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Abstract

Artificial intelligence is increasingly reshaping labor markets worldwide, yet its impact remains understudied in regions with weaker digital infrastructure and significant skill-supply constraints, such as the Middle East and North Africa (MENA). This study investigates how the diffusion of AI may transform employment in MENA, where structural vulnerabilities and heterogeneous digital infrastructure may mediate the transition from theoretical task exposure to actual productivity gains and heighten the risks of unequal technological penetration. Using detailed occupational microdata from Egyptian (2018, 2023), Jordanian (2016, 2025) and Tunisian (2014, 2022, 2023) nationally representative labor-market surveys, we classify workers by their AI exposure and complementarity using alternative task-based indices. Further, we evaluate the feasibility of AI-driven augmentation by cross-referencing these indices with realized worker access to computing and high-speed internet at work. The analysis documents substantial cross-country and within-country heterogeneity. While highly educated and formal workers in high-skill occupations are theoretically positioned to benefit from performing AI-complementary tasks, their ability to realize these gains is severely constrained by an infrastructural bottleneck. Across all three economies, between 33% and 39% of workers are trapped in functional obsolescence-holding high-complementarity jobs without workplace digital access. Notably, while highly educated women are concentrated in AI-complementary roles, they face a disproportionate workplace digital divide that blocks their capacity to leverage these skills. Comparative results show that Jordan exhibits the highest exposure, Tunisia the lowest, and Egypt a prominent concentration of high-exposure, low-complementarity employment. By quantifying the gap between theoretical complementarity and infrastructural readiness, the study offers targeted recommendations for firm-level digital connectivity, education systems, and social protection to facilitate an inclusive AI transformation.

Keywords: AI Exposure, Task Complementarity, Digital divide, MENA Labor Markets, Occupational transformation

JEL Classifications: J24, O33, O53

ملخص

يعيد الذكاء الاصطناعي تشكيل أسواق العمل عالميًا بوتيرة متسارعة، غير أن أثره لا يزال يفتقر إلى الدراسة الكافية في المناطق التي تعاني ضعف البنية التحتية الرقمية ومحدودية المهارات المتاحة، كمنطقة الشرق الأوسط وشمال أفريقيا. تستقصي هذه الدراسة تداعيات تبنّي الذكاء الاصطناعي على التوظيف في المنطقة؛ حيث قد تتدخل مواطن الضعف الهيكلية وتفاوت البنية التحتية الرقمية في مسار التحول من مجرد التعرض النظري للأتمتة إلى تحقيق مكاسب إنتاجية فعلية، مما يفاقم مخاطر التفاوت التقني. وبالاعتماد على البيانات المهنية التفصيلية المستمدة من المسوحات التتبعية لأسواق العمل في مصر (2018، 2023)، والأردن (2016، 2025)، وتونس (2014، 2022، 2023)، تصنّف الدراسة العاملين وفقًا لمستوى تعرضهم للذكاء الاصطناعي ودرجة تكاملهم معه عبر مؤشرات بديلة قائمة على المهام. كما تقيّم الدراسة جدوى تعزيز الإنتاجية بالذكاء الاصطناعي من خلال مقارنة هذه المؤشرات بمستوى الوصول الفعلي للعاملين إلى أجهزة الحاسوب والإنترنت فائق السرعة في مقارّ عملهم. تكشف النتائج عن تباينات حادة بين الدول الثلاث وداخل كل منها؛ فبينما يمتلك العاملون في القطاع الرسمي من ذوي التعليم العالي والمهارات المتقدمة مؤهلات نظرية تتيح لهم الاستفادة من تكامل الذكاء الاصطناعي مع مهامهم، فإن اختناقات البنية التحتية تقيّد قدرتهم على جني هذه المكاسب بشدة. ففي الاقتصادات الثلاثة، يظل ما بين 33% و39% من العاملين عالقين في وظائف ذات قابلية عالية للتكامل مع الذكاء الاصطناعي، لكنها مهددة بالتقادم لغياب الوصول الرقمي في بيئة العمل. ومن اللافت أن النساء ذوات التعليم العالي، رغم تركزهن في أدوار وظيفية تتكامل مع الذكاء الاصطناعي، يواجهن فجوة رقمية غير متكافئة في أماكن العمل تعيق استثمارهن لهذه المهارات. وتُظهر المقارنة بين الدول أن الأردن يسجل أعلى مستويات التعرض للذكاء الاصطناعي، وتونس أدناها، فيما تبرز في مصر فئة واسعة من العمالة عالية التعرض ومنخفضة التكامل. وختامًا، ومن خلال قياس الفجوة بين إمكانات التكامل النظري وجاهزية البنية التحتية، تطرح الدراسة توصيات موجّهة لتعزيز الربط الرقمي على مستوى المنشآت، وتطوير المنظومات التعليمية، وتوسيع مظلة الحماية الاجتماعية، بما يضمن تحولًا شاملًا وعادلًا نحو الذكاء الاصطناعي.

