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How Generative AI is Going to Affect the Georgian Labor Market

This policy paper investigates the potential impact of generative artificial intelligence (GenAI) on the Georgian labor market, identifying which occupations and demographic groups are most affected. Drawing on the International Labor Organization's (ILO) 2025 exposure scores and detailed 2023 Georgian Labor Force Survey data, our findings reveal that 26% of Georgian workers are in occupations where part of their tasks could potentially be performed, fully or partially, by GenAI, with over a third of those in medium- to high-exposure roles. Compared with the broader Europe and Central Asia region, Georgia has fewer workers in occupations vulnerable to full automation, while a larger share of the workforce is engaged in roles with potential for task augmentation. The analysis also reveals that GenAI's impacts are uneven, with women, urban workers, younger individuals, and those with higher education being disproportionately represented in high-exposure occupations. Importantly, exposure scores measure technological feasibility rather than actual displacement risk - actual outcomes will depend on adoption rates, regulatory frameworks, and organizational decisions. Thus, timely and active policy involvement - from targeted upskilling to addressing digital disparities - is crucial to turn AI challenges into opportunities and fully harness its benefits by strengthening workers' capacity to complement AI in their tasks.

Introduction

Generative artificial intelligence is playing an increasingly prominent role in workplaces worldwide. Tools such as ChatGPT, Midjourney, Google Gemini, and others are transforming how tasks are performed, changing work routines, and creating new forms of collaboration between humans and machines.

GenAI represents both a challenge and an opportunity. While different GenAI tools offer productivity gains and cost savings, their implementation may deepen regional disparities and pressure vulnerable groups - especially if targeted upskilling and digital-inclusion measures are not in place. At the same time, GenAI can reshape occupations by creating AI-specific and complementary roles. Balancing these opportunities and challenges is therefore critical to harness the full potential of GenAI.

A structured way to understand the effects of AI in the workplace is by considering two distinct channels: automation and augmentation. Automation refers to the complete substitution of human-performed tasks that can now be executed independently by AI without human involvement. Typically, such tasks are routine and cognitive, such as basic content generation or data classification. In contrast, augmentation captures scenarios where GenAI acts as a complementary tool, enhancing human performance without replacing the worker. The distinction between automation and augmentation is crucial for evaluating the implications of GenAI: while the former may lead to job displacement, the latter suggests changes in task composition, potential shifts in skill demand, and enhancements in labor productivity.

Consequently, the way GenAI shapes the new labor market reality will be affected by the composition of these two effects. In particular, in developing countries like Georgia, the extent of automation and resulting job displacement might be limited, as a large share of employment is in manual, physical sectors largely insulated from AI. At the same time, developing countries might underutilize the benefits of augmentation because many workers lack digital skills or access to GenAI tools, limiting productivity gains.

This policy paper aims to investigate the potential impact of generative artificial intelligence on the Georgian labor market through the automation-augmentation lens. In doing so, we utilize the approach used in the International Labor Organization's (ILO) Global Index of Occupational Exposure to Generative AI (Gmyrek et al., 2025). Rather than treating automation and augmentation potentials as two opposing categories with a large area of uncertainty in between, Gmyrek et al. (2025) apply a more refined classification that captures a spectrum of AI exposure. The ILO's task-based framework categorizes occupations into six distinct groups by evaluating the extent to which their tasks can be automated by Generative AI. These groups are constructed considering both the average exposure score of tasks within each occupation and the standard deviation of exposure scores across those tasks. This enables the differentiation of jobs not only by their average exposure to GenAI but also by distinguishing between occupations where exposure is relatively evenly distributed across tasks and those where it is concentrated in only a subset of tasks. Aligning closely with the notions of augmentation and automation potential in the earlier ILO framework described in Gmyrek et al. (2023), an occupation is considered to have an "augmentation potential" when the average exposure score is low, but deviation across tasks is high. In other words, while some tasks in these jobs may have high automation potential, many others continue to require human involvement (Gmyrek et al., 2025). Conversely, an occupation is said to have an "automation potential" when the average exposure score is high and there is a high consistency of exposure across tasks (i.e., there is low standard deviation). Occupations that fall in between these two categories can be viewed as being in transition, slowly shifting from augmentation toward automation potential.

By using the ILO's 2025 exposure scores and detailed Georgian Labor Force Survey data from 2023, we identify which occupations and demographic groups have the highest exposure to GenAI. Findings suggest that a significant share (26%) of Georgian workers face some level of exposure to generative AI, ranging from low to high, with over a third of them (100,584 individuals) falling into the medium- to high-exposure categories. The remainder are either not exposed (59%) or minimally exposed (15%). In comparison to other countries in Europe and Central Asia, Georgia is less affected by the threat of job displacement coming from automation, while the potential for augmentation is higher.

The exposure trends vary markedly by gender, age, and region. Urban workers, particularly in Tbilisi, are the most exposed, while rural workers face lower immediate exposure, reflecting existing digital divides and regional occupational characteristics. Gender disaggregated analysis shows that women, who are slightly overrepresented in AI-exposed clerical and administrative roles, account for 63% of workers in medium- and high-exposure occupations. Age-wise, younger and more digitally skilled workers tend to occupy the roles most affected by generative AI.

This paper proceeds as follows. First, we describe the methodology and data used to assess exposure to Generative AI in the Georgian labor market. Next, we present the ILO's global estimates of GenAI-exposed occupations. The subsequent sections provide the results for Georgian workers, disaggregated by occupation, education, demographic groups, and region. The final section summarizes the findings and offers some policy insights.

