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How Exposed Are Workers in MENA to AI?

Evidence on Employment Risk and Task Complementarity

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Abstract

Generative artificial intelligence (AI) is taking over production processes worldwide and is making inroads even in regions with weaker digital infrastructure and less qualified workforce, such as the Middle East and North Africa (MENA). This study investigates how the diffusion of AI is reshaping labor markets in MENA, where structural vulnerabilities heighten risks of unequal technological impacts. Using detailed occupational data from Egyptian (2018 and 2023), Jordanian (2010, 2016) and Tunisian (2014, 2022, 2023) nationally-representative labor-market surveys, we classify jobs and workers by their exposure and complementarity to AI using several alternative task-based indices. The analysis documents substantial cross-country and within-country heterogeneity: while many high-skill, urban and younger workers are positioned to benefit from AI-complementary tasks, large segments – particularly rural residents, older workers, and those in routine or low-digitized sectors – face elevated substitution risks. Consistent with studies from other world regions, women are found to be more affected by AI than men. Comparative results show that Jordan exhibits the highest exposure, Tunisia the lowest, and Egypt an intermediate profile once complementarity is considered. By quantifying emerging skills gaps and identifying at-risk groups, the study offers targeted recommendations for education systems, workforce development, and sectoral strategies to support an inclusive growth-enhancing AI transformation.

Keywords: Artificial Intelligence (AI), AI Exposure and Complementarity, Automation, Task-based occupation classification, MENA
JEL Classification: J24, O14, O33, O53

I. Introduction

Generative artificial intelligence (AI) is rapidly proceeding in demonstrating its high transformative potential for productive activities and economic organization worldwide. The rapid advancement, diversification and take-up of AI tools (henceforth, AI transformation) is also beginning to reshape the production models across the global South including in the developing MENA countries. As with previous technological revolutions, equity in the diffusion of AI and in its impacts is an important concern. While many technologically-advanced employers and high-skilled workers – especially in industrialized and transition economies – are expected to adapt technologically and reap benefits from the technological leap, sectors and enterprises where production and workers cannot adjust adequately – especially as in the low and lower-middle income MENA countries – are feared to be left behind or made redundant, causing disruption for thousands of self-employed and wage workers.

In light of the rapid adoption of AI tools by firms and governmental and non-governmental institutions, the impacts are expected to be profound on the MENA-region workers, who are already facing multiple challenges including a high degree of informality and precariousness, low and stagnating productivity, and low employment rates among groups such as youth and women. The prospects are particularly dire today amid population ageing, displacement due to natural

disasters and conflicts, financing and debt crises, and the income and remittance effects of recent oil shocks and a decarbonization drive.

Given the heterogeneity of the MENA economies and sectors, the impact will surely vary dramatically between countries as well as within them, as some skilled workers will be able to maintain their jobs and even improve their productivity and incomes, while those without means to adapt will become ever more vulnerable given the proliferation of AI applications in all spheres of the economy and life, and the shrinking pool of domestic employment for such workers.

This study aims to contribute to the emerging projections of the impacts of the AI transformation on distinct economic sectors and occupations, and by extension on different economies. Categorizing occupations by the degree of exposure to the AI technology, and by the degree of complementarity of workers' skills and tasks with AI, the study endeavors to project the distributional impacts – both vulnerabilities and aspirations – of the AI transformation. Essentially, the study examines the connection between AI-exposed and AI-complementary skills, jobs and sectors in several Arab economies, and assesses their prevalence, characteristics and demographic makeup across countries.

Specifically, the study asks: How many jobs in the MENA currently use AI-exposed and AI-complementary skills, and how is this changing over time? How many and which workers are currently endowed with these skills, and how will AI transformation affect different groups of workers? The analysis facilitates the identification of the potential skills gap and the worker groups (by sex, age, educational attainment, location of residence, etc.) who are likely to be most affected or in need of support. The analysis will also allow us to pinpoint the potential skills shortages and provide recommendations on how university, and technical and vocational (industry–)academic programs could be adapted to meet the anticipated skills demand given the sectoral transformations expected over the next decade. Ultimately, the study provides recommendations on the types of skills that industry leaders, educators and policymakers need to focus on fostering or building around, and on the economy-wide support mechanisms conducive to an inclusive AI transformation.

The study is organized as follows. The next section reviews the existing literature on the prevalence of AI-exposed and AI-complementary jobs worldwide and in the region, and the current projections of the AI transformation's impacts on various classes of workers. The following section introduces the multi-step approach to classifying jobs and workers as exposed and complementary to AI and the data used. Main results are presented in section IV. Finally, section V discusses the relevance of the findings, and the public policies needed for achieving growth-enhancing and inclusive diffusion of AI.

II. Literature Review

Literature on the economic impacts of AI of the past five years follows previous streams of research on the impacts of technological change, automation and computerization (e.g., Frey and Osborne 2017; Acemoglu and Restrepo 2020; Acemoglu et al. 2022). For example, LMI Institute (2019) proposed indices of occupations encompassing tasks requiring abstract analytical skills, abstract interpersonal skills, nonroutine manual skills, routine cognitive skills, and routine manual skills. Since 2020, researchers have worked on forecasting the transformative effect of AI on labor markets worldwide as well as on specific groups of workers.[1]

[1] Literature estimating the impact on the economies at large has also surged. For example, in the MENA region, AI deployment could yield an additional US$ 14.1 billion in GDP by 2035 and generate a net increase of 118,000 jobs.

Measuring exposure to AI

At the level of industries and narrow occupation groups, a growing body of research has proposed alternative and increasingly nuanced ways to classify jobs according to the impact of AI on them, starting with general AI(-automation) exposure indices, to indices of complementarity of AI to particular work tasks, or the exposure to generative AI or to large language models (LLM).

Existing studies adopt different operationalizations of occupational exposure. Felten et al. (2021) define exposure as the degree to which access to large language models could reduce the time needed to complete a task by at least 50 percent. They construct an AI Occupational Exposure (AIOE) index based on the overlap between AI capabilities and the tasks that define each occupation. Webb (2020) measures exposure by comparing the semantic similarity between AI patent descriptions and the tasks associated with each occupation. Carbonero et al. (2023) rely on semantic similarities between work tasks in O*NET and workers' skills elicited in individual (developing) countries' surveys. Hatzius et al. (2023) manually identify work activities that are susceptible to AI and assess whether the complexity of these activities is low enough for AI to fully perform them, thereby indicating labor substitutability. Gmyrek et al. (2023) classify occupations as having high automation or augmentation potential based on the distribution of task-level AI-automation scores; occupations with both a high mean and low dispersion of automatability scores are considered particularly vulnerable. Pizzinelli et al. (2024:7) describe exposure more generally as "the potential for AI to be integrated into each occupation based on the tasks and skills that characterize each job," and develop an AI Occupational Complementarity (AIOC) index evaluating the extent to which AI might augment or substitute for human labor by considering the skill requirements of different tasks.[2]

Building on the task-based literature, Eloundou et al. (2024) propose a Generative AI Susceptibility Index, while Henseke et al. (2025) refine O*NET-based measures for the UK by incorporating individual-level task information from labor force surveys to estimate a Generative AI Susceptibility Index of exposure to LLM. Benítez-Rueda and Parrado (2024) produced an AI generated index of the likelihood of job replacement by AI. Using the AIOE and AIOC frameworks, Cazzaniga et al. (2025) compare the gendered impacts of AI across advanced and developing economies. They categorize occupations into three groups: those at high risk of labor substitution (high exposure and low complementarity, HELC), those likely to gain productivity and wage benefits (high exposure and high complementarity, HEHC), and those relatively insulated from AI (low exposure, LE). Eckhardt and Goldschlag (2025) evaluate four distinct measures of AI exposure from prior literature and find that, despite methodological differences, the measures produce similar estimates of employment impacts for US workers.

Globally, Hatzius et al. (2023) projected that generative AI could raise GDP by 7% and US labor productivity growth by 1.5 percentage point a year over a 10-year period following widespread adoption. Baily et al. (2023) also estimated that AI could lead to an 18% productivity boost over 10 years plus 1 percentage point sustained growth rate increase, leading to near-doubling of output over 20 years. Korinek and Suh (2024) concluded that if full automation is achieved within 20 years, growth increases tenfold to 18% annually, but wages collapse by 85%. BIS (2024) estimate that AI will raise annual productivity growth by 1.5 percentage points, resulting in GDP rising 30% over 10 years.

Cerutti et al. (2025), using a global general equilibrium model, conclude that AI is likely to widen cross-country income inequality. Advanced economies benefit disproportionately, particularly in non-tradable sectors such as education and health, which in turn strengthens their external competitiveness. Nonetheless, these gains also generate positive spillovers for the global economy.

[2] We thank Carlo Pizzinelli and his co-authors for sharing with us their estimates.

These various studies reach fairly consistent findings that AI can have substantial effects on labor demand, especially at the tails of the distribution of skills and earnings. Labor substitution is prevalent among lower-skill and lower-income workers, while labor complementarity is higher among their higher-skill and higher-income counterparts.

AI effects on workers

Empirical evidence from country-level studies aligns with these broad patterns. In the United States, Brynjolfsson et al. (2025) show that occupations heavily exposed to generative AI – especially where AI substitutes rather than complements labor – experience reductions in labor demand for early-career workers. AI-exposed workers differ markedly from non-exposed workers: they tend to be more educated, higher-paid, and less likely to experience unemployment (Eckhardt and Goldschlag 2025). Employers generally reallocate these workers toward tasks that complement AI rather than replacing them with AI. Albanesi et al. (2025) examine the effects of software development and AI on employment between 2011 and 2019 in the United States. They find that employment shares increased in occupations more exposed to AI, particularly those with younger and more skilled workers, though they do not detect clear wage effects.

Relocation of workers is also selective and contingent on workers' own choice. Automation during 1980–2017 was found to have positive effects on sex segregation and skill gaps. Women generally benefited from automation through their higher propensity to shift out of routine task-intensive (low social skill, low math skill) low wage occupations to high wage (high social skill, high math skill) occupations (Cortés et al. 2024).

In Germany, Engberg et al. (2025) show that workers in highly AI-exposed occupations perform different sets of tasks and require different skills, and that task and skill content of occupations adjust in anticipation of exposure to new technologies.

By contrast to these findings, Henseke et al. (2025) found that exposure to LLMs in the UK is most concentrated in high-skilled scientific and technical occupations, and that AI has contributed to declining wage returns and reduced hiring in AI-susceptible roles.

Alas, the impact of AI also depends on the tasks involved. Del Rio-Chanona et al. (2025) concluded that novice workers tend to benefit more from LLMs in simple tasks, while across complex tasks, evidence on whether low or high-skilled workers benefit more is mixed. While productivity gains are systematically large, at 20–60 %, the labor-substitution effects vary strongly by task complexity and worker skill level.

AI effects in the global south

Das and Hilgenstock (2022) estimated that the risk of 'routinization' or the displacement of labor by information technology has been much lower in countries they classify as developing (including Egypt 1996–2015, Iraq 1997, Jordan 2004, Kuwait 2005-2011, Lebanon 2004-2007, Libya 2006, Morocco 1982-2008, Oman 1993-2000, Qatar 1997-2013, Saudi Arabia 2014, Sudan 2008, Syria 2007, United Arab Emirates 1995-2008, Yemen 1999). Coupled with the observation that weaker initial exposure may be followed by stronger exposure in the long term, they project that the proliferation and advances in information technology may increase developing countries' exposure and labor polarization.

Zooming in on the task content of occupations, Caunedo et al. (2023) on the other hand found that workers in developed countries used non-routine analytical and interpersonal tasks more intensively than developing countries but used routine cognitive and routine-manual tasks less intensively, suggesting a lesser risk of displacement by information technology. Countries with

high initial task intensities experienced a decline in these intensities over time, suggesting a measure of convergence in task intensities across countries, and the existence of systemic differences between developed and developing countries.

Comparing 25 higher and lower income countries, Demombynes et al. (2025) found that AI has a greater effect on higher-income workers. It has a high potential impact on 37% of occupations in low-income countries and 44% in lower-middle income countries, but as much as 49% in upper-middle income countries (including MENA's Egypt) and 63% in high-income countries. Within countries, youth workers (15–24yo) are the least exposed to AI, as those without tertiary education are distinctly less exposed than those higher educated. AI exposure is also higher in urban areas and in occupations held by women.

Cazzaniga et al. (2024b) studied workers' scope for reallocation across occupations given heterogeneous AI exposure, and found that – in both industrialized (UK and US) and developing economies (Brazil, Colombia, India, South Africa) – women and tertiary-educated workers were more exposed but also better prepared to benefit from AI. Women are generally more exposed to AI than men – placing them at greater risk in lower-income roles yet offering greater potential benefits in higher-income roles (Cazzaniga et al. 2025).

Digital divide hampers the possible positive effects of generative AI on jobs, particularly in poorer countries where both infrastructure and skills development lag behind (Liu and Wang 2024). In Latin America, Gmyrek et al. (2024) found that urban, higher-educated and higher-income workers are more likely to be exposed to augmentation by generative AI, facilitated in part by better access to digital technologies at work.

In Southeast Asia, Carbonero et al. (2023) found significant differences across countries in skill use, and in exposure to labor-displacing machine learning tools and AI. Specifically, workers in Vietnam are more exposed to AI than in Laos, partly because Vietnam has undergone greater change of its labor market through previous technological transformations. In both countries, women are more exposed to AI than men, but youth workers are more exposed than older workers in Vietnam, and less exposed in Laos, on account of their different skill endowments. In the Philippines, Cucio and Hennig (2025) estimate that roughly one-third of workers, especially in services, face high AI exposure, and nearly two-thirds of them perform tasks for which AI is complementary, indicating potential productivity gains. However, the business process outsourcing (BPO) sector is vulnerable to displacement by AI.

In India, Copestake et al. (2023) found that the emergence of AI led to an increase in offerings of jobs with routine tasks benefiting from AI complementarity, and a fall in offerings and wages of non-routine jobs.

AI effects in MENA

In MENA, understanding of the labor-market impacts of generative AI is in early stages and remains fragmented. An early study by Rizk (2020) concluded that AI could be an equalizing or unequalizing force depending on the stand of public policy and targeting of public investment. More recent studies conclude that AI in MENA is more likely to augment than to displace jobs, but the prospects and risks appear to be uneven and favoring higher human-capital workers in higher infrastructure settings. Across 12 Arab countries, ILO (2025) suggested that there was a modest job displacement risk but a more significant job-augmentation potential, contingent on inclusive policy. Roughly 14.6% of jobs in the region could be augmented by AI, whereas only 2.2% were deemed automatable and replaceable.

There are notable demographic disparities: women are more exposed to the automation risk (5.3% of female-held jobs vs. 1.6% for men), largely because they occupy a higher proportion of routine clerical roles, yet they also stand to gain more from job augmentation (22.7% vs. 13.0% of male-held jobs) if AI is adopted inclusively. Older workers (above 55) are particularly vulnerable due to reskilling challenges, while youth (15–24) might disproportionately benefit from the creation of new tech-driven occupations, particularly in the Gulf countries. In middle human development countries, prospects are less rosy. In Egypt, Iran, Jordan and Tunisia, Cazzaniga et al. (2024a) estimate that only one-third of jobs are substantially exposed to AI, but that in many cases AI is more likely to substitute than to enhance labor due to relatively low complementarity.

Our study contributes to the limited literature by disaggregating the labor-market impacts of AI in Egypt, Jordan and Tunisia by industry and type of activity using microdata from up-to-date labor market surveys. The following section describes the empirical strategy and data used.

III. Data and Estimation Strategy

Assessing workers' exposure to AI and complementarity with AI capabilities comprises several critical steps based on detailed occupation-content and worker data. First, one must delineate sets of AI-exposed and AI-complementary skills and tasks (henceforth summarily 'AI skills and tasks') based on existing patterns and use that to develop an index of the prevalence of AI skills among a country's working-age population. Existing surveys on the daily activities of workers in various occupations provide insight into the types of skills that tasks in each job require. This allows us to identify occupations requiring at least a minimal number of AI skills, as well as the AI-skill intensity of various jobs.

The occupation-level information is mapped to worker-level data in labor-market surveys, potentially requiring cross-walking of occupational codes between the occupation-tasks data and the worker data (e.g., between the Standard Occupational Classification SOC in the US O*NET database, and the International Standard Classification of Occupations ISCO in labor market surveys) to classify MENA-region jobs and workers as AI-skill intensive.

The study describes the existing trends of workers' propensity to be matched to such jobs as a function of their demographic profiles, including through probability estimations. Robustness exercises over the job classification approach and over future projections are reported. The following paragraphs elaborate.

Data

The analysis sketched out above requires large microdata on skill content at the level of detailed occupation groups, and worker backgrounds and outcomes at the level of individual workers. To study the fate of jobs and workers across different socioeconomic groups and across MENA countries, we assemble the necessary data from several public sources.

Microdata on individual workers' detailed ISCO occupation group – 2 to 6 digit groups – come from Labor Market Panel Surveys (LMPS) for Egypt (2018 and 2023), Jordan (2010 and 2016) and Tunisia (2014) obtained from the Economic Research Forum (ERF), supplemented by the Survey of the Population and Employment (Enquête nationale sur la population et l'emploi, ENPE) for Tunisia (trimester rounds in 2022 and 2023) obtained from the Tunisian National Statistical Institute (Institut National de la Statistique, INS). The Egyptian LMPS surveys have the most

detailed disaggregation of ISCO codes, at 6 digits, the Tunisian LMPS and ENPE at the 5 digit level, and the Jordanian LMPS at the 4 digit level.

Identifying AI-exposed and AI-complementary workers

Information on the skill content of detailed occupation groups is taken from existing studies based on the data on workers' skills and job tasks contained in the US Occupational Information Network (O*NET 2020) database (for a summary of alternative published indices, refer to the Appendix table A1). It should be noted that task content of occupations may vary significantly from one country to the other. Depending on the degree of labor, capital, or technology substitution possible in a given occupation, a job that may be performed by – or with the use of – AI in rich advanced economies may be less so in developing countries. Moreover, individual existing AI tools have various capabilities and can perform various functions, for example generative versus non-generative AI, so one AI-exposure index may not fit them all. To address these limitations, we consider three alternative indices of AI occupational exposure that have been used for countries worldwide including those in the global south. Specifically, we consider Felten et al.'s (2021) AIOE index (henceforth AIOE_all); Gmyrek et al.'s (2023, 2024, 2025) revised index of generative AI exposure (AIOE_ILO), and Pizzinelli et al.'s (2024) index of occupational complementarity with AI (denoted by theta, θ), either stand-alone or used to adjust Felten et al.'s AIOE for complementarity (C_AIOE = AIOE_all × [1 – (θ – θ_{MIN})]).