1. Introduction

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 highly 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 due to skill gaps or insufficient digital infrastructure, as in the low- and lower-middle income MENA countries, may be left behind or made redundant, causing disruption for thousands of workers.

Considering the rapid adoption of AI by firms, governments and non-governmental groups alike, the impacts are expected to be profound even in MENA, whose workers are already facing multiple challenges including low employment rates among groups such as youth and women, a high degree of informality and precariousness, and low or stagnating productivity and wages. The livelihood prospects are particularly dire today amid population ageing, displacement due to natural disasters and conflicts, financing and debt crises, and drying out natural-resource incomes and remittances due to countries oil shocks and decarbonization efforts.

Given the heterogeneity of MENA economies and sectors, the impacts will vary dramatically between as well as within countries, as some skilled workers will be able to maintain their jobs and even improve their productivity, those whose workplaces lack the digital tools required to interface with AI will be unable to realize this theoretical potential, leaving them vulnerable to functional obsolescence amid shrinking employment prospects.

This study aims to contribute to the emerging projections of the impacts of the AI transformation on different economic sectors and occupations, and by extension economies. Categorizing occupations by the degree of exposure to AI, and complementarity of workers' skills and tasks with AI, the study makes distributional-impact projections of the AI transformation while explicitly decomposing theoretical task capacity into physical workplace realization. By evaluating internet-connected computer access at work, we distinguish between workers who can achieve Realized Complementarity and those trapped in Functional Obsolescence. The study examines the connection between AI-exposed and AI-complementary jobs across three Arab economies - Egypt, Jordan and Tunisia-and assesses their prevalence, characteristics and demographic composition.

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 possess these cognitive skills, and do they possess the requisite workplace connectivity to utilize them? How does this infrastructural bottleneck interact with worker education, informal employment, and gender inequalities? The analysis facilitates the identification of critical skill gaps and structural bottlenecks, pinpointing how workplace connectivity deficits decouple human capital from economic outcomes. Ultimately, the study provides targeted recommendations for firm-level digital infrastructure, education systems, and social protection 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. Section III introduces our empirical approach to classifying jobs and workers in MENA labor market surveys. Section IV presents the baseline estimates of theoretical AI exposure and potential complementarity across sectors, occupations, and demographic profiles. Section V incorporates worker-level indicators of workplace connectivity to evaluate the gap between theoretical capacity and realized complementarity, uncovering the empirical drivers of functional obsolescence. Finally, Section VI discusses the implications of these findings for public policy.

2. 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; FII Institute 2026). 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 worldwide have worked on forecasting the transformative effect of AI on labor markets 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. 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.

2.1. Measuring exposure to AI

At the level of industries and narrow occupation groups, a growing body of research has proposed alternative 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 work tasks, or the exposure to generative AI or to large language models.

Different operationalizations of occupational exposure have been adopted. 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 surveys of developing countries. 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 gauging 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 large language models. Benítez-Rueda and Parrado (2024) describe 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.

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

These various studies reach 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 more prevalent among lower-skill and lower-income workers, while labor complementarity is higher among their higher-skill and higher-income peers.