Methodology and Data

This section outlines the methodology and data sources used to assess occupational exposure to Generative AI in Georgia, combining international GenAI exposure scores with nationally representative labor market information.

Several studies have developed indices or measures of occupational automation/AI exposure, often using different methods and classifications. A pioneering study by Frey and Osborne (2013) labeled occupations as automatable or not by applying a machine-learning classifier to the Occupational Information Network (O*NET) database of tasks - a comprehensive database of occupational information maintained by the U.S. Department of Labor. Their approach effectively treated each occupation as a unitary risk category, which has been critiqued for ignoring within-job task differences. Arntz et al. (2016), an OECD analysis, relaxed Frey and Osborne's (2013) assumptions by using PIAAC survey data to allow task variation within occupations. Felten et al. (2019, 2021) developed the AI Occupational Exposure (AIOE) index, which uses overlaps between occupations' O*NET skill and task requirements and known AI capabilities to compute exposure scores. Using AI exposure metrics sourced from Felton (2021) and the IMF Complementarity Index, PwC Global AI Jobs Barometer (2025) classifies jobs into "augmented" or "automated" categories. Specifically, occupations with high AI exposure (>0.5 on a 0–1 scale) are split by an AI-complementarity threshold: those with high complementarity are deemed "augmented" (AI enhances tasks), while low complementarity jobs are "automated" (AI replaces tasks).

The exposure framework proposed by Gmyrek et al. (2025) builds on this literature and captures the occupational exposure to generative AI by combining algorithmic prediction with extensive large-scale survey data, supplemented by expert validation and iterative revisions to arrive at a refined global index of exposure. The process begins by considering each job title as a composite of tasks, each with varying susceptibility to automation. This approach aligns with contemporary labor market research emphasizing the mixed nature of task automation potential within occupations rather than assuming uniform automation across entire job categories.

The initial steps used to develop exposure scores involve an algorithmic assessment of automation potential for 2,861 detailed tasks derived from the Polish 6-digit occupational classification system. Utilizing three advanced Large Language Models (LLMs) - GPT-4, GPT-4o, and Gemini Flash 1.5 - Gmyrek et al. (2025) assign a synthetic automation score on a continuous scale from 0 to 1, where 0 indicates no potential for automation, a score from 0 to 1 means augmentation by GenAI, and 1 signifies full automation potential without human involvement. This phase leverages sequential Application Programming Interfaces calls wherein each LLM is provided with contextual information regarding the task's occupational classification and is instructed to assign the scores and justify them. Repeated scoring by multiple LLMs for the same task enabled triangulation and helped identify inconsistencies between model outputs. The distribution of synthetic scores revealed GenAI exposure in cognitive-intensive occupational groups and lower exposure where physical tasks dominate.

Subsequently, the researchers conduct a large-scale human survey utilizing the Computer-Assisted Web Interview (CAWI) technique to capture workers' perceptions of task automation potential. The sample included respondents from all ISCO-08 1-digit occupational groups. Each respondent evaluates the automation susceptibility of a randomized set of 35 tasks from their occupation on a 0-100 scale.

To reduce biases related to uneven task familiarity and varying levels of GenAI knowledge, Gmyrek et al. (2025) supplement the survey with an expert validation stage. A smaller group of international experts from the ILO, National Research Institute of the Ministry of Digital Affairs in Poland, and the Polish Ministry of Family, Labor and Social Policy - each with extensive labor market expertise - assess a sample of tasks across occupational groups. Their evaluations focus on practical feasibility and workplace realities, helping to correct potential over- or underestimations from the general survey and ensuring that results reflect grounded, pragmatic perspectives on automation potential.

Moreover, two independent AI models then reconcile differences between survey respondents and experts, analyzing task-level scores and generating adjusted automation potentials with justifications.

The final stage constructs the Adjusted Global Index of GenAI Exposure, classifying occupations at the ISCO-08 4-digit level into six categories based on the mean and standard deviation of task-level automation scores. These range from Not Exposed and Minimal Exposure to four ascending Exposure Gradients:

- Gradient 1 (Low exposure, high task variability)
- Gradient 2 (Moderate exposure, high task variability)
- Gradient 3 (Significant exposure, high task variability)
- Gradient 4 (Highest exposure, low task variability)

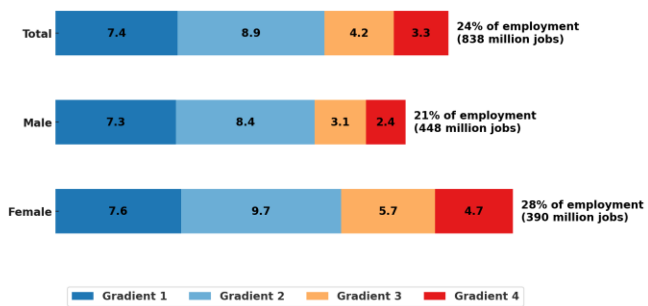
Occupations composed of tasks with low average GenAI exposure scores and substantial variability of these scores across tasks (high task variability) are more closely associated with augmentation, whereas occupations with high average exposure scores and low task variability are more closely associated with automation. This classification advances beyond the binary automation–augmentation lens of prior studies by incorporating task variability within occupations, thus reflecting the heterogeneous automation risks embedded in different tasks.

