth | Wage | Employ-ment | GPT-Based Exposure, % | | Human-Based Exposure, % | |
|---|---|---|---|---|---|---|---|
| | | | | α | γ | α | γ |
| Total | | 25,946 | 11,915 | 12 | 47 | 13 | 40 |
| Agriculture, forestry and fishing | S | 24,227 | 1,965 | 7 | 35 | 5 | 24 |
| Industry | | 28,722 | 1,595 | 11 | 40 | 8 | 33 |
| Mining and quarrying | S | 32,726 | 127 | 9 | 37 | 7 | 31 |
| Manufacturing | | 28,061 | 1,084 | 10 | 37 | 7 | 30 |
| Electricity, gas, steam and air conditioning supply | C | 33,975 | 262 | 13 | 54 | 12 | 43 |
| Water supply, sewage, waste management | C | 19,139 | 122 | 14 | 45 | 9 | 39 |
| Construction | C | 22,384 | 427 | 8 | 40 | 7 | 30 |
| Wholesale and retail trade; repair of motor vehicles and motorcycles | M | 31,106 | 3,049 | 13 | 53 | 18 | 46 |
| Transportation and warehousing, postal and courier activities | | 25,925 | 631 | 14 | 37 | 8 | 34 |
| Accommodation and food service activities | L | 19,287 | 170 | 7 | 27 | 9 | 23 |
| Information and communication | M | 66,060 | 253 | 28 | 78 | 21 | 68 |
| Financial and insurance activities | L | 53,123 | 153 | 20 | 89 | 25 | 75 |
| Real estate activities | L | 23,113 | 195 | 12 | 63 | 18 | 50 |
| Professional, scientific and technical activities | M | 33,816 | 332 | 22 | 81 | 19 | 69 |
| Administrative and support service activities | L | 20,012 | 254 | 13 | 40 | 12 | 37 |
| Public administration and defense; compulsory social security | S | 33,173 | 676 | 14 | 51 | 15 | 46 |
| Education | S | 16,110 | 1,053 | 13 | 56 | 17 | 48 |
| Human health and social work activities | S | 18,587 | 735 | 11 | 46 | 12 | 40 |
| Arts, sport, entertainment and recreation | L | 18,020 | 155 | 12 | 40 | 17 | 39 |
| Other service activities | L | 29,481 | 271 | 12 | 43 | 14 | 37 |

*Source: created by the author*

The least exposed sectors are agriculture and construction. Only 6.0% and 7.5% of tasks can be automated using LLM alone. Under the broader γ-exposure definition, exposure rises to 29.3% and 34.9%, respectively. The most exposed sectors are professional services, finance, and information where over 20% of tasks can be automated with LLM only, while additional software can boost this number to over 72%.

The average exposure in manufacturing is 8.9% and 33.6% for α- and γ-exposure, respectively, with more details provided in Table 2. In general, manufacturing subsectors are less susceptible to automation using LLMs.

As shown in Table 3, the transportation, warehousing, postal, and courier sector exhibits slightly higher exposure levels compared to manufacturing: 10.8% and 35.7% for α- and γ-exposure, respectively, with a relatively even distribution across subsectors.

We define the automated equivalent number of workers whose tasks are fully automated as follows:

$$A_t = D_t U_t E_t T_t R_t P_t \,, \quad (2)$$

where $D_t$ denotes the technology diffusion factor, $U_t$ is the share of tasks that are automated rather than augmented, $E_t$ is the share of tasks exposed to LLMs, $T_t$ represents the time savings from LLM usage, $R_t$ is share of the LLM exposure tasks profitable for automation, and $P_t$ is total employment.