2.2. 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 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.[3]

Manning and Aguirre (2026) construct an occupation-level adaptive capacity index covering 356 occupation groups representing 96% of the U.S. workforce. They find that occupations highly exposed to AI are typically held by workers with relatively strong adaptability to being displaced. Meanwhile, approximately 4% of workers are in occupations highly exposed to AI while having low adaptive capacity, particularly those in clerical and administrative jobs. It is these workers who require external assistance with re-skilling and re-employment. FII Institute (2026) conclude that, in the U.S., it is the fresh college graduates in entry-level professional jobs who are at the highest risk of being displaced.

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) find that exposure to large language models 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.

[3] 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).

The impact of AI depends on the tasks involved. Del Rio-Chanona et al. (2025) concluded that novice workers tend to benefit more from large language models 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.

2.3. 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.[4] 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 in 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).

[4] This includes 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, and Yemen 1999.

Digital divide hampers the possible positive effects of generative AI on jobs, particularly in poorer countries where both infrastructure and skills development lag (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 notably 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.

2.4. 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 the adoption of inclusive policies. Roughly 14.6% of jobs in the region could be augmented by AI, whereas only 2.2% are 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 the relatively low degree of complementarity.

Dawoud et al. (2026) sound an even more pessimistic note on reviewing 10,000 jobs in Egypt, estimating that 20.9% of the jobs face high automation risk, but less than a quarter of the at-risk workers have viable transitions while the other three quarters face a structural mobility barrier calling for comprehensive rather than just gradual reskilling.

Our study contributes to this limited regional 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, before the presentation of the main results.

3. 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 can help us 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 in 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.

3.1. 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 (2016 and 2025) and Tunisia (2014) harmonized and made available by 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.The sample includes both wage employees and self-employed workers, including own-account workers, provided that they have a valid ISCO occupational code. This is important in the MENA context, where own-account work represents a substantial component of employment. It should be noted that self-employment may involve task profiles that differ from those of employees in the same reported occupation.

A limitation of the analysis concerns the comparability of the Tunisian survey data over time. Although both the 2014 TLMPS and the 2022/2023 ENPE are nationally representative, differences in sampling and occupational measurement may affect the comparability of the occupational distributions across the two survey periods. Consequently, changes in estimated AI exposure for Tunisia over time should be interpreted with caution, and the analysis places greater emphasis on the cross-country comparisons using the most recent comparable survey rounds.

3.2. 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.[5] 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. The same 4-digit ISCO occupation may encompass substantially different task compositions in MENA than in the United States, particularly in economies characterized by high informality and different production technologies. Previous studies applying ONET-based occupational measures across countries have similarly acknowledged that such differences in task content can affect the comparability and interpretation of exposure estimates.

[5] For a summary of alternative published indices, refer to the Appendix table A1.

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 (2025). 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 index 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 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 across 1-digit occupation groups (table A4) in our survey samples.

The indices should be interpreted as measures of potential occupational exposure and complementarity rather than precise measures of workers' actual task-level exposure, and the estimated magnitudes may therefore over- or under-state exposure for particular occupations or worker groups in MENA. Moreover, it is worth noting 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.

3.3. Testable hypotheses

Using the merged micro level data we study the determinants of having AI-exposed (AI-complementary) 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.

3.4. Access to digital infrastructure and the feasibility of complementarity

While the indices of AI exposure and complementarity discussed above provide a robust theoretical framework, their practical realization in the MENA context is fundamentally constrained by the "digital divide" (Gymrek et al., 2024, Pizzinelli et al, 2024). The potential for AI to enhance productivity, rather than simply displace labor, is not a latent characteristic of an occupation alone; it is a function of the worker's access to the necessary physical and digital capital. We argue that for complementarity to materialize in practice, a worker must have consistent, high-quality access to both computing power and high-speed internet, whether at the workplace or within the household.

We therefore extend our estimation strategy to account for this infrastructural friction. Using indicators from the LMPS on workers' actual use of an internet connected computer at work, we examine whether those workers identified as holding "high-complementarity" (HC or HEHC) jobs actually possess the tools required to leverage AI. In the absence of such access, the theoretical productivity gains from AI remain out of reach, potentially trapping high-skilled workers in a state of "functional obsolescence." In such cases, the worker possesses the cognitive skills for AI integration but lacks the last-mile infrastructure to execute it, effectively decoupling their occupational profile from their economic output.