Felten et al. (2021) define AI exposure by linking the human tasks in an occupation with AI applications, building on the information provided by the Electronic Frontier Foundation AI Progress Measurement Project. They then combined information on the AI applications with the tasks and abilities as listed in the O*NET database, and computing AIOE scores for detailed 6-digit SOC occupation groups. Their AIOE_all index ranges from -1.854 for "Pressers, Textile, Garment, and Related Materials" to +1.926 for "Telemarketers."

Gmyrek et al. (2025) employed a different, machine-learning methodology: They prompted a generative AI tool, ChatGPT-4, to gauge occupational and task-level exposure to generative AI. Their index (henceforth AIOE_ILO) ranges from 0.09 for "Bricklayers and Related Workers" to 0.70 for "Data Entry Clerks."

Pizzinelli et al. (2024) built on these approaches to propose a measure distinguishing the worker-replacing and productivity-enhancing powers of AI. They considered the social, ethical, and physical context of occupations, beside the required skill level, to derive the degree of AI complementarity or substitutability of occupations. They started by evaluating the occupational work contexts (the "physical and social factors that influence the nature of work") and job zones ("occupations characterized by similar levels of education, on-the-job training, and professional experience needed"). They selected 11 contexts as the most relevant for the likelihood of AI replacing human activities or being adopted in a supervised manner and aggregated them into 5 categories. They then interacted the work-context groups with job zones to score jobs along 6 dimensions of potential complementarity: communication, responsibility, physical conditions, criticality, routineness, and skills. The composite complementarity was computed as the arithmetic mean of the six components divided by 100 to be bounded between 0 and 1. They reported that their complementarity index ranges from 0.309 for "Hand Cutters and Trimmers" to 0.781 for "Oral and Maxillofacial Surgeons," and their C_AIOE ranges from 3.133 for "Oral and Maxillofacial Surgeons" (again) to 6.206 for "Telephone Operators."

We adopt the three indices above (plus standalone complementarity θ) and map them to the LMPS and ENPE surveys so as to evaluate our hypotheses. We report the prevalence of the AI-

exposed or AI-complementary jobs among the current workforce, disaggregate the results by worker characteristics (sex, age, region of residence within country, sector of employment, and educational attainment), and estimate the partial effect of various characteristics at predicting workers' predisposition for AI-exposed and AI-complementary occupations. Tables A2–A4 in the appendix report the values of the AI-exposure indices across selected demographic groups (table A2), across economic activities of workers' current jobs (table A3), and 1-digit occupation groups (table A4) in our survey samples.

We acknowledge that the nature of jobs expected post-AI transformation will be an artefact of the conditions in economic sectors at large, due to evolving competitiveness, engagement in global value chains, technology and regulation, or inter-occupational mobility of labor (Cazzaniga et al. 2024b). Skills in non-digitized (or non-AI) sectors are already showing signs of digitalizing (adopting elements of AI, respectively). These projection challenges are mitigated by the relatively short time window of our forecasting (5 years), and relatively broad, 4-digit ISCO, categories of jobs.

Testable hypotheses

Using the merged micro level data we can study the determinants of having an AI-exposed job at the individual level. Differences in AI job potential by individual and household characteristics such as sex, age, education, sector of employment, family background and region of residence are examined. This provides insights into the characteristics of individuals and households that have low AI job potential – and could therefore allow a concise targeting strategy for policy makers looking to mitigate the impact of AI transformation on specific classes of workers and households.

Following Pizzinelli et al. (2024), we hypothesize that occupation groups that are highly exposed but highly potentially complementary with AI may benefit from the technological transformation if the corresponding workers and employers grasp the opportunity, which may translate into the number of jobs, job content and skill composition, as well as worker productivity and compensation. Occupations with high exposure but low potential complementarity with AI may be downscaled, substituted out by the new technology (or transformed to harness the productivity-raising power of AI), or their compensation may be reduced to match reduced labor productivity. Finally, occupations with low direct exposure may be transformed, or left behind by the technological trend, finding themselves at a productivity or cost disadvantage compared to the sectors leaping forward.

Following stylized evidence provided in existing studies, we form hypotheses regarding the socioeconomic groups particularly affected by the technological transformation. We surmise that younger cohorts but also more highly educated workers, being more endowed with AI-complementary skills and holding jobs in relevant occupation groups, stand to benefit from the diffusion of AI. Workers commanding higher wages, and those in urban markets and highly-digitized sectors are more exposed to the AI transformation, but their skills are not necessarily AI-complementary, so the implications for them are unclear.

Regression specification

To test these hypotheses, we run probabilistic regressions of workers' propensity to hold highly AI-exposed, highly AI-complementary, or HELC jobs – binary indicators – as a function of their backgrounds, circumstances and characteristics (X). Validity of these models assumes that worker i's (latent) probability of holding an AI-affected job $AIjob_i$ is a linear function $E(AIjob_i|x_i) = f(x_i, \beta) = x_i\beta$. This probability $AIjob_i$ is related to the observed outcome $AIjob_i$ as follows:

$\dot{AIjob}_i = 1[AIjob_i > 0] = 1[\varepsilon_i > -x_i\beta]$. Here ε_i accounts for other uncontrolled factors including the worker's latent characteristics and exposure to latent signals. Under the commonly made assumption that ε_i follows the normal distribution, the maximum-likelihood probit model is appropriate for estimating $\Pr(\dot{AIjobs}_i = 1|x_i)$. Worker i's employment outcome in local market j in a year t is thus estimated by the following probit model:

$$AIjob_{ijt} = \alpha + \beta X_{ijt} + \varepsilon_{it} \quad (1)$$

where X_{ijt} is a vector of socio-economic determinants of i's employment outcome at the individual, household, regional and temporal level.[3] To account for local-market heteroskedasticity, robust standard errors clustered at the level of sectors are computed.

IV. Main Results

We begin our analysis by studying AI exposure first within the three MENA countries over time, then across countries. We examine the cumulative employment share at different levels of AI exposure, using alternative measures of exposure – based on Felton et al.'s (2021) AIOE_all of exposure to all types of AI, Gmyrek et al.'s (2025) AIOE_ILO of exposure to generative AI, and Pizzinelli et al.'s (2024) C_AIOE correcting for AI complementarity.

Figures 1-3 present the cumulative employment shares across varying levels of AI exposure across unique occupation titles (at the ISCO-08 4-digit level; normalized to 0–1) for the three countries, using the alternative AIOE indices under consideration. Distinct lines (blue solid, red dashed, or grey dotted) show the employment shares in different survey waves. Lower (higher) percentiles represent occupation groups with lower (higher, respectively) values of the particular AIOE index. The y-axis reports the share of employment in all occupations with an exposure up to the respective percentile for that country.

Figure 1 shows that in both 2018 and 2023, Egypt had about 50% of employment below the lowest 40th percentile of AIOE_all (value of 0.4 on the x-axis). Using the AIOE_ILO, this share is just under 45% in both years. Examining the degree of complementarity, Figure 1 shows a relatively high degree in both years but slightly higher in 2023 for low exposure occupations. Hence, once complementarity is taken into account, slightly over 60% of employment in 2018 was below the 40th percentile of the complementarity-adjusted C_AIOE, and in 2023 it was 56%. This reflects the role of potential complementarity in reducing the risk of worker replacement. This is also true at higher levels of AI exposure. Using the AIOE_all measure, about 84% of employment in both years was below the 80th percentile of AIOE_all. Adjusting for complementarity, this share rises to about 88%. AIOE_ILO tends to show slightly lower exposure rates across the employment distribution. For example, AIOE_ILO shows that less than 10% of workers are in the high exposure category, above the 80th percentile of AIOE _ILO,

[3] To minimize endogeneity of explanatory variables in the regressions, we consider restricting the set of variables to those reflecting pre-existing conditions in the years prior to taking the specific employment. We acknowledge that this may not eliminate endogeneity due to omitted variables, or workers' longer-term predispositions, expectations and behavioral responses (e.g., family status, education choice). We consider instrumental variables (IV) – specifically, prevalence of selected characteristics in the worker's community, notably excluding the worker him/herself – which may help to distil the exogenous part of an individual's potentially endogenous choice that is explained by tendencies prevalent in the larger community rather than the individual's own expectations, character or performance.

while AIOE_all shows slightly higher share of 16–18% in the high exposure category in the two years, but in general is very similar to Felten et al.'s AIOE_all.

For Jordan, Figure 2 shows that the exposure of occupations to AI was very similar in both years, with about 50% of employment below the lowest 40th percentile of AIOE_all (0.4 on the x-axis). Using AIOE_ILO in Jordan, we find somewhat higher exposure in 2016 with only 45% of employment below the 40th percentile. AI complementarity is also quite similar across both years, and suggests that once the degree of occupational complementarity is accounted for, 60% of employment is below the 40th percentile of C_AIOE. About 20% of workers are in the high exposure category, above the 80th percentile of AIOE_All and slightly less by the complementary adjusted level (C_AIOE). The ILO index again shows slightly higher share of workers in the high exposure category (about 25% of employment is above the 80th percentile of AIOE_ILO).

For Tunisia, Figure 3 shows a substantial difference in exposure between 2014 and 2022/2023, but the latter two years are almost identical which is expected and reassuring. In 2014, 38% of employment is shown to have been AI-exposed at the 40th percentile, and the remaining 62% of employment was exposed at higher rates. By contrast, in 2022/2023, 50% of employment was exposed at the 40th percentile or less, seemingly showing diminishing exposure to AI over time. Similarly, 15% of employment was in the high exposure category (above the 80th percentile of AIOE_all) in 2022/20233, while as many as 24% were in that category back in 2014. At face value, this points to significant changes in occupational mix in Tunisia over the decade.[4] The AIOE_ILO index suggests low exposure compared to AIOE_all in 2014 – 45% of employment was below the 40th percentile of AIOE_ILO – but similar exposure in 2022/2023. The complementarity theta (Figure 3 panel c) suggests a reversal of AI complementarity of employment over time, with 2014 occupational mix showing less AI complementarity at lower levels of exposure. The complementarity-adjusted C_AIOE suggests that 60% of employment was below the 40th percentile of AI exposure in 2022/2023, while in 2014 only 40% of employment appeared in this low AI-exposure category.

Examining how the three countries compare according to the most recent years of data, Figure 4 shows the employment AI-exposure according to the alternative AIOE indices in the latest year available for each country. The cumulative exposure curves show that Jordan lies consistently below Egypt, which in turn lies consistently below Tunisia, indicating that Jordanian workers tend to be employed in occupations with higher AI exposure levels across most of the distribution by both the AIOE_all and AIOE_ILO measures. Tunisia has the highest density of workers in the lower-exposure levels of the cumulative curve. Egypt lies between Jordan and Tunisia in terms of the distribution of jobs.

Once complementarily is taken into consideration, these shares fall for all countries but Jordan's curve remains to the right of the others at higher exposure levels, illustrating the vulnerability among larger shares of workers. It is worth noting that Egypt's C_AIOE curve is to the right of those for the other two countries for low exposure levels, indicating that under C_AIOE there is higher concentration of workers at the lower levels. For completeness, Figure A1 in the Appendix shows the same figures for the countries' all survey rounds.

[4] This presumably reflects the differences between the ENPE for 2022/2023 versus the TLMPS for 2014, despite both being nationally representative. We are in the process of examining this as we are including additional surveys from Tunisia, particularly the 2017 ENPE, in our analysis.

Next, we categorize the AIOE scores into four exposure levels (high, moderately high, moderately low and low exposure) by dividing each AIEO index into 4 quartiles based on the pooled sample of countries and years. We analyze these across countries and time, and by subgroups such as broad occupation group, broad industrial group, and demographic characteristics such as gender, age, education and region of residence.

Figure 5a shows the employment shares by exposure level using AIOE-all. The results confirm that Jordan has the highest share of workers in the higher exposure categories, although this share fell slightly over time, followed by Egypt and then Tunisia[5]. Tunisia has the largest share of workers that are least exposed, and this share has increased over time. It also has the lowest share of highly exposed workers in the most recent year. Egypt on the other hand has witnessed a slight increase in highly exposed workers between 2018 and 2023 and a decrease in low and moderately low exposure workers over this period. Figure 5b presents results based on the AIOE-ILO and the same conclusions can be drawn from this index with slight differences in shares of low vs moderately low exposure occupations and high and moderately high exposure. Overall similar conclusions apply. Figure 5c presents the results after accounting for complementarity (C-AIOE) and imply a significant decline in exposure across all country-years once complementarity is accounted for. Among the latest years, Egypt now has the highest combined share of moderately and highly exposed workers.

It is useful to develop a summary measure of jobs that are highly exposed (HE) and whether they may also benefit from high complementarity (HC) -and therefore at less risk of replacement by AI, vs those that are both highly exposed and with low complementarity (LC) potential and therefore at more risk of replacement. We classify occupations as 'HEHC' if both AIOE-all and θ are above their median, 'HELC' if AIOE-all is above the median but θ is below the median, while 'LE' refers to jobs with low exposure (AIOE-all below the median). Results are in Figure 6. Results suggest that while Jordan had the highest share of HE jobs overall, most of these were also HC, therefore less likely to be replaced and more likely to be enhanced by the ability to use AI. In Egypt, a sizable share of employment (25% in 2023) is HELC, suggesting a higher potential replacement risk. Tunisia has the lowest HELC shares in 2023, confirming earlier results of lowest overall exposure to AI among the three countries in the most recent available year.

Exposure Risk and Occupation Characteristics

Figure 7 presents the AI exposure indices by 1-digit ISCO occupation. The figure also depicts the relative size of each broad occupation group in each country. Figure A2a in the appendix depicts the within occupation share of each exposure category. The occupations with relatively high employment shares, such as Service and Sales, Professionals and Clerical occupations are also those more likely to be exposed. Crafts, skilled agriculture, machines operators and elementary occupations are least exposed overall. While Egypt has sizable share of workers in agricultural and craft and related occupations, the white-collar occupations (managers, professional, technician and clerical occupations) are highly exposed and together account for over a third of all occupations. Jordan's workers are concentrated in Professional occupation and

[5] Results for Tunisia 2022 were almost identical to 2023 and we therefore only report 2023 to save on space, unless there is a major difference in conclusions.

sales and service jobs which are both highly exposed to AI. has an even smaller share of but those have relatively smaller proportion of workers. Tunisia has relatively more workers in elementary occupations which accounts for its lower overall exposure. Figure 7b (and A2b in the appendix) shows that while in most occupations accounting for complementarity reduces the exposure risk substantially, the start exception is clerical occupations for which exposure actually rises reflect the high risk from AI that workers in these occupations face. These makeup relatively small shares of employment overall, however in most countries this is an occupation with high concentrations of women workers.

Figure 8 presents results by major industrial group, and that industry's relative size within overall employment (these are aggregated from ISIC 4 industry classifications-full results are in the descriptive statistics tables in the appendix). Figure A3 in the appendix presents the analogous results within each industry. Relatively large employers such as Commerce, Public Administration and Education and Health services are more highly exposed and within these industries 40-60% of workers are in exposed occupations. When Complementarity is accounted for, exposure falls but within the financial and professional service industries 30-40% of employment is still exposed to AI.

Exposure Risk and Worker Characteristics

Next, we examine exposure risk by worker characteristics. Across all countries, years and by the various indices women are more likely to be moderately highly and highly exposed than men (Figure 9). Older workers (Figure 10) are also more strongly represented in occupations that are more highly exposed to AI, although once complementarity is accounted for, those aged 15-29 are also heavily represented in moderately highly exposed occupations especially in Tunisia. As confirmed by other studies, workers with higher education levels (defined above secondary/intermediate levels, university and or post graduate education) are much more highly exposed across all three countries (Figure 11). Accounting for complementarity reduces this exposure somewhat but it remained the case that those with higher education levels are at highest risk of exposure to AI. Similarly, formal workers (defined as having either a contract or social security insurance) are far more likely to be highly exposed to AI risk than informal workers across all countries and years (Figure 12).

Determinants of workers' employment in AI-exposed or complementary occupations

Table 1 reports the results of probit regression of workers' employment in highly AI-exposed, highly AI-complementary, and HELC occupations. These multivariate regression results corroborate the findings from figures 5–12 regarding the role of worker sex, age, education, broad occupational group, and main economic activity of the job. (Table A5 in the appendix shows the equivalent 'baseline' regression results omitting the interaction terms from the models.)

In Jordan, women – particularly those aged 30–64 – are systematically less likely to work in AI-exposed and AI-complementary occupations. They are more likely to be in AI-exposed non-complementary occupations than men. In Egypt, similarly, women - especially those aged 30–64

– are systematically less likely to work in AI-complementary occupations, but nothing can be said about their propensity to work in AI-exposed occupations. In Tunisia, women are slightly less likely to work in AI-exposed or AI-complementary occupations, but significantly less likely – especially those 30–64 years old – to be in HELC occupations. This is in contrast to the findings in Jordan, while the evidence in Egypt is in between of the two countries' cases. Workers' education level is not associated with a propensity to work in AI-exposed or AI-complementary jobs, but in Egypt it is significantly associated with a higher propensity to hold HELC jobs, especially among men. It should be noted that the coefficients on all interaction terms as well as on related variables were evaluated for joint significance using F tests.

Regarding 1-digit occupational categories, managers, professionals and technicians in all three countries (managers only in Egypt and Tunisia, since in Jordan this variable was excluded) are significantly more likely to work in AI-exposed and AI-complementary jobs - especially women - but also HELC occupations. Clerical staff in all three countries are significantly more likely to hold AI-exposed and HELC jobs, but less likely to hold AI-complementary jobs (in Egypt and Jordan; in Tunisia this latter result cannot be evaluated). Service and sales workers in all three countries are more likely to work in AI-exposed and AI-complementary jobs, and in Egypt they are more likely to work in HELC jobs. Crafts workers and machine operators in all three countries are more likely to hold AI-complementary jobs, and slightly more likely to hold AI-exposed jobs, while in Tunisia they are significantly less likely to hold HELC jobs. Whether this applies more to men or women is unclear.