Due to the lack of direct country-level forecasts, the diffusion factor $D_t$ is assumed to follow logistic process:

$$D_t = \frac{K}{1 + e^{-r(t - t_0)}} \,, \quad (3)$$

where $t_0$ denotes the midpoint year of fastest diffusion (assumed to be 2028), $K$ is the long-run saturation level (set to 1.0), and $r$ is the diffusion speed. The parameters are

Table 2

**Manufacturing subsectors LLM exposure, employment, and wages as of 2025**

| Sector | Growth | Wage | Employ-ment | GPT-Based Exposure, % | | Human-Based Exposure, % | |
|---|---|---|---|---|---|---|---|
| | | | | α | γ | α | γ |
| Total | | 28,061 | 1,084 | 10 | 37 | 7 | 30 |
| Food products, beverages and tobacco products | M | 26,162 | 281 | 9 | 30 | 7 | 26 |
| Textiles, wearing apparel, leather, leather articles and other materials | M | 17,259 | 67 | 10 | 35 | 7 | 29 |
| Wood articles, paper and printing | C | 23,731 | 73 | 10 | 37 | 7 | 29 |
| Coke and refined petroleum products | S | 28,725 | 8 | 10 | 45 | 8 | 36 |
| Chemicals and chemical products | S | 28,427 | 43 | 11 | 47 | 11 | 37 |
| Basic pharmaceutical products and pharmaceutical preparations | M | 46,815 | 28 | 12 | 53 | 13 | 43 |
| Rubber and plastic products; manufacture of other non-metallic mineral products | C | 25,752 | 98 | 10 | 35 | 7 | 28 |
| Basic metals, fabricated metal products; except machinery and equipment | C | 31,022 | 141 | 11 | 38 | 6 | 30 |
| Computers, electronic and optical products | S | 41,105 | 28 | 19 | 63 | 13 | 50 |
| Electrical equipment | C | 25,536 | 34 | 10 | 41 | 8 | 33 |
| Machinery and equipment not elsewhere classified | C | 27,012 | 64 | 12 | 46 | 9 | 36 |
| Motor vehicles, trailers and semi-trailers and other vehicles | S | 34,247 | 131 | 10 | 38 | 7 | 30 |
| Furniture, other manufacturing, repair and installation of machinery and equipment | S | 25,983 | 88 | 9 | 36 | 6 | 28 |

*Source: created by the author*

Table 3

**Transportation and warehousing, postal and courier activities LLM exposure, employment, and wages as of 2025**

| Sector | Growth | Wage | Employ-ment | GPT-Based Exposure, % | | Human-Based Exposure, % | |
|---|---|---|---|---|---|---|---|
| | | | | α | γ | α | γ |
| Total | | 25,925 | 631 | 14 | 37 | 8 | 34 |
| Land transport and transport via pipelines | S | 23,057 | 311 | 17 | 44 | 8 | 38 |
| Water transport | L | 25,044 | 2 | 12 | 46 | 13 | 41 |
| Air transport | L | 57,471 | 21 | 11 | 45 | 11 | 40 |
| Warehousing and support activities for transportation | S | 28,250 | 250 | 9 | 29 | 8 | 28 |
| Postal and courier activities | L | 18,759 | 47 | 15 | 36 | 4 | 36 |

*Source: created by the author*

calibrated such that $D_{2025} = 0.145$, corresponding to the average percentage of people who use AI for work or for own needs every day or almost every day in 2025-2026, and $D_{2030} = 0.8$ implying 80% adoption by 2030. Although 14.5% reflects the usage by population which may have higher penetration rate than workers, this is daily usage percentage, and we expect higher adoption levels for the occupations and sectors that are highly exposed to LLM [13]. Evidence from A. Bick et al. [14] suggests that workplace adoption of generative AI is at least as rapid as the historical diffusion of personal computers and the internet in the United States. For instance, internet adoption increased from 10% to 60% in approximately seven years. Furthermore, the correlation between LLM exposure and actual adoption in 2024 is positive and equals 67%. Taking these facts into account, 80% penetration for Ukraine in 2030 is a reasonable assumption.