ILO's global estimates of GenAI-exposed occupations

This section presents the ILO's global estimates of occupations exposed to Generative AI, illustrating potential impacts on labor markets worldwide.

As noted by Gmyrek et al. (2025), approximately 24% of the global workforce is engaged in jobs that involve some level of exposure to GenAI (Figure 1). This exposure is more prevalent in higher-income nations, where 34% of total employment is affected, compared to just 11% in low-income countries (Gmyrek et al., 2025).

Figure 1. Global estimates of occupations potentially exposed to GenAI (% of employment by sex)

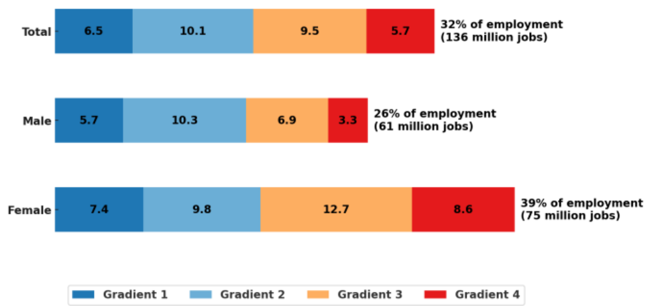


Source: Figure 20 from Gmyrek et al. (2025).

As Figure 1 shows, women are disproportionately overrepresented in higher-exposure roles, while men are slightly more concentrated in lower-exposure jobs. Among male employees, approximately 21% of positions fall into one of the exposure levels, with 3.1% classified in gradient 3 and 2.4% in the highest exposure level, gradient 4. Conversely, the proportion of female employment in potentially exposed roles is significantly greater, particularly in the upper two gradients, where 5.7% of female workers are in gradient 3 and an additional 4.7% are in gradient 4. These gender disparities also widen with country income levels, increasing to 9.6% for women in gradient 4 versus 3.5% for men in high-income countries (Gmyrek et al., 2025).

When it comes to Europe and Central Asia, as Figure 2 shows, in this region, about 32% of employees (136 million jobs) are exposed to GenAI, with 5.7% considered highly exposed.

Figure 2. Estimates of occupations potentially exposed to GenAI for the Europe and Central Asia region (% of employment by sex)



Source: Figure 20 from Gmyrek et al. (2025).

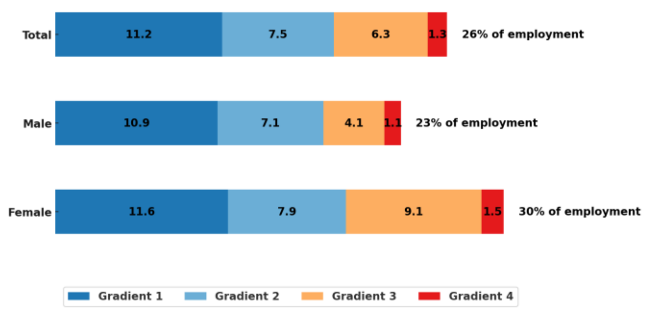
This region exhibits a notable gender disparity: 26% of men compared to 39% of women are exposed, and 3.3% of male-held jobs (61 million) versus 8.6% of female-held jobs (75 million) are highly exposed to GenAI.

Results for the Georgian Labor Market

For the current analysis, we applied the above-described exposure gradients to 361 ISCO-08 4-digit occupations from the 2023 Georgian Labor Force Survey (LFS), covering a workforce of 1,313,636, of whom 45% (594,064) were women. Occupations lacking sufficient detail or unclassified under ISCO-08 were excluded.

As shown in Figure 3, overall, about 26% of Georgian workers fall within one of the four exposure gradients, with over a third (7.6%) of those falling in upper (Gradient 3 and Gradient 4) exposure categories.

Figure 3. Estimates of occupations potentially exposed to GenAI in Georgia (% of employment by sex)



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

Notably, female workers in Georgia are more concentrated in higher-exposure occupations compared to men. Among female workers, 30% of positions fall within the exposure gradients, compared to 23% among male employees. The gap is particularly evident in the upper gradients - 9.1% of women are in gradient 3 and 1.5% in gradient 4, versus 4.1% and 1.1% of men, respectively.

Compared to the broader Europe and Central Asia region, where 32% of employees are exposed to GenAI (versus 26% in Georgia), Georgia has a lower overall AI exposure. Moreover, the distribution across gradients also differs. Among those exposed to GenAI, higher gradients (Gradient 3 and Gradient 4) represent a smaller share of total employment in Georgia, while lower gradients (Gradient 1 and Gradient 2) represent a larger share. This indicates that, compared to the Europe and Central Asia region, fewer workers in Georgia are employed in jobs prone to automation, whereas a larger portion of workers are in jobs with potential for augmentation. One likely explanation of low overall exposure to AI in Georgia is the structure of the Georgian labor market, where a substantial share (16.5%) of employment is in agriculture, which is largely insulated from AI and automation. As for the higher share of Gradient 1 and Gradient 2 in Georgia, it is primarily driven by employment in the service industries, as shown in the sectoral analysis below. Following agriculture, a significant portion (15.5%) of Georgian workers are employed in the trade sector, with a large share of employment falling within the first two exposure gradients, aligning closely with the notion of augmentation (Figure 4).