Across all three countries, rural and urban workers have similar tendencies in regard to occupation choice. Regarding economic-activity sectors, mining workers have slightly higher chance of holding AI-exposed, AI-concentrated and HEHC. Construction workers in Tunisia have a somewhat higher propensity to hold AI-exposed and AI-complementary jobs, but lower propensity for HELC employment. Workers in commerce, and transportation and communication have a higher propensity to be in AI-exposed and HELC jobs.

These patterns are broadly consistent with prior empirical evidence showing that AI-exposed but highly complementary occupations are clustered in higher-skilled professional categories, that clerical and certain service jobs face high AI displacement risks, and that gender gaps in technology-complementary employment remain persistent. However, the finding that education is generally not predictive of AI exposure or complementarity once other characteristics are accounted for in the regressions, except in Egypt, deviates somewhat from studies in other economies worldwide (and the descriptive figures), where education is usually a strong determinant of AI exposure and complementarity.

V. Conclusions and Policy Implications

This study aimed to provide an evidence-based assessment of the distributional consequences of the unfolding AI transformation within MENA's heterogeneous economies. The analysis relied on occupational microdata from up-to-date labor-market surveys for Egypt, Jordan and Tunisia to examine the effects on different sectors, occupations and worker groups. The analysis categorized workers' skills and job tasks as exposed or complementary to AI according to several alternative classifications from existing literature with the aim to identify robustly which sectors, occupations, and population groups are most likely to face heightened vulnerability or, conversely, to gain in their opportunities and productivity amid the technological upheaval. This analysis was critical to

outlining which public policies could mollify general anxiety about the transformation's impacts and ensure that no groups are left behind.

We found substantial cross-country and within-country heterogeneity. While many demographic groups are positioned to benefit from AI-complementary tasks, large segments – particularly rural residents, and those in routine or low-digitized economic activities – face elevated AI substitution risks.

Across the three countries, the evidence points to systematic gender disparities in exposure to AI-related labor-market risks and opportunities, with women, especially those aged 30–64, generally less likely than their male counterparts to work in AI-complementary occupations and, in Jordan and partly in Tunisia, more likely to work in HELC jobs. Education levels show little consistent association with AI exposure or complementarity, except in Egypt where higher-educated men are more likely to hold HELC jobs. Occupational patterns are strong and broadly consistent across countries with managers, professionals and technicians (especially women) far more likely to be in AI-exposed and AI-complementary roles, clerical workers more likely to be in exposed and HELC roles but less likely to be in AI-exposed complementary jobs, service and sales workers performing AI-exposed and complementary work, and crafts and machine operators showing moderate exposure to AI but relatively strong complementarity. Differences by main economic sector also emerge: mining, commerce, transport, and communication workers often show higher exposure to AI but low complementarity.

Consistent with studies from other world regions, women are found to be more affected by AI than men. The findings underscore that without deliberate and ambitious policy interventions, generative AI may amplify existing disparities – particularly among rural, older workers, and those employed in routine or poorly digitized activities – while offering substantial gains primarily to more educated and urban labor segments. However, the finding that education is generally not predictive of AI exposure or complementarity, except in Egypt, deviates somewhat from studies in advanced economies, where education is usually a strong determinant of AI complementarity.

Across the three evaluated countries, Jordan exhibits the highest exposure, Tunisia the lowest, and Egypt an intermediate profile once complementarity is considered.

Moving forward, the region would also benefit from more research on the process of diffusion of generative AI across MENA economies and the impacts on firms' production processes and workers' livelihoods. Comparative studies across MENA sub-regions – between GCC and non-GCC middle-income and least-developed economies – are also needed to clarify how differences in institutional capacity, labor-market structures, and digital ecosystems shape AI's distributive impacts. Equally important is rigorous assessment of emerging policy tools, including reskilling initiatives, social protection instruments, and data-governance regimes, to determine which interventions effectively enhance adaptability and inclusiveness. This calls for building richer, more granular data systems that capture disparities across sexes, ages, formal and informal statuses, locations and other divides.

The study's results point to several concrete policy directions. First, regional governments and educational institutions must prioritize large-scale upskilling and reskilling programs, with a strong focus on AI-complementary abilities, such as advanced digital skills, problem-solving, communication, and managerial capabilities. Second, a coordinated governance framework for the Arab region is needed to ensure ethical data use, equitable access to digital tools, and safeguards for privacy and fairness (ESCWA 2025). Third, governments should pursue an integrated package of reforms covering an expansion of digital infrastructure, institutionalizing lifelong learning, modernizing labor regulations to protect platform, gig, and informal workers, and strengthening

social protection systems that can cushion households during structural change. Social dialogue between governments, employers, unions, and civil society will be crucial to maintaining legitimacy and inclusiveness (ILO 2025).

Finally, targeted support for micro, small, and medium enterprises, as well as entrepreneurs who lack resources to integrate AI, will be essential for broad-based adoption, productivity gains. With the right mix of skills development, industry regulation and social protection, policymakers can help ensure that AI becomes a driver of inclusive growth rather than a source of deepening unemployment and inequality across the MENA region.

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Figure 1 Egypt AI Exposure Employment Curves, various AIOE indices, 2018-2023.

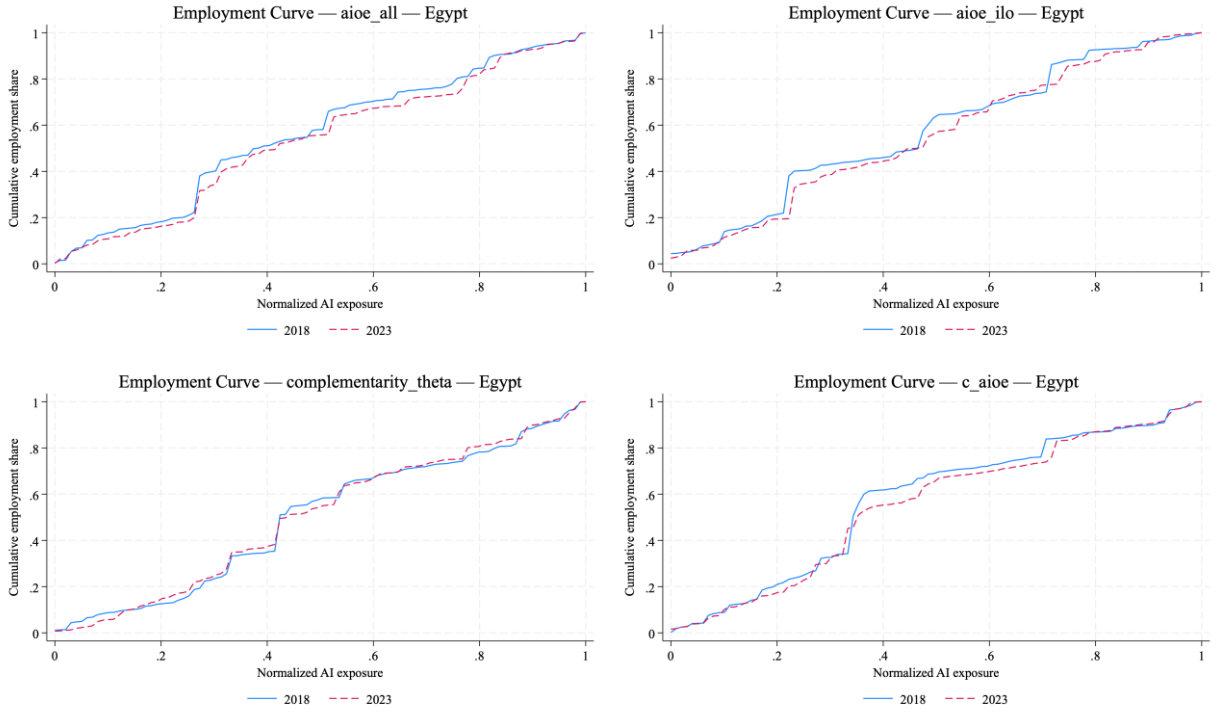


Figure 2: Jordan AI Exposure Employment Curves, various AIOE indices, 2010-2016.

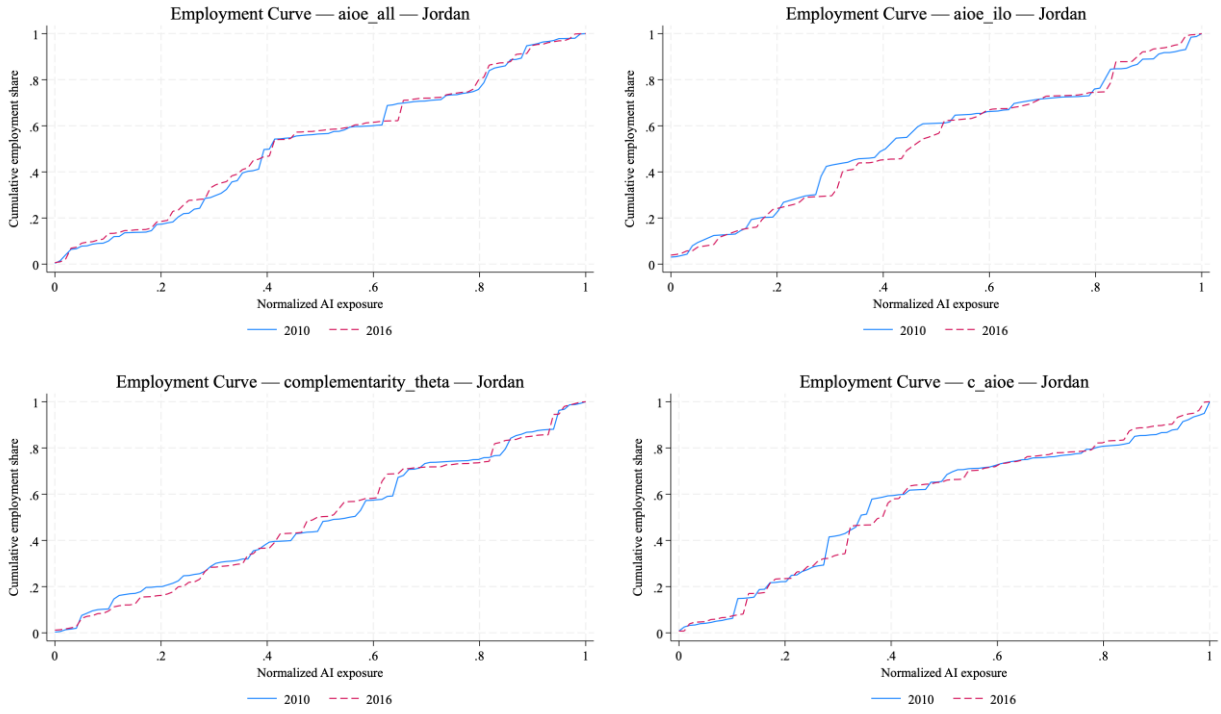


Figure 3 Tunisia AI Exposure Employment Curves, various AIOE indices, 2014-2023.

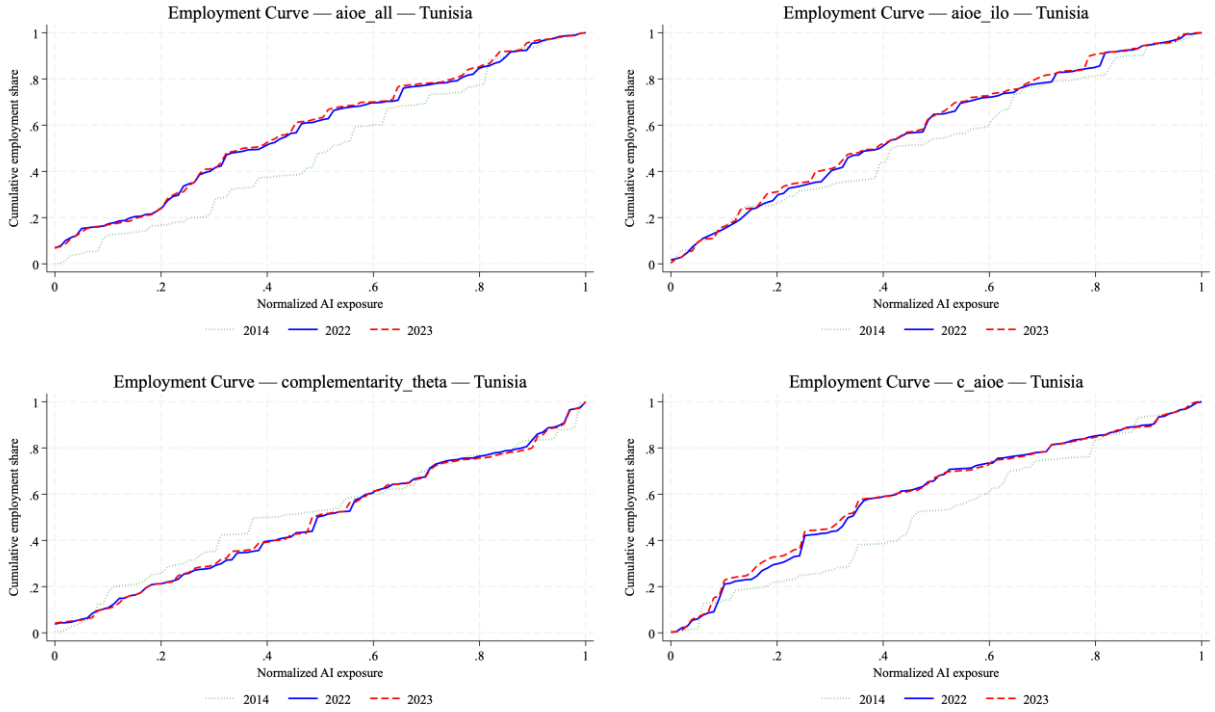


Figure 4 AI Exposure Employment Curves, various AIOE indices, all countries, latest rounds

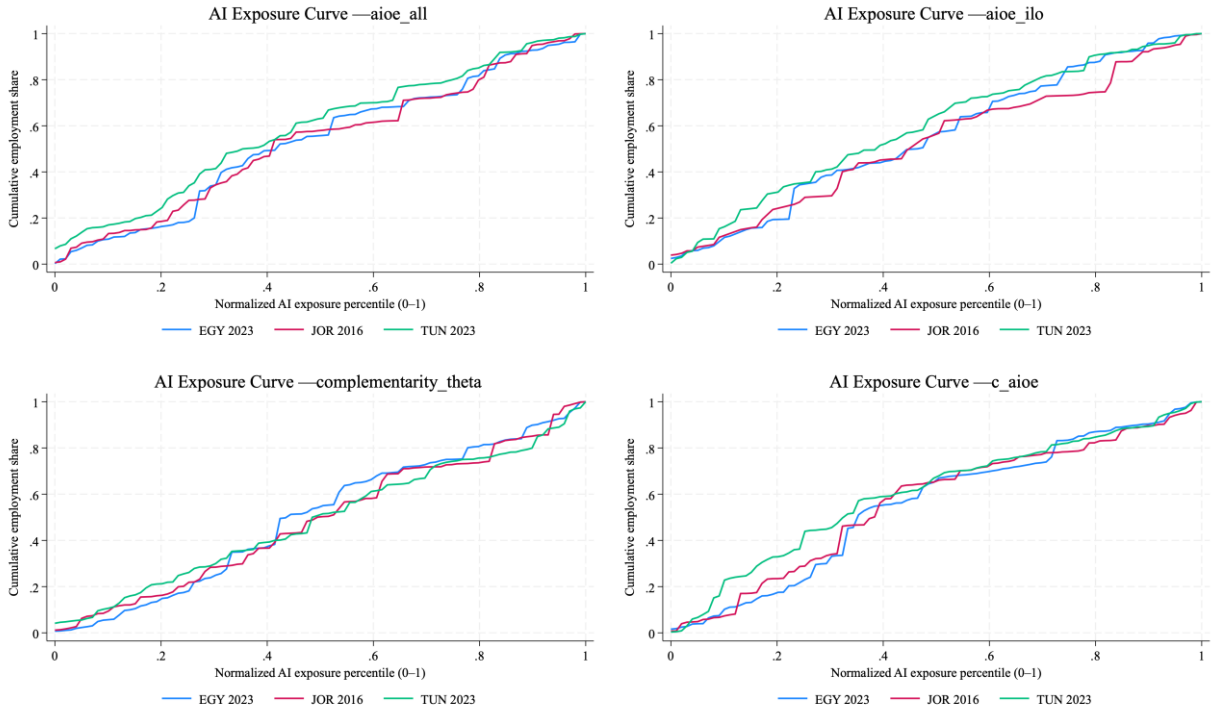
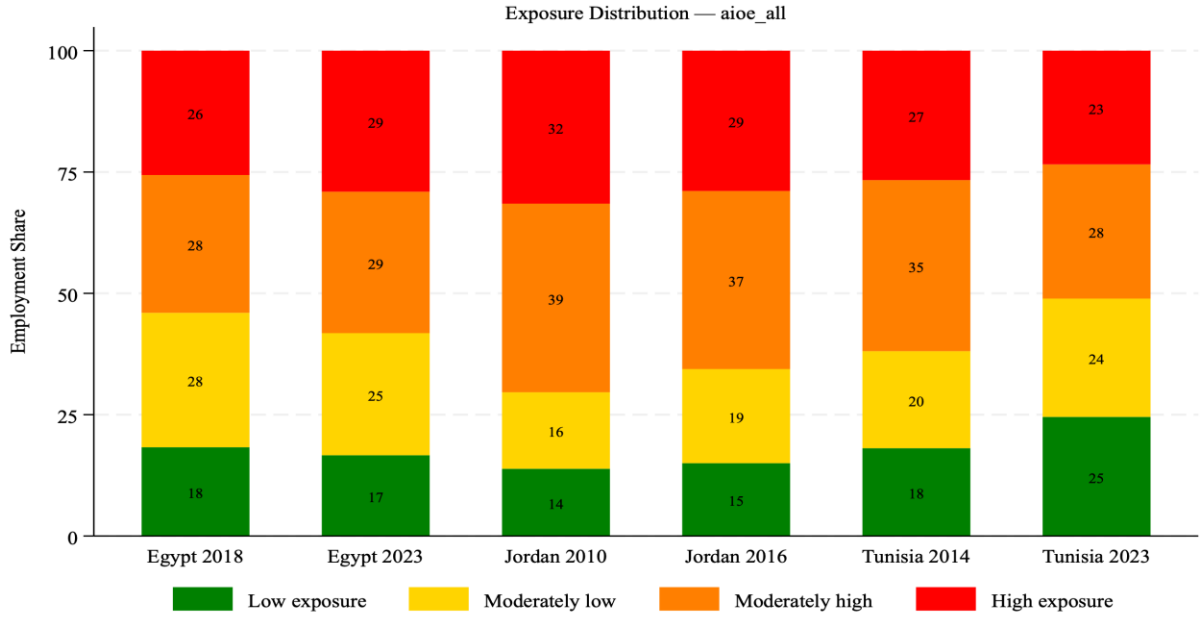
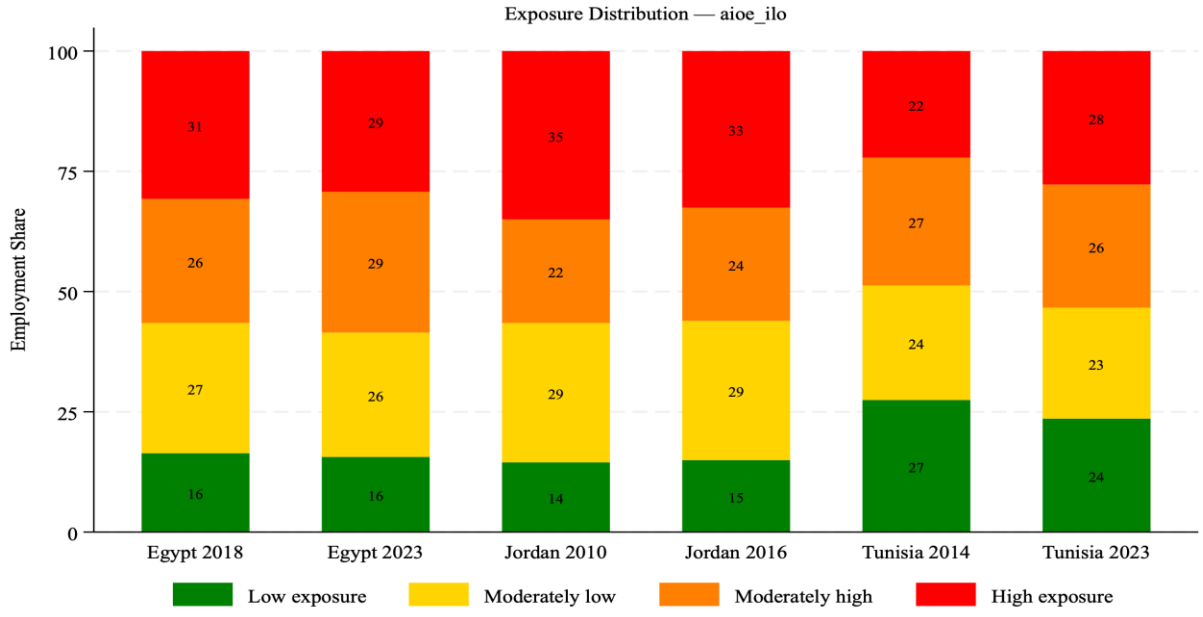