Our analysis acknowledges a sharp asymmetry in how the digital divide affects exposure versus complementarity. While complementarity requires direct, active access to technology, high AI exposure (and the resulting risk of substitution) does not. A worker in a low-connectivity region can be displaced by automation processes or AI-driven services managed in high-connectivity urban hubs or international markets (Brynjolfsson et al., 2023). Consequently, workers in the MENA region may face the "worst of both worlds": they remain highly vulnerable to displacement from external AI adoption while being structurally barred from the compensatory benefits of AI augmentation due to local infrastructure deficits. We thus incorporate individual computer access as a conditioning factor in our regressions to test whether the digital divide serves as a mediator that converts potential complementarity into realized substitution.[6]

3.5. Regression specification

To test the hypotheses of AI exposure among various groups of workers, we run probabilistic regressions of workers' propensity to hold highly AI-exposed, highly AI-complementary, or HELC jobs – all of them 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

[6] Data on computer use at work is only available for Tunisia in the TLMPS 2014. We attempted to find additional sources of information on computer usage at work by geographic region, occupation, sex, etc. Data from the International Telecommunication Union (ITU) only provides the country average for Tunisia however which is not useful for our analysis.

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 $\dot{AIjob_i}$ 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 can be used 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, including their interaction terms.[7]

Because occupational groups and economic sectors are not independent dimensions of employment, some degree of correlation between these sets of controls is expected, particularly given that the AI exposure measures are constructed from occupational characteristics. We therefore interpret the coefficients on individual characteristics as conditional associations, holding both occupation and sector constant, and recognize that collinearity between these controls may reduce the precision of some estimates. Nevertheless, the inclusion of both sets of controls is intended to distinguish worker characteristics from the occupational and sectoral composition of employment rather than to interpret the occupation or sector coefficients themselves as causal effects.

In light of these issues, coefficients on all interaction terms as well as correlated variables are evaluated for joint significance using F tests. To account for potential arbitrary heteroskedasticity and autocorrelation of model errors in the local market, robust standard errors clustered at the level of sectors are computed.

4. Main results

4.1. The distribution of occupational AI exposure

We begin our analysis by studying AI exposure within each of the three MENA countries over time, and then compare exposure across countries. We examine the cumulative employment share

[7] Our primary analytical goal is to provide a comprehensive structural mapping of how AI exposure, potential complementarity, and workplace digital infrastructure are jointly distributed across worker groups, rather than to estimate causal treatment effects of individual demographic characteristics. Given the presence of unobserved worker heterogeneity and occupational sorting, these regression estimates should be interpreted as conditional associations reflecting labor-market sorting rather than causal relationships. The models are designed to map joint distributions across countries while holding background characteristics constant. Although panel data are available for a subset of countries in our sample, we restrict this analysis to harmonized cross-sectional specifications to ensure cross-country comparability, leaving dynamic panel estimations for future research.

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 measure, which incorporates potential AI complementarity.

Figures 1–3 present the cumulative employment shares of varying levels of AI exposure – using the three AIOE indices under consideration across unique occupation titles at the ISCO-08 4-digit level. The levels of AI exposure on the x-axis are normalized to 0–1. 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. Thus, at any given percentile, a lower cumulative employment share indicates a greater concentration of employment in occupations with higher AI exposure.