Exposure by Occupations

Table 1 represents the top 20 most exposed occupations, disaggregated by gender. The occupations with the highest automation scores are predominantly clerical, administrative, and routine office roles (e.g., Data Entry Clerks; Typists and Word Processing Operators; Statistical, Finance, and Insurance Clerks, Financial Analysts, Payroll Clerks, and others). Among the occupations most exposed to AI, where gender disaggregation is feasible based on representativeness criteria, many are observed to be female-dominated in Georgia (Table 1).

Table 1. Top 20 AI-exposed occupations (by Gender)

Occupation Name	Mean Automation Score	Male Employees (%)	Female Employees (%)
Data Entry Clerks	0.7		
Typists and Word Processing Operators	0.65		
Statistical, Finance and Insurance Clerks	0.64	40%	60%
Clerical Support Workers Not Elsewhere Class	0.63	51%	49%
Financial Analysts	0.62	49%	51%
Contact Centre Salespersons	0.61		
Payroll Clerks	0.61		
Credit and Loans Officers	0.6	48%	52%
General Office Clerks	0.6		
Web and Multimedia Developers	0.6		
Translators, Interpreters and Other Linguists	0.59	24%	76%
Contact Centre Information Clerks	0.58		
Bank Tellers and Related Clerks	0.58	19%	81%
Financial and Investment Advisers	0.57	30%	70%
Receptionists (general)	0.57	15%	85%
Systems Aministrators	0.57		
Applications Programmers	0.57		
Database Designers and Administrators	0.57		
Inquiry Clerks	0.57		
Mathematicians, Actuaries and Statisticians	0.56		

Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.
Note: The table presents gender disaggregation only for occupations with more than 25 survey participants to ensure data representativeness

According to Webb (2020), sectors with high shares of routine cognitive tasks, such as public administration, finance, education, and clerical services, typically feature a lot of communication-heavy, document-based, or repetitive analysis that is becoming increasingly feasible for generative AI tools such as ChatGPT and Copilot to automate or assist in. Especially clerical and administrative roles demonstrate a strong concentration of high exposure categories, which indicates a large share of activities - e.g., scheduling, documenting, and internal correspondence - can be effectively executed by AI systems.

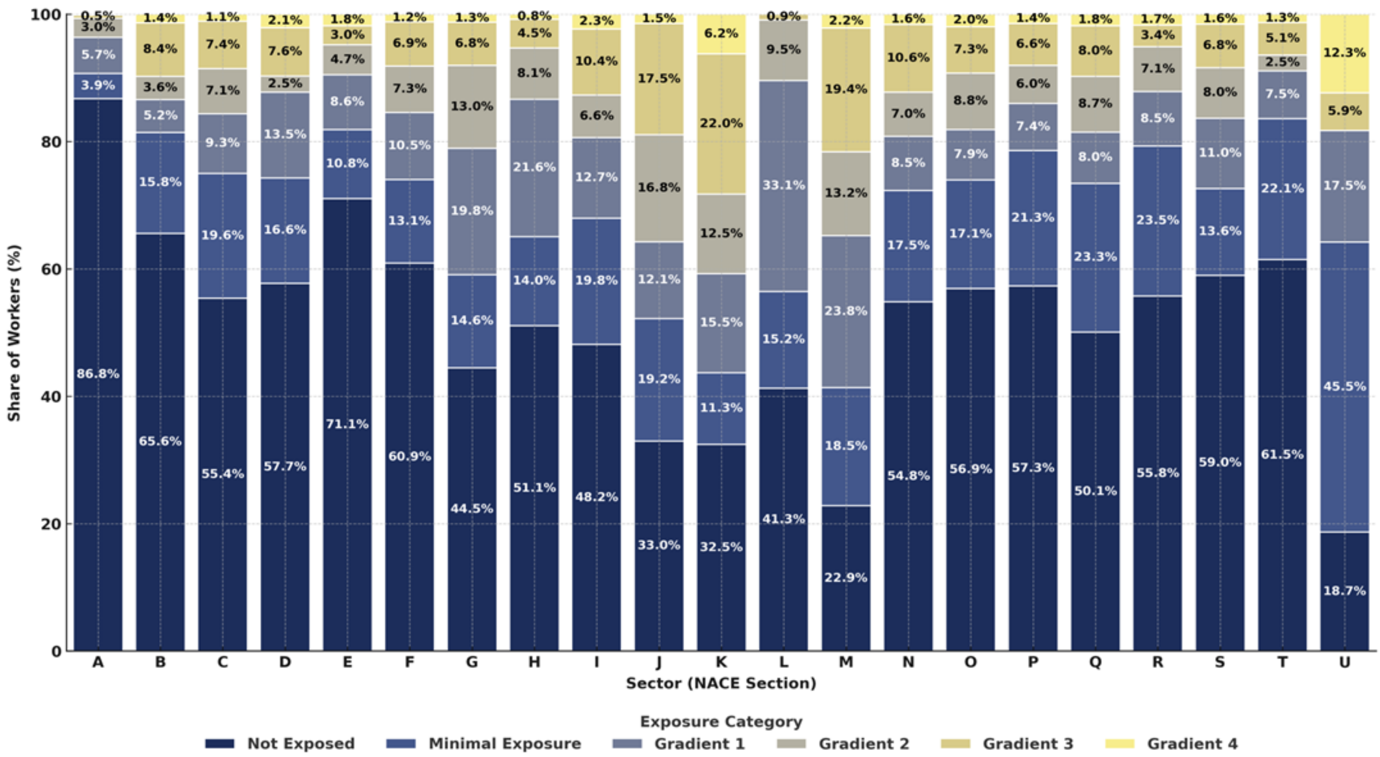
Exposure by Sector

The sector-level exposure of Georgia's labor force to GenAI reveals stark sectoral differences in exposure to AI-driven transformation. This analysis highlights NACE Rev.2 section-level economic activities that face the most significant automation risks or the potential for augmentation, as well as those largely insulated from GenAI.