Figure 5a AI Exposure of Employment, AIOE-all, Employment Share (percent)



Note: Population weighted employment shares for workers aged 16-64. AIOE-all was normalized to 0-100 and divided into quartiles, with cutoffs at 32,42,75, using the pooled sample of all countries.

Figure 5b AI Exposure of Employment, AIOE-ILO, Employment Share (percent)

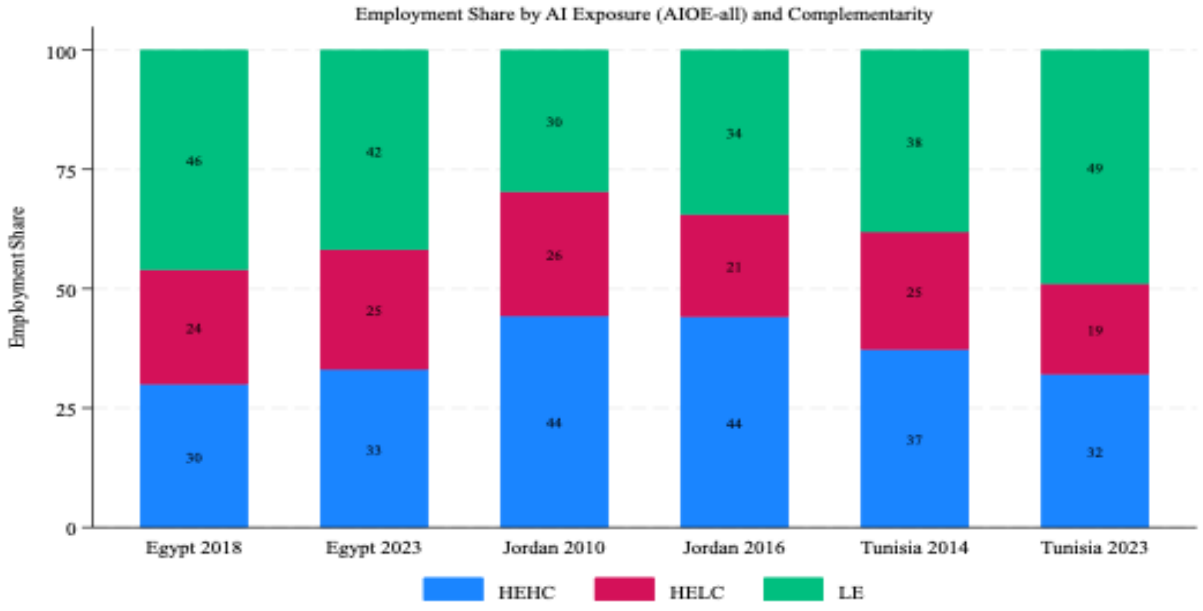


Note: Population weighted employment shares for workers aged 16-64. AIOE-ILO was normalized to 0-100 and divided into quartiles, with cutoffs at 10, 18,38, using the pooled sample of all countries. Note: Gymrek et. al. (2025) use a different classification of exposure based on exposure "gradients" but we elected to follow the same method for all indices here for comparability.

Figure 5c Complementarity Adjusted AI Exposure of Employment, C-AIOE, Employment Share (percent)

Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and divided into quartiles, with cutoffs at 32,42,75 (same as AIOE-all) using the pooled sample of all countries.

Figure 6 Employment Share by AIOE and Complementarity



Note: The figure plots the share of employment in each group of occupations for each country.'High' and 'Low' values are constructed as being above and below the country and year specific median of exposure AIOE-all and complementarity θ.

Figure 7a Employment share by exposure (AIOE_all) across major occupation groups, reflecting the relative size of employment in each occupation

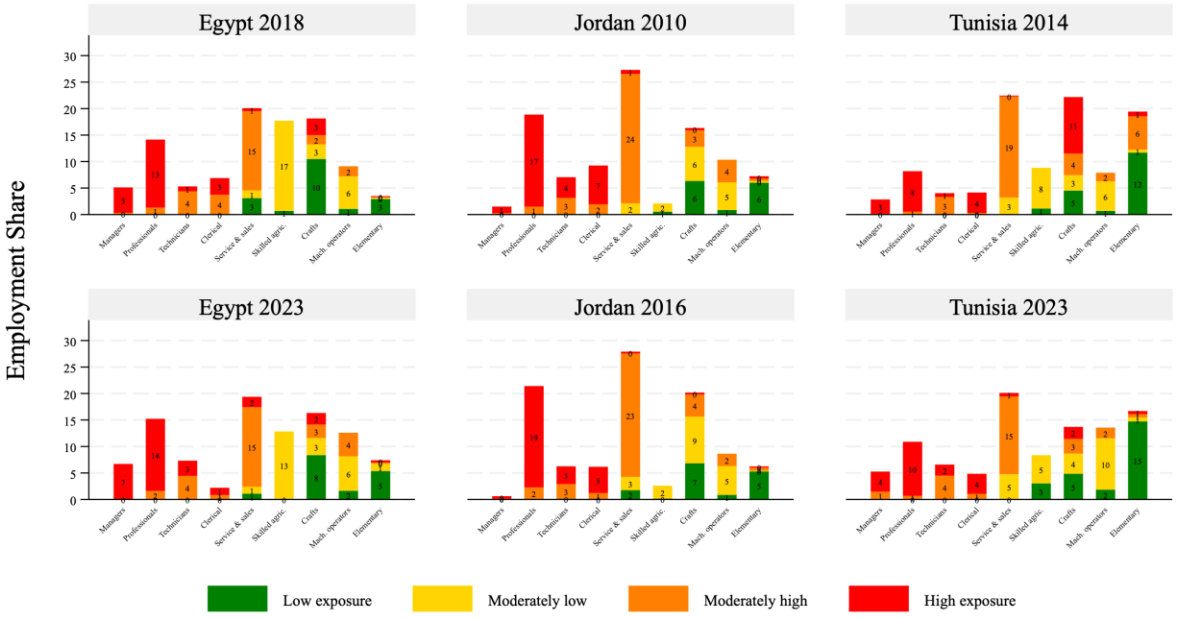


Figure 7b Employment share by exposure (C-AIOE) across major occupation groups

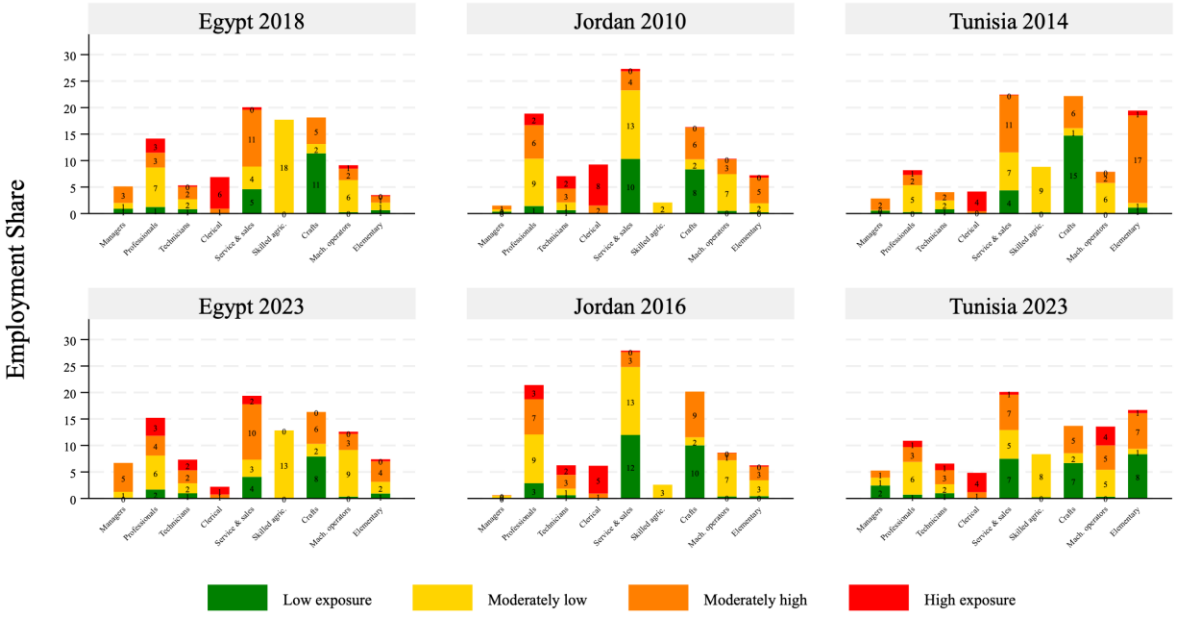


Figure 8a Employment share by exposure (AIOE_all) across major industries, reflecting the relative size of employment in each industry

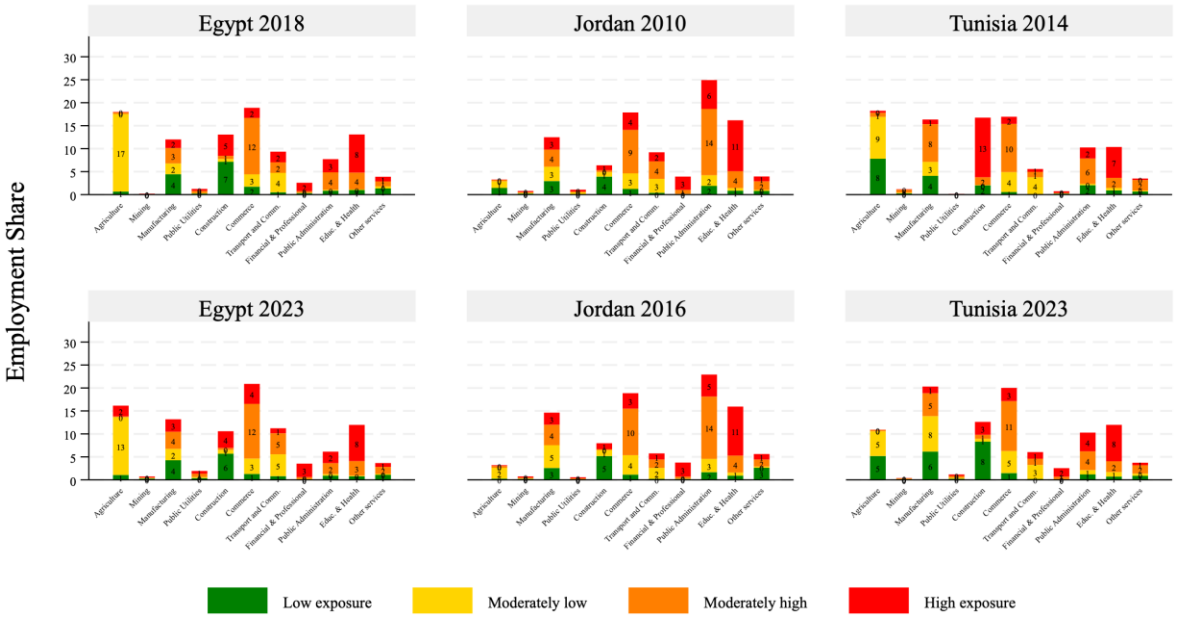


Figure 8b Employment share by exposure (C-AIOE) across major industries, reflecting the relative size of employment in each industry

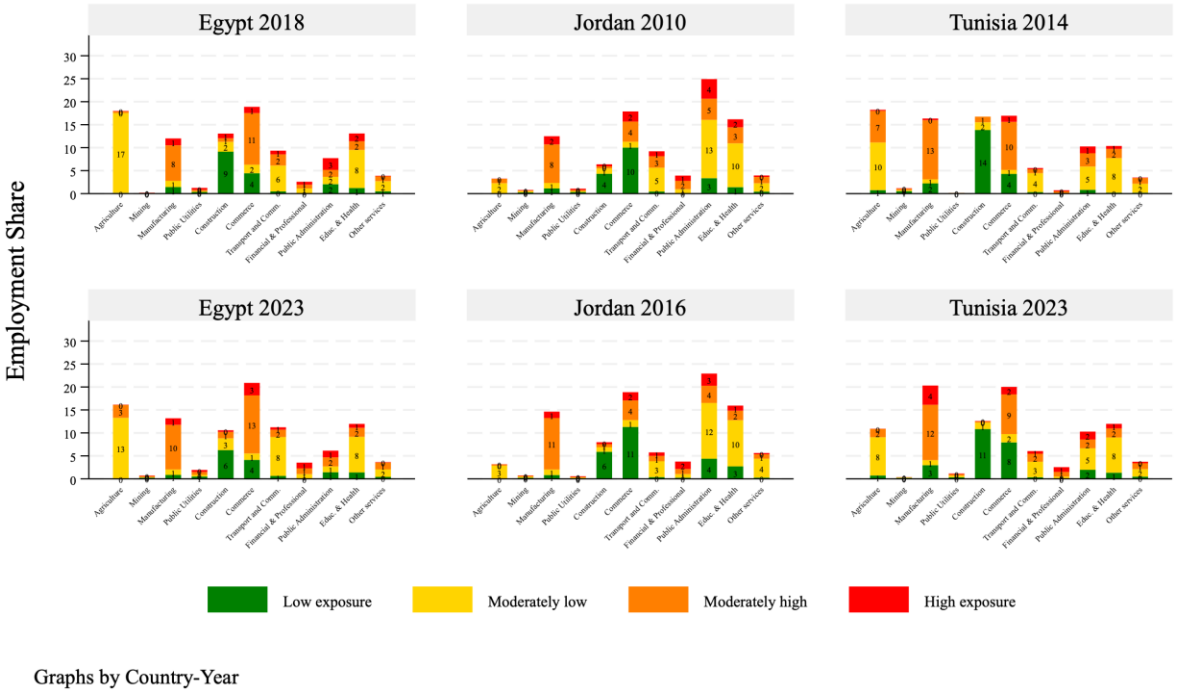


Figure 9 Exposure distribution by sex


Exposure Distribution by Sex — aioe_all
Employment Share
100
75
50
25
0
23
27
29
21
38
33
22
7
27
28
26
19
40
32
21
7
26
41
18
15
59
27
4
11
23
39
22
16
65
24
3
8
27
36
21
17
25
35
18
23
19
28
26
27
34
26
21
19
Male
Female
Egypt 2018
Egypt 2023
Jordan 2010
Jordan 2016
Tunisia 2014
Tunisia 2023
Low exposure
Moderately low
Moderately high
High exposure


Exposure Distribution by Sex — aioe_ilo
Employment Share
100
75
50
25
0
28
25
28
19
42
29
22
7
28
28
27
17
36
33
21
10
34
18
33
14
39
36
9
16
32
20
32
15
35
43
10
12
21
27
26
26
26
25
15
33
26
25
29
20
31
26
10
32
Male
Female
Egypt 2018
Egypt 2023
Jordan 2010
Jordan 2016
Tunisia 2014
Tunisia 2023
Low exposure
Moderately low
Moderately high
High exposure