There are two main channels of AI impact on labor market: automation (replacement of human labor) and augmentation (enhancement of human productivity through time savings). For upper-income countries, P. Gmyrek et al. [15] estimate that 2.5% of employment is subject to automation and 12.8% to augmentation. This implies that 16.3% of AI-exposed tasks are automated with the remainder augmented. Similarly, K. Handa et al. [16], based on four million Claude.ai conversations, find that 43% correspond to automation and 57% to augmentation. We take the average estimate of 29.7% as the share of AI-exposed tasks $U_t$ that are automated.

In contrast to D. Acemoglu [7], we treat T. Eloundou et al. [5] estimates not as pure exposure percentages but as a share of tasks for which LLMs can complete them at least 50% faster. Instead of direct 50% mentioned by T. Eloundou et al. [5] in exposure rubric description ("using the described LLM via ChatGPT or the OpenAI playground can decrease the time required to complete the DWA or task by at least half (50%)"), D. Acemoglu [7] used labor savings time from external experiment-based papers resulting in a much lower value of 27%. Next, the author applied M. Svanberg et al. [8] estimate that only 23% of AI-exposed projects are profitable for automation. However, the latter focused their analysis on computer vision specifically which corresponds to E2 measure from T. Eloundou et al. [5] (included into β- and γ-exposure) and is not relevant for E1 α-exposure. Instead, we assume that all α-exposure occupations are profitable for automation since LLM costs are zero or much smaller even with subscription than actual wages of the employees. We only apply M. Svanberg et al. [8] profitability measure to E2 exposure that explicitly mentions usage of additional to LLM software or computer vision tasks. Specifically, tasks requiring additional to LLM software or computer vision capabilities (difference between γ- and α-exposure) are assumed to be profitable in 23% of cases as in M. Svanberg et al. [8]. We interpret time savings as labor-equivalent reduction under full reallocation assumption (no labor market frictions within the sector or subsector).

The State Statistics Service of Ukraine reported total employment last time in 2021. Due to the war, no official updates have been published since. Moreover, subsector-level data is unavailable for industry and transportation. On the other hand, there is detailed data for full-time employees (firms with 10 or more people) covering 2021 and 2025. We use it to assess the growth in the total number of employed people between 2021 and 2025 and to find employment shares in not reported subsectors. For example, the number of full-time employees decreased by 24% (from 7.1 to 5.4 million), and we extrapolate this change to total employment changes between 2021 and 2025. The drop by 24% from 15.6 million results in 11.9 million total employment in 2025. This estimate excludes military personnel and is broadly consistent with other projections: Ministry of Economics [17] consensus forecast of 12.5 million made in October 2025, Dragon Capital [18] estimate of 11.7 million, and Cabinet of Ministers of Ukraine [19] estimate of 13.3 including military.

Reconstruction needs vary significantly across sectors, and precise labor demand forecasting remains highly uncertain under wartime and post-war conditions. For instance, International Labour Organization [20] assumes a linear recovery of productivity to pre-war levels in 2032 leading to estimated employment level of 18.5 million in 2025, which substantially exceeds realistic estimates of 13.3 million (including military). To avoid spurious precision and to be more transparent, we divided all economic sectors and subsectors into four groups based on reconstruction-intensity growth: core, strong, moderate, and limited. Their employment growth rates over the next 5 years (2026-2030) are assumed to be as follows: 35%, 20%, 10%, and 3%, respectively. We applied tree-based classification referring to the fifth rapid damage and needs assessment (RDNA5) from World Bank [21] and subjective judgement. At the first stage, if the sector is directly involved in rebuilding damaged housing, infrastructure, utilities, transport systems, or productive capacity, it is assigned to the core group or to the strong group if the relationship is not fully direct. If the impact on reconstruction is substantial but indirect, sector is an important supplier or enabler, then strong label is selected. If spillover effect is low, then moderate group is selected. Sectors with only weak links to reconstruction are assigned limited labels. The results of classification are provided in Tables 1-3 in the column “Growth”.