As Figure 4 below illustrates, at the high-exposure end, Financial and Insurance Activities stand out.

Although only 6.2% of jobs (1,660 out of 26,606 workers) fall into Gradient 4 (the very high exposure category to GenAI), this is the highest

Figure 4. AI-exposure by Sector



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.
Note: A – Agriculture, forestry and fishing, B – Mining and quarrying, C – Manufacturing, D – Electricity, gas, steam, E – Water supply and waste management, F – Construction, G – Wholesale and retail trade, H – Transportation and storage, I – Accommodation and food services, J – Information and communication, K – Financial and insurance activities, L – Real estate activities, M – Professional, scientific and technical, N – Administrative and support services, O – Public administration, P – Education, Q – Human health and social work, R – Arts, entertainment and recreation, S – Other service activities, T – Households as employers, U – Extraterritorial organizations.

share among service sectors. When Gradient 3 is included, the combined high-exposure share is even larger, further distinguishing this sector. Close behind Financial and Insurance Activities, Professional, Scientific, and Technical Activities also register elevated risk, with 2.2% of workers in Gradient 4 and 19.4% in Gradient 3. The Information and Communication sector - often seen as being at the forefront of digital transformation - has 19% of its workforce in Gradients 3 and 4. However, the majority of workers fall under Not Exposed (33.0%) or Minimal Exposure (36.1%).

The lowest exposure is found in sectors dominated by manual labor and physical tasks. Agriculture, Forestry and Fishing, Georgia's one of the largest employing sectors with around 225 thousand workers, is overwhelmingly shielded: 86.8% are not exposed, and only 0.1% fall into Gradient 4. Construction shows a similar pattern, with 60.9% (71,721 of 117,770) unexposed and just 1.2% (1,412) in Gradient 4. Transportation and Storage, and Mining and Quarrying also report high insulation, with 51.1% and 65.6% of their workforces not exposed, respectively.

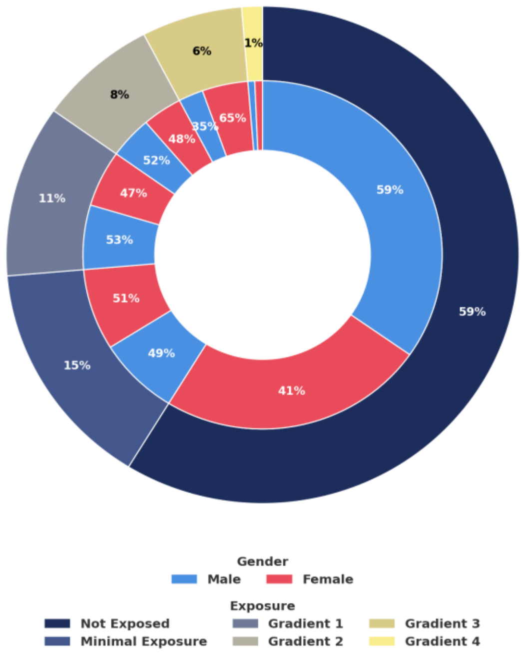
Furthermore, as Figure 4 shows, the higher prevalence of Gradient 1 and Gradient 2 roles, aligning closely with the notion of augmentation, is largely attributable to employment in Georgia's service industries. After agriculture, a substantial portion of the workforce is employed in the trade sector, where most jobs fall within the first two exposure gradients, indicating strong potential for augmentation.

Exposure by Gender

The analysis uncovers stark gender differences in exposure to generative AI in the Georgian labor market. A larger share of the women falls in the middle to high exposure categories as compared to men. This is especially important in domains like clerical work, customer service, and administrative support, fields where women are typically overrepresented.

As Figure 5 shows that more men hold occupations with little or no exposure, while a larger share of women hold jobs in the Gradients 3 and 4 categories.