Figure 10 Exposure and complementarity by age group

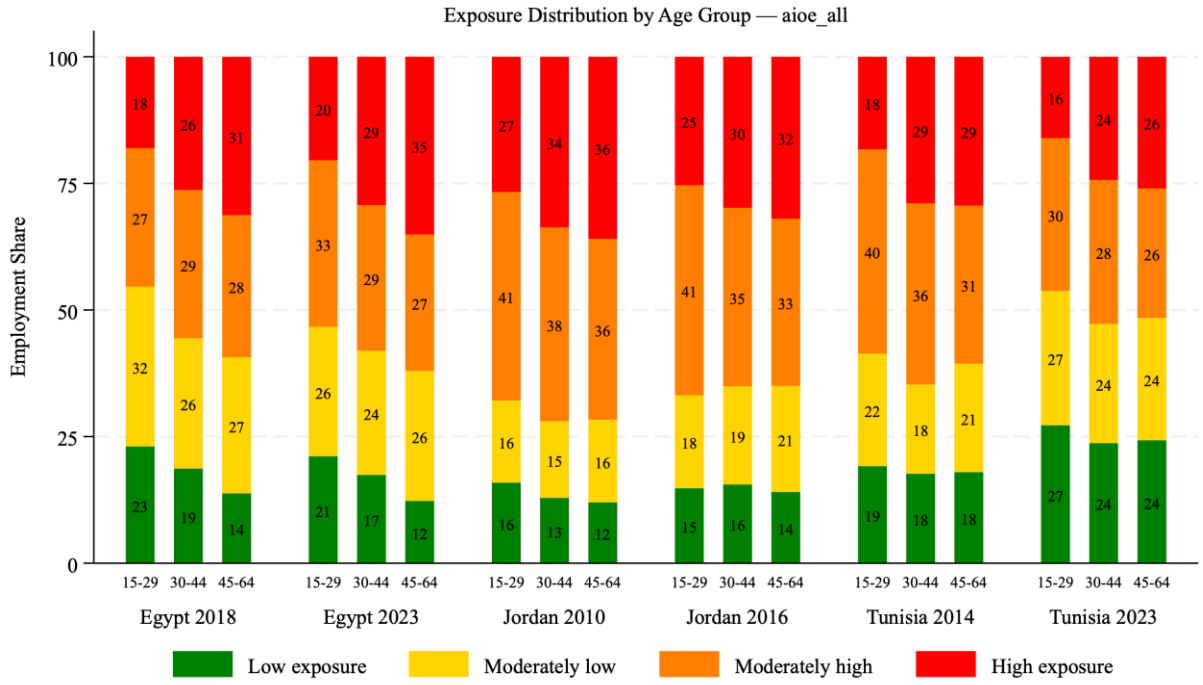
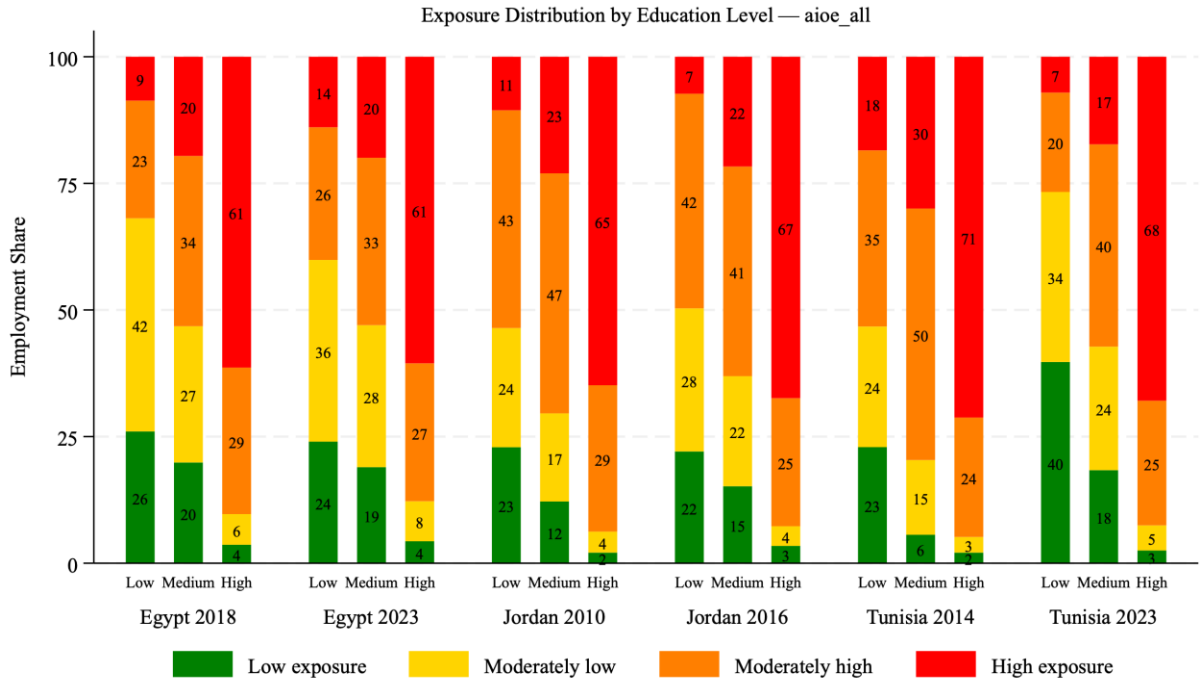


Figure 11 Exposure and complementarity by education level



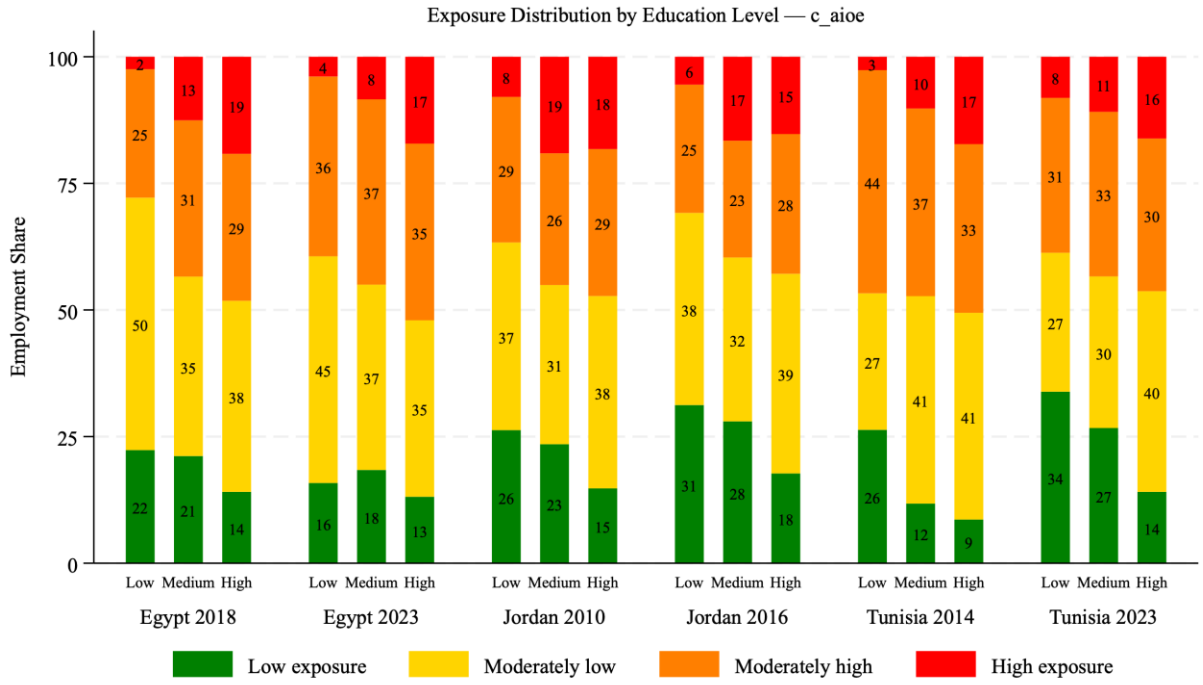


Figure 12 Formality of employment

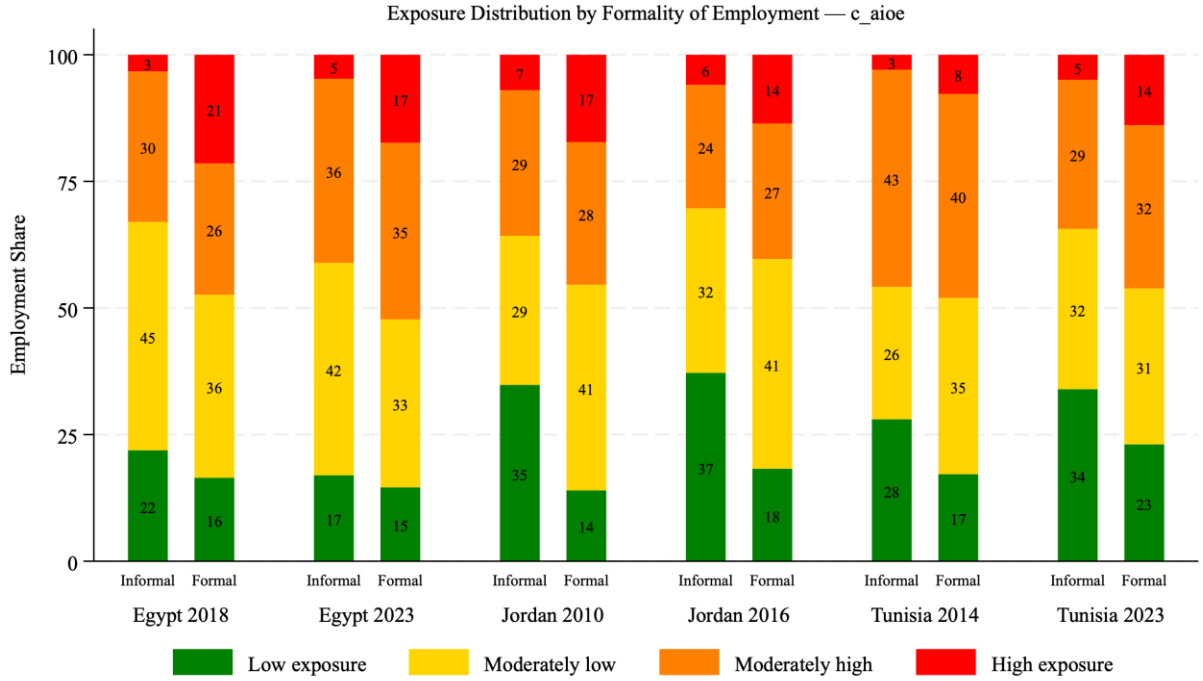


Table 1. Probit regression results for high exposure, high complementarity, or HELC, by country

	High exposure			High complementarity			High Exposure + Low Complementarity (HELC)		
	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia
Female	0.250	-1.486**	-0.150	-1.023**	-2.145***	-0.459	0.236	2.016***	-0.751***
	(0.215)	(0.515)	(0.316)	(0.363)	(0.535)	(0.342)	(0.144)	(0.195)	(0.187)
Age 30-44	-0.002	0.139	0.157	0.032	-0.062	0.124	-0.019	0.084	-0.051
	(0.103)	(0.103)	(0.099)	(0.088)	(0.095)	(0.094)	(0.028)	(0.059)	(0.040)
Age 45-64	0.080	0.183*	0.181	0.128	0.127	0.123	-0.031	-0.098	-0.08
	(0.159)	(0.084)	(0.155)	(0.143)	(0.129)	(0.120)	(0.068)	(0.156)	(0.051)
Fem. × 30-44	-0.199	-0.356*	-0.120	-0.060	-0.014	-0.118	-0.051	-0.042	-0.109
	(0.128)	(0.168)	(0.085)	(0.133)	(0.162)	(0.152)	(0.093)	(0.147)	(0.107)
Fem. × 45-64	-0.099	-0.241	-0.184*	-0.221	-0.145	0.013	0.081	0.159	-0.307
	(0.116)	(0.277)	(0.087)	(0.133)	(0.159)	(0.174)	(0.077)	(0.140)	(0.212)
Intermed. ed.	-0.001	-0.055	0.01	-0.069	-0.034	0.045	0.116**	-0.051	-0.040
	(0.085)	(0.065)	(0.164)	(0.055)	(0.072)	(0.084)	(0.041)	(0.029)	(0.067)
Above intermed. ed.	0.206	0.077	0.292	-0.021	-0.193	0.087	0.146**	0.237*	0.165
	(0.153)	(0.089)	(0.178)	(0.093)	(0.108)	(0.101)	(0.052)	(0.118)	(0.109)
Fem. × Interm.	0.240	-0.39	0.156	0.095	-0.136	-0.151	0.140	-0.088	0.226
	(0.254)	(0.315)	(0.231)	(0.158)	(0.342)	(0.212)	(0.116)	(0.253)	(0.119)
Fem. × Above interm.	0.082	0.038	-0.220	0.430	0.027	-0.253	-0.329*	-0.094	-0.003
	(0.431)	(0.259)	(0.268)	(0.250)	(0.271)	(0.153)	(0.151)	(0.220)	(0.116)
Managers	4.317***		3.033***	4.610***		3.527***			
	(0.413)		(0.598)	(0.437)		(0.540)			
Professionals	4.771***	3.727***	2.839***	1.707***	1.176*	1.682***	1.791***	1.603***	0.222
	(0.357)	(0.299)	(0.505)	(0.308)	(0.586)	(0.505)	(0.351)	(0.374)	(0.284)
Technicians	4.208***	3.217***	2.807***	1.422***	1.296**	1.307***	1.996***	1.468***	0.735**
	(0.341)	(0.346)	(0.496)	(0.345)	(0.477)	(0.351)	(0.507)	(0.422)	(0.260)
Clerical	3.825***	3.007***	2.600***	-1.067***	-1.044**		4.282***	3.606***	2.834***
	(0.335)	(0.413)	(0.467)	(0.301)	(0.385)		(0.539)	(0.369)	(0.463)
	2.309***	2.310***	1.737***	1.092***	2.161***	1.736**	1.481***	-0.064	-0.273

Service & sales	(0.107)	(0.238)	(0.441)	(0.235)	(0.149)	(0.528)	(0.130)	(0.241)	(0.213)
Skilled agric.				0.774	-0.369	0.785***			
				(0.638)	(0.293)	(0.177)			
Crafts	0.804	0.181	0.759	1.534***	1.369*	1.686**	0.369	0.177	-0.857**
	(0.413)	(0.450)	(0.766)	(0.313)	(0.552)	(0.522)	(0.575)	(0.644)	(0.312)
Mach. operators	0.817**	0.358	0.328	0.784**	0.512	0.746*	0.398	0.356	-1.340***
	(0.311)	(0.340)	(0.396)	(0.273)	(0.470)	(0.379)	(0.389)	(0.407)	(0.305)
Female × Managers	-0.285		0.225	0.647*		0.281			
	(0.324)		(0.474)	(0.296)		(0.442)			
Female × Professionals	-0.155	2.095***	0.703	1.353***	2.666***	0.872	-0.535	-2.362***	0.832**
	(0.335)	(0.524)	(0.520)	(0.307)	(0.687)	(0.481)	(0.319)	(0.352)	(0.322)
Female × Technicians	0.687*	1.844***	0.224	0.554	1.499*	0.523	0.383	-1.187***	1.025***
	(0.267)	(0.425)	(0.854)	(0.403)	(0.714)	(0.470)	(0.225)	(0.353)	(0.281)
Female × Clerical	0.309		1.186				0.922***		2.319***
	(0.310)		(0.620)				(0.163)		(0.457)
Fem. × Svc. & sales	0.002	1.888**	0.628	0.762*	1.559**	0.344	0.075	-0.987	1.145***
	(0.221)	(0.668)	(0.500)	(0.314)	(0.586)	(0.487)	(0.254)	(0.628)	(0.175)
Female × Skilled agric.				2.240***		0.597			
				(0.312)		(0.361)			
Female × Crafts	0.937***	3.533***	1.271*	0.107	0.718	-0.289	1.053***		2.410***
	(0.200)	(0.523)	(0.619)	(0.550)	(0.502)	(0.356)	(0.160)		(0.263)
Fem. × Mach. operators	-1.038**		-0.414	0.134		-0.961*	-0.877*		0.837**
	(0.337)		(0.361)	(0.481)		(0.487)	(0.400)		(0.297)
Rural	0.073	-0.007	0.135	0.085	0.047	0.102	-0.143	-0.070	-0.088
	(0.055)	(0.058)	(0.087)	(0.058)	(0.064)	(0.113)	(0.077)	(0.053)	(0.085)
Formal	-0.193	-0.042	-0.028	-0.053	0.080	0.302**	-0.034	0.023	-0.258**
	(0.139)	(0.211)	(0.059)	(0.136)	(0.187)	(0.093)	(0.119)	(0.128)	(0.093)
Mining	0.053	0.063	0.540***	1.280*	0.352**	0.331**	-0.032	0.259*	0.584***
	(0.166)	(0.201)	(0.154)	(0.526)	(0.113)	(0.122)	(0.128)	(0.111)	(0.173)
Manufacturing	0.398	0.178	0.28	0.048	-1.179***	-0.789***	0.571*	0.805**	1.163***
	(0.260)	(0.287)	(0.266)	(0.519)	(0.267)	(0.210)	(0.233)	(0.299)	(0.212)
Public Utilities	1.084***	0.099	0.559***	1.262*	0.288	0.068	0.335*	0.077	0.484***
	(0.194)	(0.257)	(0.026)	(0.500)	(0.151)	(0.075)	(0.139)	(0.182)	(0.130)
Construction	0.574	-0.571*	0.871**	0.908	-0.487	0.143	-0.456	-0.339	-0.544***
	(0.329)	(0.285)	(0.275)	(0.548)	(0.416)	(0.242)	(0.248)	(0.285)	(0.058)
Commerce	0.789***	-0.167	0.573**	0.719	-0.207	-0.504	0.683***	0.477**	1.249***
	(0.137)	(0.134)	(0.202)	(0.593)	(0.181)	(0.259)	(0.206)	(0.156)	(0.170)
Transport and Comm.	0.781***	0.343*	0.310*	1.119*	-0.111	-0.784***	-0.002	0.353*	1.345***
	(0.210)	(0.174)	(0.127)	(0.566)	(0.210)	(0.170)	(0.139)	(0.166)	(0.222)
Financial & Professional	-0.319*	0.399	0.162	0.873	-0.321	-0.752**	-0.177	0.216	1.192***
	(0.128)	(0.278)	(0.171)	(0.532)	(0.263)	(0.269)	(0.157)	(0.175)	(0.269)
Public Admin.	0.550***	0.115	0.742***	1.212*	0.130	0.303	-0.222**	-0.004	0.387*
	(0.161)	(0.223)	(0.134)	(0.552)	(0.129)	(0.164)	(0.071)	(0.114)	(0.158)
Educ. & Health	-0.267	-0.273	0.094	1.892***	0.745**	0.540*	-1.346***	-0.995***	-0.424
	(0.141)	(0.212)	(0.172)	(0.526)	(0.248)	(0.275)	(0.172)	(0.190)	(0.264)
Other services	0.049	-0.946***	0.627***	1.467**	-0.589***	0.428**	-0.749***	0.040	0.316*
	(0.118)	(0.120)	(0.178)	(0.536)	(0.134)	(0.166)	(0.041)	(0.138)	(0.149)
Constant	-2.017***	-1.041***	-1.725***	-2.489***	-1.012***	-1.527***	-1.846***	-1.826***	-1.209***
	(0.134)	(0.204)	(0.217)	(0.637)	(0.266)	(0.205)	(0.229)	(0.300)	(0.039)
Observations	26,728	10,420	27,356	32,027	10,690	29,332	24,743	10,230	25,609

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Some variables are excluded from particular regressions for incidental perfect collinearity or perfect prediction of the dependent variable. Regression for Tunisia also includes a binary indicator for the y2022 round, but this is not reported here for simplicity of presentation.