According to I. Ippolitova et al. [1], out of 1.6 million refugees who plan to return back to Ukraine, working adults constitute 0.7 million. Dragon Capital [18] estimates that only 1 million refugees will return after the war with 0.3 million adding to the labor force. The National Bank of Ukraine [22] expects net outflow of 0.2 million people in 2026, net inflow of 0.1 in 2027, and 0.5 million in 2028. We assume the same 0.5 million will return in 2029 and 2030 with the total number of 1.6 that coincides with I. Ippolitova et al. [1] estimate – the share of employed returnees is 42%.

The National Bank of Ukraine [22] forecasted real wage growth for 2026-2028 is 7.6%, 6.2%, and 5.9% respectively. We assume that 5.9% will remain thereafter.

The results of the modelling are provided in Figure 1. As we can see, based on described assumptions, the share of LLM-based automated equivalent jobs as a percentage of total number of employees is very small in 2026 and constitutes only 0.2%. It increases to 1.2% in 2030 but labor shortage is still much higher and constitutes from 3.5 to 8,7% of gross demand during 2026-2030 period. Expectedly, when considering more advanced technologies (LLMs with the possibility to extend their functionality with built-up software and computer vision capabilities – γ-exposure), automated share is from 0.4 to 2.6% over 2026-2030. Labor deficit is slightly smaller than under α-exposure and is in the range from 3.3 to 7.5%.

Under α-exposure, all sectors and subsectors of the Ukrainian economy are facing a labor deficit even taking into account potential automation. If we consider γ-exposure, the only sector that has a labor surplus starting from 2028 is financial and insurance activities; however, it is relatively small and reaches a maximum of 1.1% of sector employment in 2030. The reason for this result is the high exposure of financial sector to automation and the limited expected growth in labor demand.

In order to calculate potential monetary benefits from automation, we use average wage information by sectors and subsectors provided in Tables 1-3. Next, we assume that all tasks with α-exposure are suitable for automation with the cost per employee equal to the average subscription price of such popular LLMs as ChatGPT and Google’s Gemini (20 USD and 909.99 UAH, respectively), which are assumed to grow with the real wage rate. In terms of additional software (including computer vision capabilities) required for γ-exposure automation, we assume that its cost constitutes a quarter of person’s salary, treating it as a conservative