Figure 5. AI-exposure by Gender



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

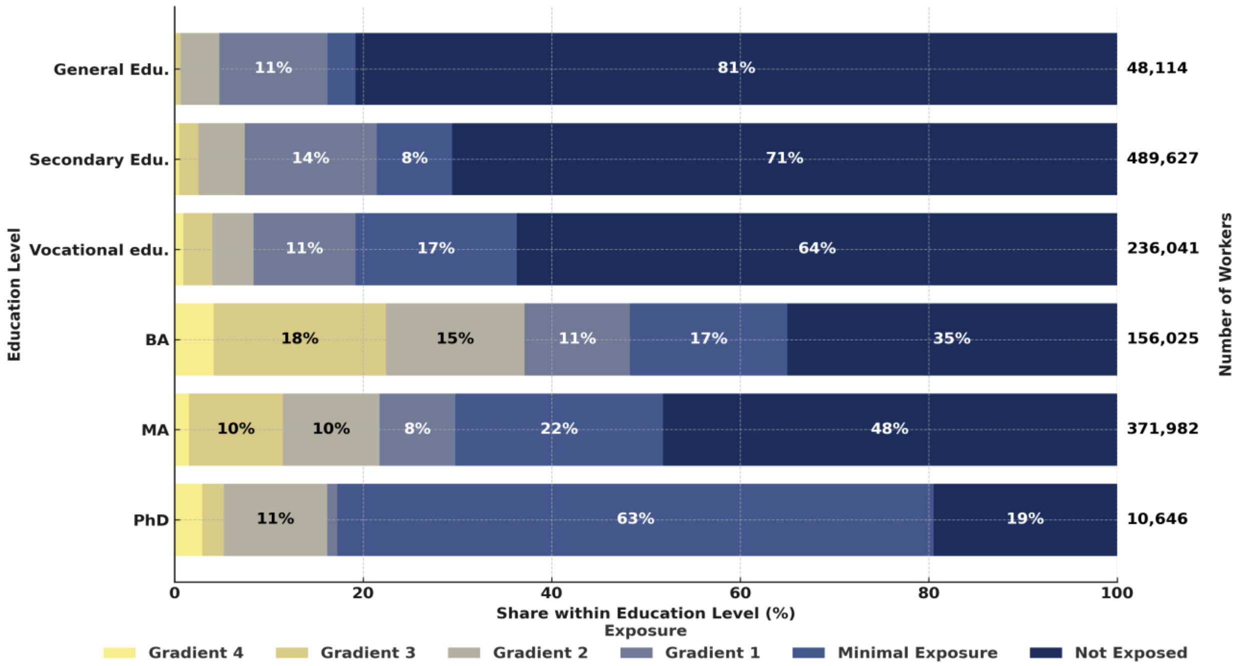
In particular, women make up more than 60% of workers in the highest-exposure occupations, while men represent the large majority of workers in low-gradient occupations where AI-driven task substitution is less likely to have significant effects.

Exposure by Age and Education

Traditionally, education has been viewed as a means of shielding workers from technological displacement (e.g., Acemoglu and Autor, 2011; Autor, Levy, and Murnane, 2003). However, as Webb (2020) shows, artificial intelligence will affect the labor market very differently than previous automation and computerization in earlier waves (technologies like software and industrial robots), primarily by impacting high-skilled, high-wage occupations rather than low- or middle-skilled ones. As the author claims, highly educated workers (with college degrees, including Master's degrees), higher-wage earners, and more experienced workers are most exposed to AI. Many tasks that require higher education - such as drafting legal documents, producing code, preparing reports, analyzing data, or writing content - are precisely the kinds of tasks GenAI can now perform or augment.

Analysis of Georgian labor market data demonstrates that a significant proportion of Georgian workers with bachelor's or master's level degrees are employed in occupations (administrative, legal, or financial services) with mid to high exposure gradients (Figure 6). Less educated workers tend to take occupations that are shielded from GenAI exposure.

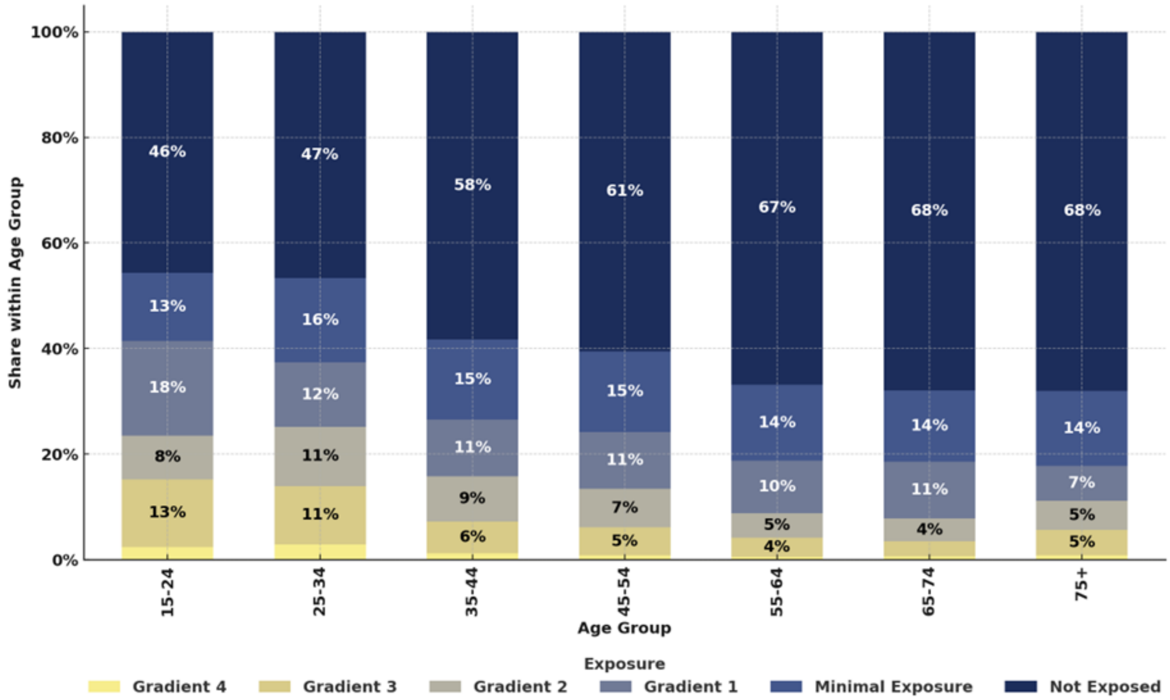
Figure 6. GenAI-exposure by Educational Level



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

Analysis by age categories reveals that younger, more digitally skilled workers generally occupy occupations currently more affected by generative AI (Figure 7). In contrast, older workers tend to be more represented in the "Not Exposed" categories. This reflects that individuals aged 55 and above are less likely to work in roles requiring computer use or modern digital technologies, with many in this group being pensioners who remain active in agriculture and other physically demanding jobs.