Appendix

Table A1. Selected alternative relative indices of occupational exposure to technological change

Authors	Index description	Occupation group coverage
Benítez-Rueda and Parrado (2024)	AI-generated index of job replacement likelihood within 1, 5, and 10-year horizons	759 6-digit SOC 2018 (& O*NET SOC 2019) occup. groups
Eisfeldt et al. (2023)	Generative AI OE_estz,	840 6-digit SOC 2010 occup. groups
Eloundou et al. (2023)	GPT4 & Automation	923 8-digit SOC 2010 occup. groups
Felten et al. (2023)	Occupation exposure	774 6-digit ISCO 2008 occup. groups
Gmyrek et al. (2025)	Occupation exposure	417 4-digit ISCO 2008 occup. groups
Henseke et l. (2025)	Generative AI Susceptibility Index of exposure to large language models (LLMs)	
Lennon et al. (2023)	Digital skill requirement of occupations	422 ISCO 2008 occup. groups
Pizzinelli et al. (2024)	Occupation complementarity to AI, combinable with Felten's occupation exposure	757 6-digit SOC 2010 occup. groups, cross-walked to 583 4-digit ISCO 2008 occup. groups
Schaal (2025)	AI automation expos indices	923 8-digit SOC 2010 occup. groups
Schendstok and Schreiner Wertz (2024)	Relative Importance of Work Activities by AI Exposure: Share of activities with high, medium, low exposure	50 top exposed occupational titles
Septiandri et al. (2024)	AII	873 8-digit SOC 2010 occup. groups
	Augmented AII	877 6-digit SOC 2010 occup. groups
LMI Institute (2019)	Automation exposure 10-point scale	873 8-digit ONET occup. groups
Webb (2020)	1990 codes; Labor-supply weight in terms of FTEs from ACS 2010	341 1990-Census-based occup. groups (Dorn 2009)

Source: Compiled by authors.

Table A2. Descriptive statistics for AIOE indices for selected worker groups

Survey	Group	AIOE.all	AIOE.ILO	Theta θ	C.AIOE	Commu-nication	Respons-ibility	Physical condition	Criti-cality	Routine	Skills
EG18	Adult 30-65	5.976	0.275	0.571	4.396	59.739	60.631	51.585	65.093	51.640	54.071
	Youth 15-29	5.853	0.249	0.560	4.370	56.748	61.567	54.181	64.901	50.611	48.269
	Rural	5.876	0.240	0.572	4.315	58.257	62.609	55.477	65.078	51.343	50.500
	Urban	6.043	0.309	0.563	4.496	60.012	58.374	47.609	64.995	51.429	55.598
	Female	6.103	0.305	0.565	4.525	61.300	57.135	46.367	63.160	52.797	58.244
	Male	5.906	0.260	0.569	4.356	58.409	61.784	53.685	65.505	51.031	51.211
	Formal	6.150	0.321	0.574	4.513	62.785	57.620	45.613	64.854	51.597	61.739
	Informal	5.817	0.236	0.565	4.313	56.622	62.862	56.329	65.153	51.240	46.929
	All	5.945	0.269	0.569	4.389	58.978	60.869	52.245	65.044	51.378	52.594
EG23	Adult 30-65	5.996	0.275	0.571	4.413	60.454	59.462	50.945	65.980	51.693	54.245
	Youth 15-29	5.893	0.259	0.558	4.415	57.793	60.140	52.177	65.413	50.425	48.998
	Rural	5.913	0.249	0.570	4.355	59.007	61.046	53.773	65.668	51.506	51.226
	Urban	6.051	0.302	0.565	4.494	60.899	57.673	47.764	66.080	51.213	55.351
	Female	6.097	0.293	0.569	4.500	61.772	55.775	46.863	64.707	53.204	59.002
	Male	5.944	0.266	0.568	4.395	59.381	60.453	52.186	66.084	50.992	51.665
	Formal	6.160	0.319	0.578	4.497	63.366	56.584	45.598	66.806	51.518	62.912
	Informal	5.865	0.244	0.563	4.367	57.805	61.329	54.420	65.300	51.309	47.349
	All	5.971	0.271	0.568	4.413	59.803	59.628	51.247	65.841	51.383	52.960
JO10	Adult 30-65	6.068	0.303	0.576	4.445	61.020	59.367	49.705	67.518	51.928	55.942
	Youth 15-29	5.993	0.282	0.575	4.397	60.166	59.587	51.402	67.641	51.840	54.374
	Rural	5.973	0.266	0.578	4.364	60.192	59.759	55.043	68.416	51.522	51.885
	Urban	6.054	0.302	0.575	4.440	60.808	59.385	49.367	67.388	51.972	56.074
	Female	6.234	0.329	0.569	4.602	65.294	53.077	43.104	62.437	53.868	63.406
	Male	6.000	0.289	0.577	4.391	59.760	60.757	51.820	68.616	51.490	53.707
	Formal	6.123	0.311	0.574	4.503	61.839	56.541	49.336	67.094	51.721	57.657
	Informal	5.903	0.270	0.579	4.302	58.818	64.271	51.993	68.342	52.183	51.548
	All	6.040	0.296	0.576	4.427	60.703	59.449	50.336	67.563	51.895	55.359
JO16	Adult 30-65	6.022	0.291	0.580	4.386	60.580	60.950	49.904	67.719	51.942	56.655
	Youth 15-29	5.987	0.275	0.586	4.326	60.421	61.295	52.499	69.026	51.942	56.381
	Rural	6.011	0.271	0.588	4.332	61.174	59.843	56.002	68.993	52.049	54.859
	Urban	6.011	0.288	0.581	4.372	60.459	61.191	50.097	68.019	51.930	56.764
	Female	6.293	0.322	0.584	4.548	67.303	53.487	42.537	64.328	54.342	68.580
	Male	5.962	0.280	0.581	4.337	59.349	62.377	52.120	68.779	51.523	54.473
	Formal	6.122	0.306	0.584	4.440	62.187	57.814	49.964	68.286	52.060	59.969
	Informal	5.865	0.260	0.578	4.272	58.330	65.361	51.654	67.892	51.783	52.060
	All	6.011	0.286	0.582	4.368	60.532	61.055	50.695	68.117	51.942	56.571
TU14	Adult 30-65	5.971	0.250	0.575	4.365	59.699	60.809	54.134	65.838	52.133	52.141
	Youth 15-29	5.883	0.242	0.552	4.440	57.191	58.737	53.182	63.932	50.375	47.634
	Rural	5.888	0.208	0.570	4.325	57.496	60.933	58.787	65.022	52.057	47.703
	Urban	5.980	0.267	0.569	4.408	59.879	60.062	51.674	65.579	51.582	52.684
	Female	5.917	0.261	0.534	4.569	57.271	55.327	47.070	61.224	51.518	47.990
	Male	5.958	0.245	0.579	4.327	59.644	61.746	55.947	66.585	51.777	51.947
	Formal	5.998	0.273	0.570	4.422	60.367	58.900	51.705	65.947	51.598	53.202
	Informal	5.892	0.218	0.570	4.328	57.674	62.056	56.838	64.789	51.884	48.619
	All	5.951	0.249	0.569	4.382	59.127	60.337	53.917	65.404	51.732	51.113
TU22	Adult 30-65	5.924	0.267	0.570	4.360	59.839	60.876	51.418	65.686	51.701	52.591
	Youth 15-29	5.826	0.254	0.542	4.462	56.541	58.406	50.686	63.094	50.015	46.501
	Urban	5.969	0.285	0.568	4.408	60.480	60.176	49.035	65.503	51.390	54.256
	Rural	5.749	0.213	0.557	4.309	56.120	60.977	56.771	64.443	51.361	44.545
	1.Male	5.871	0.260	0.577	4.285	59.489	62.612	54.692	67.037	51.343	51.083
	2.Female	5.990	0.276	0.534	4.615	58.534	54.924	42.786	60.611	51.478	52.324
	Formal	5.991	0.282	0.569	4.416	60.717	60.224	48.674	65.701	51.213	55.037
	Informal	5.741	0.226	0.556	4.312	56.217	60.650	56.407	64.167	51.759	44.338
	All	5.905	0.265	0.565	4.380	59.215	60.408	51.279	65.196	51.382	51.439
TU23	Adult 30-65	5.917	0.266	0.570	4.357	60.018	61.215	51.556	65.490	51.626	52.055
	Youth 15-29	5.826	0.258	0.542	4.465	56.541	58.387	50.634	63.274	49.860	46.319
	Urban	5.956	0.282	0.566	4.412	60.342	60.353	49.105	65.085	51.281	53.389
	Rural	5.761	0.218	0.562	4.290	57.029	61.567	57.039	65.097	51.368	45.147

Male	5.862	0.258	0.579	4.269	59.667	63.084	55.115	67.101	51.448	50.794
Female	5.999	0.280	0.530	4.652	58.678	54.640	41.903	59.966	50.945	51.582
Formal	5.992	0.283	0.567	4.430	60.907	60.168	48.431	65.356	51.207	54.355
Informal	5.732	0.225	0.560	4.284	56.491	61.517	56.874	64.569	51.560	44.715
All	5.900	0.265	0.565	4.377	59.388	60.703	51.389	65.089	51.306	51.016

Source: Authors' analysis based on ELMPS 2018, 2023; JLMPS 2010, 2016; TLMPS 2014; ENPE 2022 and 2023.

Table A3. Descriptive statistics for AIOE indices by economic activity

Econ. activity	AIOE.all	AIOE.ILO	Theta θ	C.AIOE	Commu-nication	Respons-ibility	Physical condition	Criti-cality	Routine	Skills
[EG18] A:Agriculture, forestry and fishing	5.675	0.183	0.557	4.252	52.163	64.152	63.548	62.671	50.804	41.105
B:Mining and quarrying	6.063	0.302	0.560	4.535	60.462	59.245	45.666	65.083	47.875	57.819
C:Manufacturing	5.810	0.237	0.522	4.564	53.970	58.985	41.856	62.435	48.295	47.574
D:Electricity,gas,steam and air conditioning supply	6.189	0.335	0.546	4.734	57.156	54.374	44.428	65.999	48.052	57.293
E:Water supply;sewage,waste management and remediation activities	5.904	0.309	0.556	4.455	53.962	60.579	53.007	66.699	49.761	49.868
F:Construction	5.834	0.179	0.608	4.065	59.326	71.636	62.021	68.182	50.467	53.384
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.052	0.358	0.562	4.517	59.468	57.951	49.616	67.078	53.475	49.689
H:Transportation and storage	5.901	0.293	0.579	4.303	59.365	60.338	60.311	69.147	49.568	48.480
I:Accomodation and food service activities	5.861	0.288	0.527	4.573	58.686	59.231	45.929	59.179	48.377	44.748
J:Information and communication	6.352	0.464	0.522	5.001	58.326	47.092	34.489	62.482	48.218	62.655
K:Financial and insurance activities	6.255	0.453	0.511	4.992	54.994	48.857	32.697	62.415	48.011	59.503
L:Real estate activities	6.465	0.373	0.605	4.555	65.458	55.302	46.119	70.928	52.005	72.968
M:Professional, scientific and technical activities	6.374	0.358	0.603	4.487	66.045	56.713	33.738	72.471	52.482	80.149
N:Administrative and support service activities	5.989	0.348	0.543	4.590	57.569	57.051	46.995	63.776	50.607	49.508
O:Public administration and defense; compulsory social security	6.106	0.335	0.567	4.538	58.236	59.417	47.983	64.940	50.624	58.872
P:Education	6.367	0.308	0.615	4.402	76.346	53.399	46.395	61.700	56.784	74.457
Q:Human health and social work activities	6.022	0.301	0.571	4.440	56.930	63.135	43.107	67.970	50.701	60.656
R:Arts, entertainment and recreation	5.958	0.284	0.580	4.331	61.181	60.920	48.357	65.708	52.784	58.981
S:other service activities	5.959	0.223	0.581	4.317	62.031	59.102	45.724	65.585	55.492	60.483
T:Activities of households as employers	5.569	0.232	0.497	4.500	54.567	55.237	42.772	55.056	50.786	39.674
[EG23] A:Agriculture, forestry and fishing	5.776	0.200	0.565	4.278	53.746	63.371	60.310	63.742	51.882	46.144
B:Mining and quarrying	5.904	0.272	0.573	4.351	58.560	61.793	54.352	66.940	49.416	52.820
C:Manufacturing	5.868	0.241	0.524	4.598	54.850	58.675	39.954	63.795	47.475	49.475
D:Electricity,gas,steam and air conditioning supply	6.140	0.318	0.563	4.594	57.437	55.391	48.194	68.098	50.529	58.362
E:Water supply;sewage,waste management and remediation activities	5.865	0.290	0.564	4.371	55.691	59.138	55.601	69.257	49.883	48.886
F:Construction	5.810	0.180	0.608	4.047	59.259	70.830	60.941	68.352	51.776	53.621
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.108	0.354	0.550	4.637	60.506	54.353	48.092	65.310	53.736	48.034
H:Transportation and storage	5.780	0.274	0.575	4.237	58.183	61.165	65.118	70.412	48.339	41.895
I:Accomodation and food service activities	5.863	0.252	0.525	4.584	63.112	62.188	43.961	59.434	44.955	41.645
J:Information and communication	6.311	0.422	0.530	4.919	60.707	47.553	34.465	62.440	50.535	62.267
K:Financial and insurance activities	6.454	0.484	0.531	5.023	59.535	47.811	33.391	65.823	47.184	64.738
L:Real estate activities	6.317	0.379	0.574	4.626	64.636	52.728	45.810	65.451	50.786	65.195
M:Professional, scientific and technical activities	6.507	0.386	0.598	4.627	66.448	54.535	31.351	73.305	51.257	81.853

N:Administrative and support service activities	5.914	0.281	0.538	4.550	58.177	58.199	45.387	64.150	49.357	47.811
O:Public administration and defense; compulsory social security	6.116	0.323	0.585	4.440	61.118	56.525	50.833	68.468	52.451	61.896
P:Education	6.407	0.296	0.628	4.352	79.053	52.486	47.770	62.923	57.479	77.292
Q:Human health and social work activities	6.033	0.280	0.602	4.258	58.605	65.460	43.936	72.400	51.288	69.502
R:Arts, entertainment and recreation	6.100	0.340	0.560	4.565	62.760	51.211	45.130	61.823	54.076	60.797
S:other service activities	5.945	0.224	0.575	4.344	60.648	59.286	46.091	64.712	55.087	59.086
T:Activities of households as employers	5.483	0.220	0.474	4.567	51.970	55.817	38.262	52.297	50.040	35.931
U:Activities of extraterritorial organizations and bodies	6.382	0.443	0.610	4.462	66.561	53.205	32.425	58.319	60.204	95.150
[JO10] A:Agriculture, forestry and fishing	5.614	0.164	0.536	4.327	50.395	59.661	64.941	59.683	50.002	37.106
B:Mining and quarrying	5.915	0.290	0.570	4.388	57.421	60.845	55.253	67.395	51.685	49.311
C:Manufacturing	5.882	0.268	0.521	4.633	53.935	58.287	40.776	63.999	48.260	47.428
D:Electricity,gas,steam and air conditioning supply	6.100	0.333	0.554	4.626	55.892	53.369	48.721	67.079	52.199	54.897
E:Water supply;sewage,waste management and remediation activities	5.887	0.331	0.573	4.341	55.867	61.808	57.823	70.808	50.734	46.592
F:Construction	5.662	0.179	0.588	4.079	54.313	67.632	64.388	67.006	51.933	47.701
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.158	0.370	0.613	4.280	65.139	67.505	44.092	72.058	55.952	63.246
H:Transportation and storage	5.873	0.290	0.572	4.328	57.427	61.458	62.090	71.766	47.798	42.922
I:Accomodation and food service activities	5.982	0.326	0.528	4.669	59.516	59.956	41.164	60.723	48.148	47.355
J:Information and communication	6.360	0.440	0.540	4.894	60.638	46.351	37.497	61.617	50.180	67.945
K:Financial and insurance activities	6.345	0.474	0.506	5.091	56.439	46.880	34.116	61.422	46.367	58.427
L:Real estate activities	6.488	0.395	0.600	4.603	65.536	54.562	48.971	68.713	52.717	69.500
M:Professional, scientific and technical activities	6.464	0.387	0.601	4.575	66.409	53.585	35.155	71.522	52.236	81.514
N:Administrative and support service activities	6.016	0.257	0.564	4.488	58.012	61.444	54.706	69.409	48.245	46.484
O:Public administration and defense; compulsory social security	6.010	0.287	0.574	4.430	58.166	57.995	56.898	70.227	50.465	50.732
P:Education	6.385	0.298	0.617	4.409	76.965	51.632	47.884	63.057	57.686	72.730
Q:Human health and social work activities	6.125	0.314	0.585	4.438	58.425	62.296	42.600	69.522	52.338	66.061
R:Arts, entertainment and recreation	5.937	0.337	0.563	4.438	61.364	57.568	49.661	64.179	53.735	51.516
S:other service activities	5.989	0.217	0.579	4.355	61.274	56.658	47.541	64.326	56.855	60.827
T:Activities of households as employers	5.755	0.207	0.485	4.720	53.846	54.623	44.013	57.032	45.625	35.799
U:Activities of extraterritorial organizations and bodies	6.318	0.402	0.520	4.992	58.779	48.492	36.976	59.624	50.263	57.604
[JO16] A:Agriculture, forestry and fishing	5.738	0.195	0.559	4.293	52.770	62.661	62.704	63.349	50.439	43.430
B:Mining and quarrying	5.952	0.291	0.579	4.361	58.431	62.668	54.738	69.916	52.105	49.536
C:Manufacturing	5.855	0.246	0.516	4.640	53.440	59.676	40.203	63.915	46.675	45.630
D:Electricity,gas,steam and air conditioning supply	6.151	0.353	0.548	4.700	56.403	51.759	44.094	64.794	52.684	59.322
E:Water supply;sewage,waste management and remediation activities	5.945	0.320	0.569	4.407	57.255	61.599	55.610	70.055	50.670	46.161
F:Construction	5.623	0.166	0.582	4.089	51.682	66.544	66.850	65.061	51.803	47.280
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.168	0.380	0.624	4.223	64.953	69.216	43.987	73.613	55.622	66.833
H:Transportation and storage	5.877	0.311	0.572	4.334	57.916	60.554	61.478	70.710	49.467	43.084
I:Accomodation and food service activities	5.802	0.250	0.524	4.549	56.212	62.820	43.265	59.129	48.395	44.524
J:Information and communication	6.465	0.453	0.521	5.103	62.054	39.083	32.161	55.498	48.024	75.877