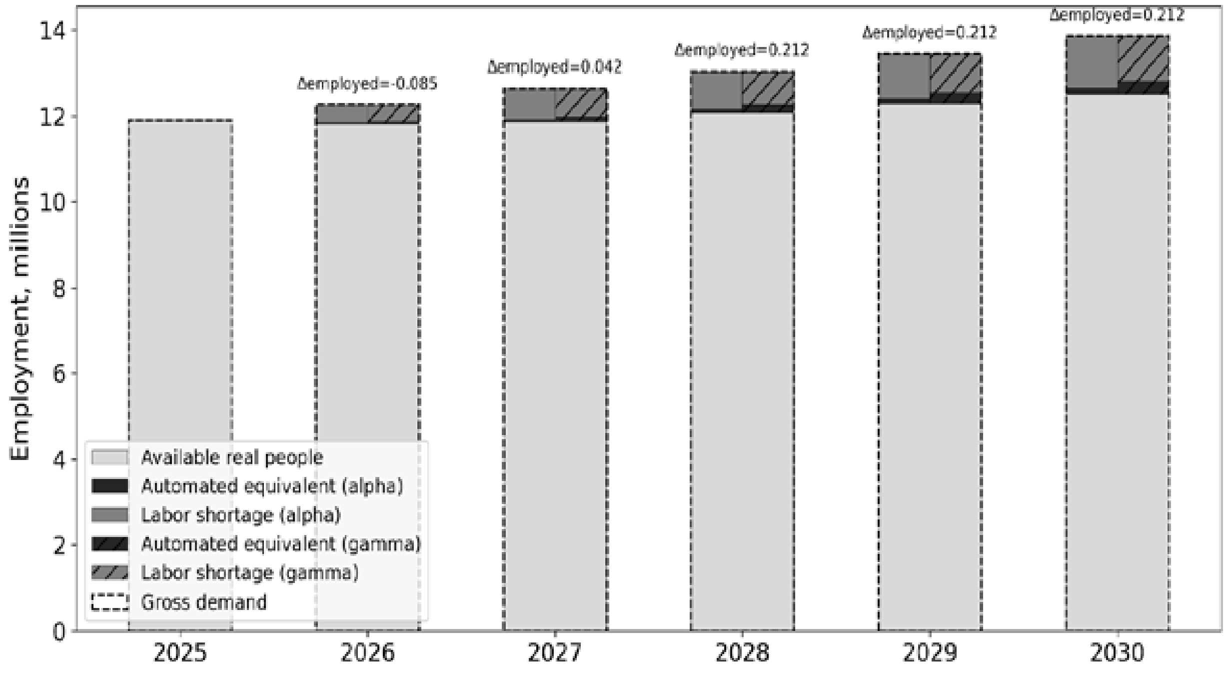


**Figure 1. Employment automation with LLMs**

*Source: estimated by the author*

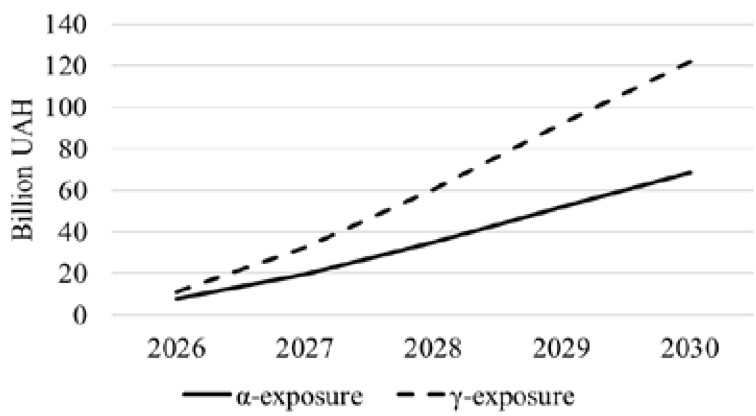


**Figure 2. Net automation savings**

*Source: estimated by the author*

estimate. As can be seen from Figure 2, the total annual net wage savings from automation are 7.9 and 11.2 billion UAH in 2026 and reach 68.5 and 122.0 billion UAH in 2030 for α- and γ-exposures, respectively.

**Conclusions.** Labor automation lies at the center of technological progress accelerating economic growth and increasing society wellbeing. Recent breakthroughs in generative AI have demonstrated that LLMs possess significant cognitive abilities with human-like reasoning and conversation flow. LLM-based automation may be one of the strategic choices that can help to address the problem of labor shortage on the Ukrainian market caused by massive internal displacement and emigration due to Russia's aggression.

In this study, we used the estimates for LLM exposure of O*NET occupations, matched them with sector-level BLS occupations, and aggregated the exposure to the macro level. Then, U.S. industries were aligned with Ukrainian sectors which, based on micro-level automation assumption, were used for the simulation. The results indicate a modest potential to replace people with LLMs or with additional built-in software (including computer vision). In 2026, the automation share may constitute less than 0.5% reaching a maximum of 2.6% in 2030. Nevertheless, net wage savings from automation are still relatively high ranging from 7.9 billion UAH in case of α-exposure in 2026 to 122.0 billion UAH for γ-exposure in 2030. To properly support this automation shift and address labor market shortages, the government can introduce and support upskilling and reskilling programs.

Most of the calibration was conducted based on research for developed economies. Within Ukrainian context, further research can focus on local analysis and experimentation to assess potential savings from LLMs and related technologies taking into account wartime conditions and disrupted labor market. In addition, future studies can relax key assumptions made in the paper including the absence of labor market frictions.

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