Figure 7. GenAI-exposure by Age Group



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

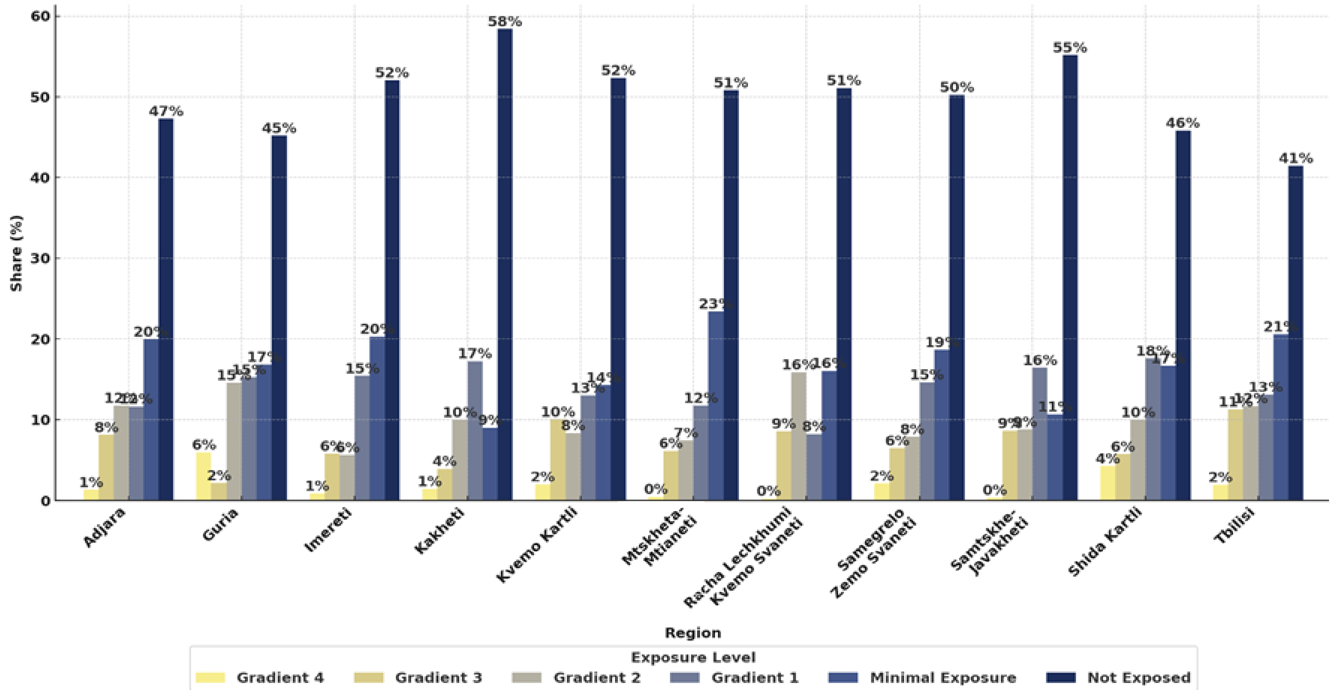
Regional Disparities in Exposure

Exposure to generative AI varies significantly across regions of Georgia, with urban areas - particularly Tbilisi - exhibiting higher levels of exposure. Considering only urban areas, approximately 35% of Georgian workers face some level of exposure (from Gradient 1 to Gradient 4), of which 11% (86,852 individuals) fall into the medium- to high-exposure categories.

In contrast, rural and mountainous regions generally exhibit lower exposure. This is primarily due to the occupational pattern in these regions, which includes agriculture, manual labor, and low-digital service industries. Such jobs are less susceptible to generative AI as they heavily rely on physical labor that currently remains beyond the capabilities of current GenAI technologies. Figure 8 and Figure 9 below illustrate this distinction.