K:Financial and insurance activities	6.468	0.468	0.518	5.122	58.638	45.329	31.612	62.866	46.295	65.804
K:Financial and insurance activities	6.468	0.468	0.518	5.122	58.638	45.329	31.612	62.866	46.295	65.804
L:Real estate activities	6.235	0.399	0.571	4.628	57.329	58.281	51.398	66.465	55.144	53.779
M:Professional, scientific and technical activities	6.459	0.412	0.574	4.746	63.730	51.665	32.195	70.725	50.050	75.777
N:Administrative and support service activities	5.956	0.260	0.564	4.438	57.680	61.302	55.212	69.001	48.377	46.970
O:Public administration and defense; compulsory social security	5.975	0.271	0.590	4.308	59.010	60.562	60.340	71.713	50.704	51.847
P:Education	6.403	0.286	0.630	4.338	79.484	52.642	49.443	63.832	58.130	74.343
Q:Human health and social work activities	6.127	0.294	0.614	4.262	59.186	63.525	44.634	74.106	53.947	72.926
R:Arts, entertainment and recreation	5.968	0.321	0.565	4.451	60.911	56.239	51.482	61.447	51.623	57.169
S:other service activities	5.927	0.221	0.578	4.322	59.042	57.889	47.699	65.285	56.629	60.179
T:Activities of households as employers	5.393	0.263	0.510	4.311	50.939	62.400	41.192	59.040	53.033	39.282
U:Activities of extraterritorial organizations and bodies	6.160	0.371	0.557	4.638	61.248	52.473	46.870	63.340	49.232	60.921
[TU14] A:Agriculture, forestry and fishing	5.578	0.163	0.526	4.358	49.005	55.985	63.753	59.573	52.391	34.726
B:Mining and quarrying	5.836	0.265	0.580	4.260	58.692	65.642	56.920	68.880	52.637	45.013
C:Manufacturing	5.786	0.229	0.527	4.521	54.030	58.562	46.317	64.279	48.064	44.939
D:Electricity,gas,steam and air conditioning supply	6.471	0.320	0.626	4.418	68.313	64.000	40.000	68.167	55.375	80.000
E:Water supply;sewage,waste management and remediation activities	5.660	0.239	0.579	4.125	55.901	60.894	66.488	72.994	49.103	41.861
F:Construction	6.294	0.158	0.688	3.882	67.795	81.251	63.103	74.586	53.612	72.397
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.054	0.345	0.562	4.519	60.327	58.395	50.137	66.619	53.802	47.927
H:Transportation and storage	5.755	0.273	0.571	4.247	58.123	57.479	68.121	70.109	48.656	39.880
I:Accomodation and food service activities	5.831	0.304	0.525	4.560	60.276	59.820	44.674	57.567	46.573	46.229
J:Information and communication	6.372	0.408	0.578	4.659	62.749	53.632	39.775	65.996	52.376	72.531
K:Financial and insurance activities	6.016	0.346	0.495	4.887	55.013	49.402	37.067	59.264	47.816	48.234
L:Real estate activities	5.854	0.272	0.533	4.530	56.207	52.852	49.806	62.539	51.158	46.979
M:Professional, scientific and technical activities	6.530	0.580	0.454	5.585	53.000	42.000	26.000	53.333	58.000	40.000
N:Administrative and support service activities	6.073	0.365	0.503	4.907	55.133	50.381	46.137	62.493	43.977	43.895
O:Public administration and defense; compulsory social security	5.934	0.268	0.559	4.457	57.188	56.825	55.659	67.493	51.197	46.874
P:Education	6.345	0.288	0.614	4.391	76.110	51.559	47.511	63.561	58.749	70.988
Q:Human health and social work activities	5.926	0.256	0.574	4.360	56.646	65.892	47.419	68.486	50.114	55.609
R:Arts, entertainment and recreation	6.191	0.300	0.585	4.485	67.393	51.944	50.501	61.936	55.126	63.873
S:other service activities	5.856	0.223	0.561	4.372	58.781	58.871	48.001	63.603	53.571	54.056
T:Activities of households as employers	5.367	0.140	0.378	4.999	49.000	47.000	29.000	38.667	43.000	20.000
[TU22] A:Agriculture, forestry and fishing	5.599	0.166	0.551	4.236	49.549	60.392	64.078	64.970	53.507	37.980
B:Mining and quarrying	5.776	0.233	0.565	4.297	57.747	65.882	52.574	66.881	48.857	46.920
C:Manufacturing	5.738	0.217	0.501	4.628	52.668	57.630	41.392	59.532	46.599	42.647
D:Electricity,gas,steam and air conditioning supply	6.072	0.312	0.564	4.527	58.269	58.682	48.008	65.738	51.458	56.061
E:Water supply;sewage,waste management and remediation activities	5.848	0.290	0.547	4.452	54.550	59.320	53.380	69.012	47.911	44.167
F:Construction	5.603	0.178	0.604	3.921	58.057	69.857	68.607	66.553	50.461	48.669
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.082	0.332	0.587	4.386	63.146	63.338	47.055	69.380	54.135	55.189
H:Transportation and storage	5.789	0.280	0.575	4.244	58.319	59.607	66.277	70.387	48.201	42.273

I:Accomodation and food service activities	5.770	0.272	0.533	4.467	60.162	66.285	45.655	58.341	47.101	42.302
J:Information and communication	6.406	0.468	0.534	4.964	59.752	48.406	31.715	62.908	49.411	68.497
K:Financial and insurance activities	6.397	0.456	0.569	4.724	63.544	58.981	35.225	67.335	49.058	67.385
L:Real estate activities	6.505	0.396	0.572	4.793	66.403	48.077	43.454	65.204	55.394	64.639
M:Professional, scientific and technical activities	6.411	0.428	0.562	4.789	62.223	49.708	34.682	64.917	51.688	73.845
N:Administrative and support service activities	6.169	0.409	0.522	4.864	58.660	54.573	43.122	61.742	46.130	49.023
O:Public administration and defense; compulsory social security	6.070	0.279	0.590	4.361	61.329	59.820	53.744	70.401	52.329	56.581
P:Education	6.374	0.290	0.627	4.333	78.573	52.480	47.437	63.111	59.597	75.162
Q:Human health and social work activities	6.019	0.272	0.592	4.302	57.833	65.983	45.303	70.379	51.505	64.372
R:Arts, entertainment and recreation	6.051	0.323	0.584	4.382	64.410	57.976	48.928	64.634	54.536	60.133
S:other service activities	5.885	0.191	0.572	4.332	58.778	58.902	47.459	63.890	56.522	57.563
T:Activities of households as employers	5.422	0.156	0.417	4.829	50.749	50.037	36.000	44.428	44.555	24.280
U:Activities of extraterritorial organizations and bodies	6.343	0.404	0.545	4.849	58.708	45.537	36.067	63.617	52.035	70.808
[TU23] A:Agriculture, forestry and fishing	5.603	0.164	0.555	4.213	50.142	61.144	63.937	66.001	53.461	38.438
B:Mining and quarrying	5.881	0.236	0.610	4.109	62.314	70.827	58.694	72.003	50.839	51.618
C:Manufacturing	5.729	0.215	0.500	4.624	53.092	58.010	41.751	59.108	46.481	41.726
D:Electricity,gas,steam and air conditioning supply	6.191	0.394	0.571	4.560	60.946	59.241	44.246	66.335	50.323	61.763
E:Water supply;sewage,waste management and remediation activities	5.796	0.300	0.566	4.305	55.291	59.681	58.269	70.449	49.524	46.125
F:Construction	5.607	0.179	0.604	3.922	58.312	69.787	68.380	66.540	50.280	48.959
G:Wholesale and retail trade; repair of motor vehicles and motorcycles	6.094	0.340	0.591	4.374	63.410	63.717	46.921	69.717	54.648	55.912
H:Transportation and storage	5.823	0.282	0.573	4.285	58.493	59.126	64.736	70.137	47.879	43.201
I:Accomodation and food service activities	5.767	0.276	0.530	4.485	60.101	64.893	46.118	57.869	46.676	42.217
J:Information and communication	6.359	0.436	0.542	4.877	61.575	48.540	35.224	62.473	49.592	67.920
K:Financial and insurance activities	6.341	0.481	0.542	4.861	60.867	55.807	36.286	64.097	47.537	60.319
L:Real estate activities	6.377	0.380	0.597	4.537	65.225	60.938	41.199	68.178	54.099	68.483
M:Professional, scientific and technical activities	6.435	0.439	0.543	4.937	59.827	46.794	35.145	63.648	49.734	70.430
N:Administrative and support service activities	6.125	0.402	0.513	4.890	58.084	53.902	43.725	60.760	45.635	45.484
O:Public administration and defense; compulsory social security	6.072	0.276	0.594	4.341	61.563	60.385	54.479	71.035	52.320	56.879
P:Education	6.378	0.289	0.628	4.331	79.171	52.890	47.548	63.147	59.674	74.400
Q:Human health and social work activities	6.056	0.296	0.580	4.418	57.531	64.743	43.441	68.834	50.902	62.263
R:Arts, entertainment and recreation	6.035	0.326	0.565	4.497	62.826	56.094	47.990	62.230	53.513	56.175
S:other service activities	5.900	0.200	0.577	4.315	58.907	58.803	47.745	65.174	57.246	58.435
T:Activities of households as employers	5.437	0.156	0.422	4.809	50.688	50.935	36.260	44.758	44.951	25.688
U:Activities of extraterritorial organizations and bodies	6.315	0.426	0.527	4.953	60.352	47.976	35.854	63.198	48.748	60.276

Source: Authors' analysis based on ELMPS 2018, 2023; JLMPS 2010, 2016; TLMPS 2014; ENPE 2022 and 2023.

Table A4. Descriptive statistics for AIOE indices by occupation group

ISCO occupation group (1 digit)	AIOE.all	AIOE.ILO	Theta θ	C.AIOE	Commu-nication	Respons-ibility	Physical condition	Criti-cality	Routine	Skills
[EG18] Clerical support workers	6.231	0.480	0.447	5.369	48.663	46.735	31.029	51.140	45.856	44.548
Craft and related trades workers	5.680	0.141	0.584	4.093	56.100	69.729	58.519	67.001	50.946	48.215
Elementary occupations	5.516	0.236	0.518	4.362	51.603	56.553	58.766	61.110	48.652	34.201
Managers	6.475	0.348	0.644	4.311	70.623	68.653	38.582	70.256	55.592	82.420
Plant and machine operators, and assemblers	5.706	0.242	0.546	4.344	55.608	59.052	61.375	67.240	45.731	38.734
Professionals	6.524	0.340	0.620	4.498	74.378	51.093	40.993	67.004	55.126	83.591
Service and sales workers	5.932	0.328	0.562	4.428	59.641	60.207	50.483	65.569	53.666	47.433
Skilled agricultural, forestry and fishery workers	5.665	0.180	0.558	4.240	51.936	64.321	64.037	62.895	50.958	40.753
Technicians and associate professionals	6.093	0.299	0.595	4.359	61.525	64.448	48.864	70.140	50.212	61.513
[EG23] Clerical support workers	6.299	0.515	0.477	5.242	57.025	46.977	32.099	58.599	45.226	46.479
Craft and related trades workers	5.681	0.150	0.571	4.177	54.872	67.475	54.019	67.076	51.315	47.607
Elementary occupations	5.536	0.190	0.510	4.423	53.984	57.903	53.888	59.405	47.815	33.278
Managers	6.478	0.337	0.633	4.379	69.590	65.872	39.334	68.745	55.279	81.075
Plant and machine operators, and assemblers	5.719	0.242	0.556	4.298	56.587	61.430	61.707	68.738	45.928	39.300
Professionals	6.518	0.355	0.611	4.554	71.801	50.717	39.740	67.520	54.133	82.844
Service and sales workers	6.027	0.331	0.557	4.533	61.165	57.192	51.093	65.200	53.617	46.095
Skilled agricultural, forestry and fishery workers	5.668	0.180	0.559	4.239	51.596	64.081	63.806	63.145	51.445	41.228
Technicians and associate professionals	6.170	0.360	0.564	4.608	59.923	56.035	43.398	67.068	51.068	61.091
[JO10] Clerical support workers	6.441	0.582	0.460	5.473	51.997	43.017	32.108	58.440	48.930	41.343
Craft and related trades workers	5.622	0.159	0.561	4.203	52.155	64.386	54.575	67.000	52.134	46.381
Elementary occupations	5.501	0.186	0.496	4.472	51.841	56.397	51.867	55.728	49.296	32.398
Managers	6.460	0.368	0.641	4.317	71.566	70.186	38.976	69.275	54.605	80.118
Plant and machine operators, and assemblers	5.743	0.235	0.571	4.231	56.787	62.939	64.693	72.283	46.418	39.660
Professionals	6.516	0.351	0.613	4.539	73.351	51.088	41.256	65.213	55.314	81.621
Service and sales workers	6.031	0.272	0.623	4.135	64.090	68.870	56.390	74.723	53.039	56.824
Skilled agricultural, forestry and fishery workers	5.634	0.167	0.555	4.238	49.272	62.736	65.656	63.069	51.553	40.784
Technicians and associate professionals	6.262	0.396	0.556	4.727	60.884	50.218	40.524	65.584	51.888	64.255
[JO16] Clerical support workers	6.443	0.574	0.458	5.486	51.613	42.179	31.643	57.851	49.728	41.993
Craft and related trades workers	5.622	0.154	0.556	4.235	51.377	65.119	54.570	66.701	50.570	45.106
Elementary occupations	5.514	0.236	0.515	4.373	51.943	58.962	55.393	59.973	48.913	34.035
Managers	6.429	0.368	0.653	4.219	72.506	73.512	39.989	69.629	54.076	82.070
Plant and machine operators, and assemblers	5.727	0.247	0.572	4.213	57.164	62.785	65.584	71.243	47.281	39.180
Professionals	6.508	0.350	0.613	4.533	72.038	52.043	40.908	66.155	54.810	82.114
Service and sales workers	5.985	0.275	0.626	4.082	63.809	70.392	54.969	74.577	53.499	58.242
Skilled agricultural, forestry and fishery workers	5.660	0.176	0.557	4.246	51.334	63.972	64.260	62.618	51.041	40.776
Technicians and associate professionals	6.250	0.397	0.562	4.679	60.703	53.036	41.630	66.659	51.413	63.570
[TU14] Clerical support workers	6.485	0.568	0.458	5.519	53.657	42.747	30.047	56.677	51.389	40.582
Craft and related trades workers	6.054	0.152	0.632	4.058	60.964	73.909	56.552	71.951	53.456	62.541
Elementary occupations	5.589	0.187	0.480	4.639	53.752	49.310	54.879	52.623	45.458	31.832
Managers	6.466	0.346	0.644	4.304	69.724	68.192	42.582	69.709	55.346	80.549
Plant and machine operators, and assemblers	5.709	0.249	0.565	4.242	56.503	63.430	63.467	70.883	47.187	37.421
Professionals	6.529	0.328	0.625	4.468	77.938	47.981	43.880	63.141	59.272	82.814
Service and sales workers	5.988	0.311	0.577	4.380	60.346	61.461	53.345	68.623	52.139	50.128
Skilled agricultural, forestry and fishery workers	5.629	0.186	0.552	4.252	46.787	58.599	62.842	66.229	56.356	40.269
Technicians and associate professionals	6.009	0.289	0.611	4.201	60.246	67.975	52.737	71.085	51.489	62.889
[TU22] Clerical support workers	6.390	0.558	0.467	5.381	55.122	44.467	32.263	56.969	48.072	43.535
Craft and related trades workers	5.745	0.163	0.571	4.220	54.990	66.119	52.338	67.449	51.615	50.091
Elementary occupations	5.408	0.154	0.522	4.260	53.206	58.955	60.365	58.594	46.946	35.010

Managers	6.429	0.344	0.655	4.203	70.193	75.175	41.205	72.861	54.882	78.862
Plant and machine operators, and assemblers	5.676	0.223	0.504	4.560	52.221	55.967	52.649	61.030	45.984	34.750
Professionals	6.521	0.338	0.627	4.446	75.756	50.308	42.217	65.894	57.984	84.332
Service and sales workers	6.009	0.293	0.596	4.281	64.005	65.728	51.828	69.547	53.229	53.288
Skilled agricultural, forestry and fishery workers	5.628	0.174	0.561	4.201	48.709	61.421	63.233	67.582	55.297	40.288
Technicians and associate professionals	6.143	0.358	0.569	4.556	60.206	58.297	43.761	66.843	50.093	62.182
[TU23] Clerical support workers	6.385	0.553	0.466	5.385	54.972	45.045	31.729	56.655	49.136	42.194
Craft and related trades workers	5.761	0.163	0.577	4.193	55.730	66.706	52.982	67.784	52.248	50.994
Elementary occupations	5.408	0.151	0.527	4.235	53.585	59.316	61.717	58.951	47.290	35.084
Managers	6.411	0.347	0.661	4.157	70.525	76.828	42.172	73.352	54.839	78.681
Plant and machine operators, and assemblers	5.670	0.217	0.493	4.618	51.729	55.582	49.861	59.458	45.396	33.878
Professionals	6.533	0.343	0.624	4.477	76.527	49.783	42.050	65.137	57.656	83.237
Service and sales workers	5.998	0.292	0.599	4.254	64.406	66.602	52.169	69.673	53.045	53.645
Skilled agricultural, forestry and fishery workers	5.628	0.170	0.566	4.172	49.332	62.180	63.484	68.899	55.018	40.688
Technicians and associate professionals	6.147	0.354	0.575	4.524	60.932	59.060	44.580	67.324	49.959	62.930

Source: Authors' analysis based on ELMPS 2018, 2023; JLMPS 2010, 2016; TLMPS 2014; ENPE 2022 and 2023.

Table A5. Probit regression results for high exposure, high complementarity, or HELC, by country – no interaction terms

	High exposure			High complementarity			HELC		
	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia
Female	0.346***	0.377	0.204***	0.181	-0.141	-0.311***	0.213	0.26	0.265**
	(0.120)	(0.364)	(0.079)	(0.257)	(0.130)	(0.115)	(0.143)	(0.237)	(0.129)
Age 30-44	-0.004	0.138	0.157**	0.024	-0.073	0.098	-0.001	0.100*	-0.073
	(0.101)	(0.099)	(0.079)	(0.073)	(0.086)	(0.096)	(0.026)	(0.052)	(0.053)
Age 45-64	0.067	0.194**	0.213	0.073	0.087	0.11	0.006	-0.031	-0.113*
	(0.162)	(0.085)	(0.143)	(0.133)	(0.131)	(0.149)	(0.082)	(0.144)	(0.068)
Intermediate ed.	-0.003	-0.092	0.180**	-0.056	-0.052	-0.012	0.106***	-0.056**	0.112
	(0.086)	(0.073)	(0.084)	(0.059)	(0.086)	(0.059)	(0.036)	(0.028)	(0.071)
Above intermediate ed.	0.182	0.062	0.357***	0.038	-0.221**	-0.008	0.074	0.266*	0.264***
	(0.146)	(0.086)	(0.102)	(0.097)	(0.106)	(0.098)	(0.060)	(0.138)	(0.093)
Rural	0.079	-0.041	0.171**	0.08	0.024	0.1	-0.125*	-0.072	-0.042
	(0.052)	(0.046)	(0.076)	(0.059)	(0.056)	(0.110)	(0.073)	(0.050)	(0.083)
Formal	-0.17	-0.053	-0.045	-0.035	0.098	0.279***	-0.031	-0.025	-0.276***
	(0.143)	(0.207)	(0.073)	(0.136)	(0.190)	(0.089)	(0.111)	(0.132)	(0.084)
Managers	4.324***		2.998***	4.646***		3.650***			
	(0.402)		(0.428)	(0.439)		(0.406)			
Professionals	4.764***	4.043***	3.002***	1.922***	1.605**	2.002***	1.683***	1.521***	0.42
	(0.330)	(0.274)	(0.412)	(0.389)	(0.632)	(0.555)	(0.430)	(0.404)	(0.322)
Technicians	4.372***	3.392***	2.725***	1.408***	1.362***	1.476***	2.128***	1.724***	1.039***
	(0.374)	(0.354)	(0.385)	(0.309)	(0.436)	(0.314)	(0.503)	(0.403)	(0.181)
Clerical	4.034***	3.298***	2.855***	-1.256***	-1.006***		4.649***	3.930***	3.462***
	(0.333)	(0.435)	(0.363)	(0.325)	(0.331)		(0.602)	(0.409)	(0.404)
Service & sales	2.365***	2.512***	1.840***	1.152***	2.295***	1.833***	1.543***	0.152	0.058
	(0.132)	(0.259)	(0.334)	(0.223)	(0.170)	(0.464)	(0.118)	(0.319)	(0.207)
Skilled agric.				1.182**	-0.162	0.874***			
				(0.556)	(0.288)	(0.160)			
Crafts	0.939**	0.458	0.935*	1.631***	1.516***	1.732***	0.487	0.436	-0.188
	(0.443)	(0.511)	(0.522)	(0.316)	(0.556)	(0.508)	(0.607)	(0.674)	(0.404)
Mach. operators	0.796**	0.544	0.193	0.872***	0.691	0.690*	0.36	0.465	-1.095***
	(0.336)	(0.367)	(0.346)	(0.277)	(0.466)	(0.399)	(0.396)	(0.416)	(0.251)
Mining	-0.003	0.311	0.709***	1.188***	0.414***	0.365***	-0.04	0.354**	0.654***
	(0.161)	(0.202)	(0.160)	(0.456)	(0.127)	(0.122)	(0.145)	(0.140)	(0.159)
Manufacturing	0.408	0.476	0.449**	-0.078	-1.131***	-0.932***	0.586**	0.890***	1.262***
	(0.252)	(0.310)	(0.210)	(0.466)	(0.271)	(0.228)	(0.242)	(0.344)	(0.246)
Public Utilities	1.075***	0.295	0.860***	1.206***	0.339**	0.036	0.303**	0.119	0.723***
	(0.186)	(0.249)	(0.088)	(0.423)	(0.160)	(0.093)	(0.146)	(0.199)	(0.141)
Construction	0.553*	-0.395	0.990***	0.838*	-0.39	0.13	-0.460*	-0.351	-0.421***
	(0.333)	(0.284)	(0.189)	(0.485)	(0.409)	(0.225)	(0.267)	(0.319)	(0.153)
Commerce	0.807***	0.074	0.755***	0.605	-0.111	-0.558**	0.678***	0.471***	1.307***
	(0.136)	(0.132)	(0.173)	(0.548)	(0.174)	(0.254)	(0.201)	(0.172)	(0.149)
Transport and Comm.	0.849***	0.566***	0.609***	1.066**	-0.033	-0.756***	0.017	0.358*	1.447***
	(0.215)	(0.210)	(0.159)	(0.494)	(0.224)	(0.175)	(0.139)	(0.185)	(0.182)
Financial & Professional	-0.306**	0.630**	0.334**	0.736	-0.259	-0.833***	-0.146	0.229	1.260***
	(0.135)	(0.263)	(0.148)	(0.480)	(0.308)	(0.290)	(0.187)	(0.199)	(0.257)
Public Admin.	0.582***	0.362*	0.872***	1.125**	0.202	0.282*	-0.230***	0.023	0.439***
	(0.167)	(0.201)	(0.129)	(0.479)	(0.133)	(0.160)	(0.069)	(0.126)	(0.143)
Educ. & Health	-0.24	-0.118	0.238*	1.729***	0.828***	0.544*	-1.399***	-1.041***	-0.406
	(0.157)	(0.216)	(0.134)	(0.539)	(0.313)	(0.290)	(0.207)	(0.255)	(0.259)
Other services	0.067	-0.709***	0.791***	1.370***	-0.516***	0.373*	-0.768***	0.108	0.311**
	(0.120)	(0.145)	(0.118)	(0.467)	(0.150)	(0.192)	(0.046)	(0.153)	(0.123)
Latest round	0.250***	-0.220**	-0.517***	0.024	-0.036	0.187	0.185***	-0.174***	-0.355***
	(0.095)	(0.093)	(0.187)	(0.063)	(0.073)	(0.210)	(0.044)	(0.067)	(0.111)
Constant	-2.242***	-1.355***	-1.661***	-2.536***	-1.233***	-1.610***	-1.994***	-1.904***	-1.366***

	(0.080)	(0.273)	(0.118)	(0.484)	(0.255)	(0.132)	(0.252)	(0.309)	(0.059)
Observations	26,728	10,623	27,356	32,473	10,937	29,332	24,743	10,610	25,609

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Some variables are excluded from particular regressions for incidental perfect collinearity or perfect prediction of the dependent variable. Regression for Tunisia also includes a binary indicator for the y2022 round, but this is not reported here for simplicity of presentation.

A1. Cumulative employment share by percentile of the occupational exposure/complementarity score: all survey rounds

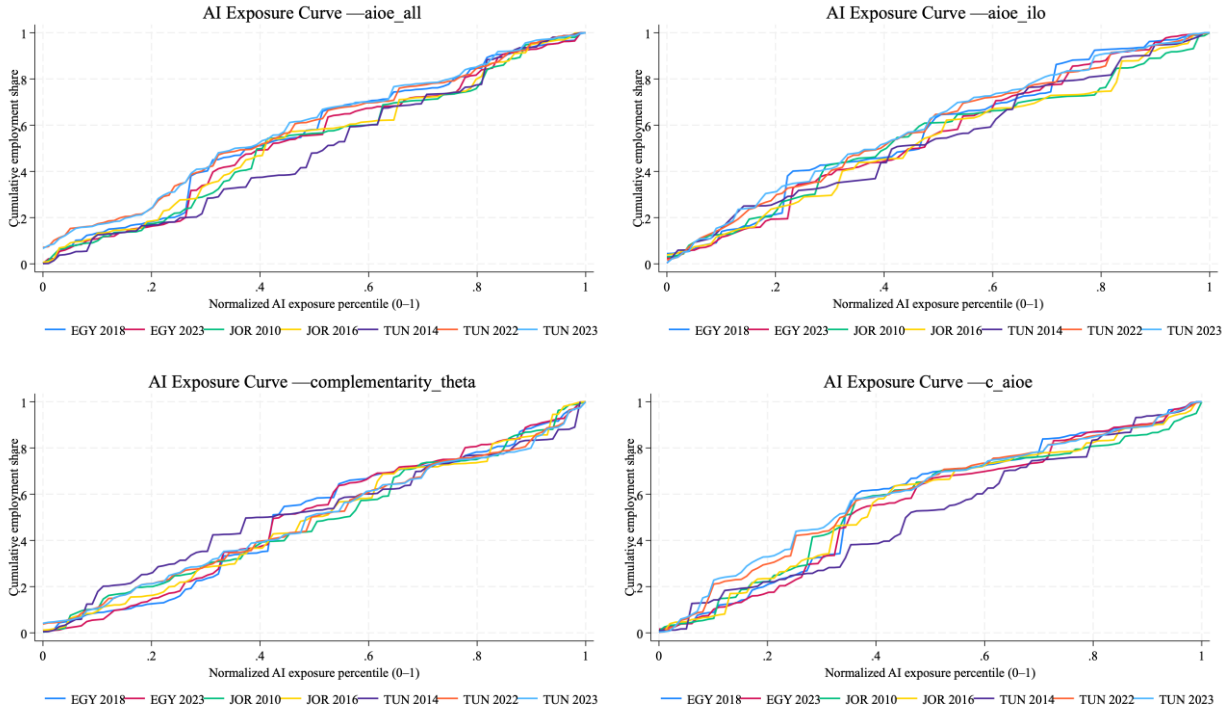


Figure A2a AI exposure by main occupation group: AIOE-All

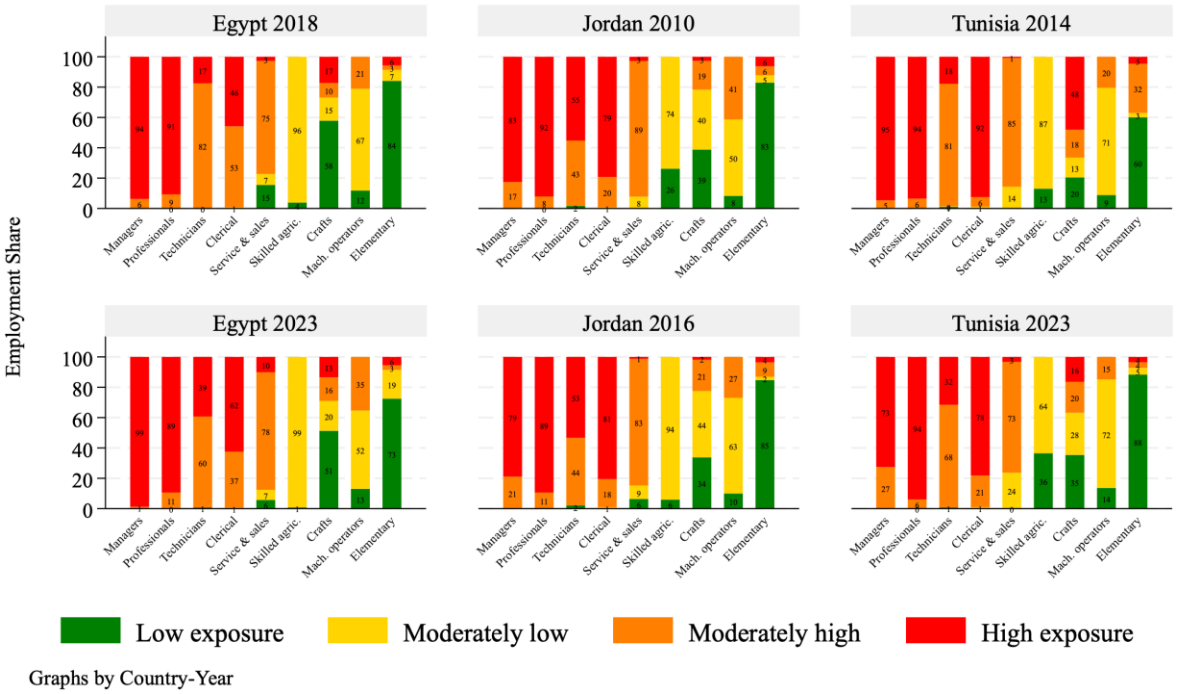


Figure A2b AI exposure by main occupation group: C-AIOE

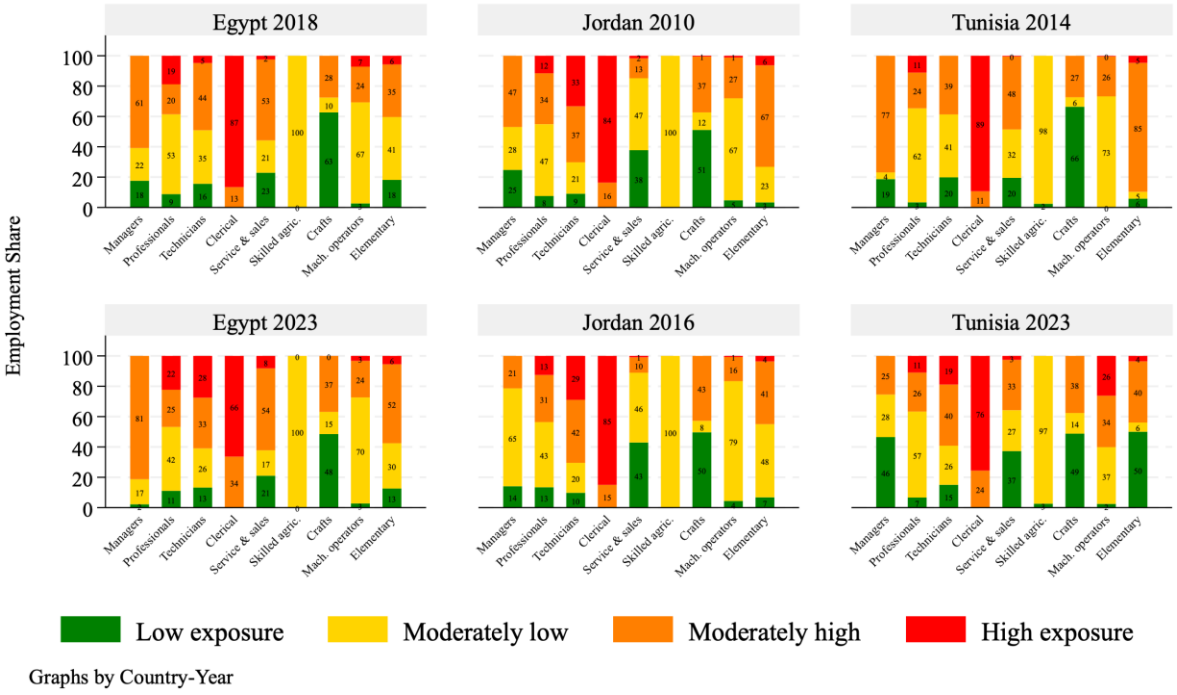


Figure A3a AI exposure by main industry: AIOE-all

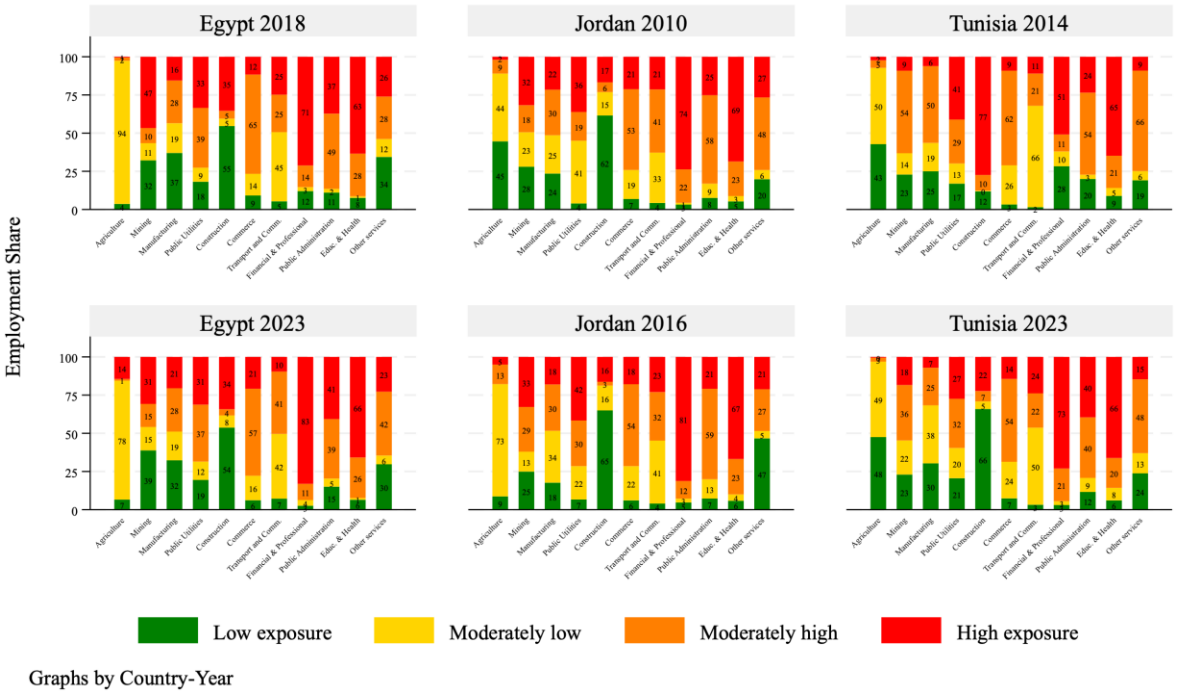


Figure A3b AI exposure by main industry: C-AIOE