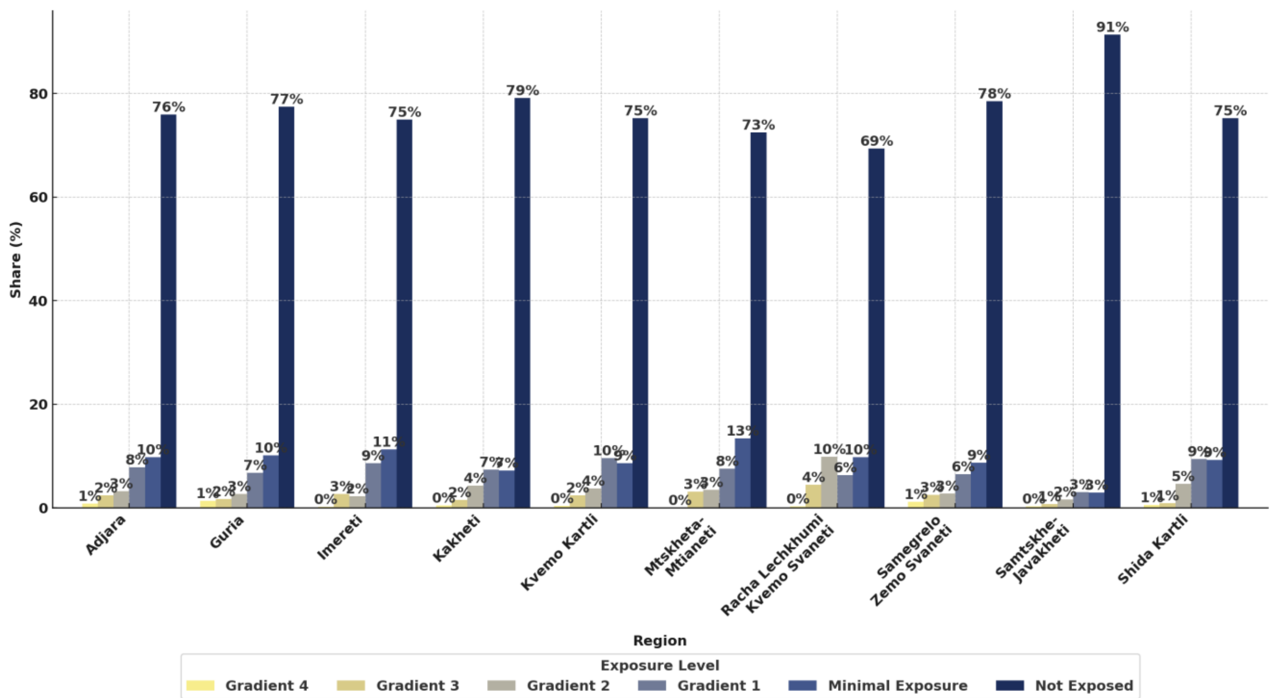
Unsurprisingly, among the urban areas, Tbilisi - home to roughly 32% of the workers - has the highest share of workers in Gradients 3 and 4 (moderate to high exposure) at 13%, followed by Kvemo- and Shida Kartli, with 12% and 10% of exposed workers, respectively. These two regions together employ around 17% of all workers in Georgia. Regions such as Kakheti and Samtskhe-Javakheti have the highest proportion of workers in the "Not Exposed" category, both in rural and urban areas, but these regions are hosting only 9% and 5% of all Georgian workers, respectively.

Figure 8. GenAI Exposure in Urban Areas



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

Figure 9. GenAI Exposure in Rural Areas



Source: Authors' calculations based on Geostat's LFS data and ILO's estimates of occupations' AI exposure.

Conclusion

Our analysis, based on ILO exposure scores and Georgian labor market data, reveals that compared to other European and Central Asian countries, where highly GenAI-exposed occupations are more prevalent, Georgia faces a lower feasibility of AI-driven displacement, with greater opportunities for task augmentation. This pattern reflects the structure of the Georgian labor market, with a large share of employment in agriculture - largely insulated from GenAI - and significant employment in service industries, particularly trade, which predominantly falls within the lower exposure gradients closely aligned with the notion of augmentation. At the same time, the observed impact of Generative AI is uneven across gender, age, region, and education. Women, urban workers, and individuals with higher education in Georgia are disproportionately represented in high-exposure roles. In contrast, rural and older workers are less engaged in occupations exposed to GenAI. This is likely due to factors such as limited connectivity, lower levels of digital literacy, fewer training opportunities, and the nature of jobs available in rural areas. Interestingly, higher education increases exposure in some cases, as graduates tend to cluster in cognitively routine jobs that are more vulnerable to automation. Regional disparities are also pronounced, with Tbilisi showing the highest concentration of high-exposure occupations.

While the above raises a serious concern, it is important to remember that the exposure scores measure technological feasibility rather than actual displacement risk; the latter will be influenced by adoption rates, regulatory frameworks, and organizational decisions.

Further, GenAI does not only substitute for existing tasks; it is actively reshaping task composition and creating new roles. These include AI-specific occupations such as machine-learning engineers, prompt engineers, AI product managers, and AI ethics/compliance officers, as well as complementary roles that augment human work through human-AI collaboration and oversight. Evidence from Acemoglu et al. (2022) demonstrates rapid growth in AI-related job postings and shifts in hiring patterns, showing that AI adoption can simultaneously reduce demand in some occupations while boosting it in others. The overall impact depends critically on the approach to technology adoption and investments in complementary skills and institutional frameworks. At this stage, no research has systematically examined these trends in Georgia. However, some examples can be observed in practice. For instance, there are services offering training on the use of AI in labor relations, including the ethical application of AI in human resources. In addition, ICT-sector vacancies often list familiarity with new technologies among the required tasks and emphasize that employees should be aware of and actively follow technological developments, including advances in artificial intelligence. Taken together, these examples suggest that AI-related specialization may gradually expand in the Georgian labor market.

Taken together, these findings highlight that generative AI presents both a challenge and an opportunity for the Georgian labor market. While certain occupations face high exposure to GenAI that could disrupt existing employment patterns, other sectors may experience productivity gains and/or new job creation. The lower overall exposure and higher prevalence of lower-gradient, augmentation-aligned roles suggest that Georgia is positioned to leverage AI for complementarity rather than face widespread automation. Acting early is crucial to turn challenges into opportunities and to fully harness the augmentation potential across all occupations. For this purpose, investing in targeted upskilling and reskilling programs is important not only for workers in high-exposure roles, enabling them to adapt and transition, but also for those in lower-gradient occupations, to strengthen their ability to complement GenAI in their tasks and enhance productivity. At the same time, the analysis highlights that exposure is unevenly distributed across regions and demographic groups, therefore underscoring the need to address digital skill and gender gaps, connectivity challenges, and regional disparities.

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