For Egypt, Figure 1 shows that in both 2018 and 2023, about 50% of employment was in occupations below the 40th percentile of AIOE_all (value of 0.4 on the x-axis). Using AIOE_ILO, this share is just under 45% in both years. The relative stability of these curves indicates little change in the distribution of occupational exposure between 2018 and 2023. Examining the degree of complementarity, Figure 1 shows a relatively high degree of potential complementarity in both years, with somewhat greater complementarity in 2023 at lower exposure levels. Once complementarity is taken into account, slightly over 60% of employment in 2018 was below the 40^{th} percentile of the complementarity-adjusted C_AIOE, compared with 56% in 2023. This suggests that accounting for potential complementarity shifts a larger share of employment toward the lower end of the effective exposure distribution, consistent with a lower potential for substitution in occupations where AI is more likely to complement workers. This pattern also holds at higher levels of AI exposure. Using AIOE_all, about 82% of employment was below the 80^{th} percentile of AIOE_all in 2023 (85% in 2018). The corresponding share rises to about 88% when potential complementarity is taken into account. AIOE_ILO tends to show slightly lower exposure rates than AIOE_all across the employment distribution. For example, AIOE_ILO shows that less than 10% of workers are employed in occupations above the 80th percentile of the exposure distribution, compared with a somewhat higher share of 16–18% using AIOE_all in the two years. Overall, however, the AIOE_all and AIOE_ILO measures produce broadly similar patterns for Egypt.

The relative stability of Egypt's occupational exposure distribution between 2018 and 2023 suggests that there was limited change in the composition of employment across occupations with different levels of potential AI exposure during this period. However, because occupational exposure measures the potential for AI to affect tasks rather than realized technology adoption, changes in exposure should not be interpreted as evidence of changes in actual AI use or AI-driven employment displacement. The stability may instead reflect the time required for AI technologies to be adopted by firms and translated into changes in task composition and employment. The

temporal comparison therefore captures changes in the occupational distribution of potential AI exposure rather than the pace or extent of AI adoption in the workplace.

For Jordan, Figure 2 shows that the exposure of occupations to AI was substantially higher in 2025 than in 2016. In 2016, close to 60% of employment was below the lowest 40th percentile of AIOE_all (0.4 on the x-axis). By 2025 however, this had declined to about 40% of employment. The 2025 curve lies approximately 10–15 percentage points below the 2016 curve across much of the distribution, indicating a substantial shift toward occupations with higher potential AI exposure. About 29% of workers were employed in occupations above the 80th percentile of AIOE_all in 2025, compared with 22% in 2016. Using AIOE_ILO confirms the higher potential exposure in 2025 than in 2016, also the difference is smaller than by AIOE_all. Potential AI complementarity is similar across the two years. Once complementarity is taken into account, the exposure distribution shifts toward lower effective exposure: about 55% of employment was below the 40th percentile of C_AIOE in 2025, compared with about 42% using AIOE_all. About 25% of workers, however, remained in occupations above the 80th percentile of C_AIOE in 2025, compared with 16% in 2016.

For Tunisia, Figure 3 shows an apparent decline in occupational AI exposure between 2014 and 2022/2023, while the 2022 and 2023 distributions are nearly identical. In 2014, 38% of employment was in occupations at or below the 40th percentile of AIOE_all, compared with 50% in 2022/2023, indicating a shift toward occupations with lower potential AI exposure. Similarly, 15% of employment was in the high-exposure category (above the 80th percentile of AIOE_all) in 2022/2023, compared with 22% in 2014. At face value, this points to a substantial change in the occupational composition of employment in Tunisia over the decade. However, this comparison should be interpreted cautiously because of differences in sampling and occupational measurement between the 2022/2023 ENPE and the 2014 TLMPS, despite both surveys being nationally representative.

The comparability issue means that the apparent decline in Tunisia's AI exposure between 2014 and 2022/2023 should not be interpreted as evidence of a definitive change in the underlying exposure of Tunisian workers. A more robust conclusion is that the most recent ENPE rounds show relatively low occupational AI exposure in Tunisia, particularly compared with Egypt and Jordan, while the magnitude and direction of the change since 2014 remain uncertain.

The AIOE_ILO index similarly suggests lower exposure than AIOE_all in 2014, with 45% of employment below the 40th percentile of AIOE_ILO, and about 50% in 2022/2023, broadly similar to AIOE_all in the latter period. The complementarity theta (Figure 3, panel c) suggests differences in the degree of potential AI complementarity across the two periods , with the 2014 occupational mix showing less 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, compared with only 40% in 2014. Again, however, these temporal differences should be interpreted cautiously given the cross-survey comparability issues noted above.

Examining how the three countries compare according to the most recent years of data, Figure 4 shows the distribution of employment across AI-exposure levels according to the alternative AIOE indices. The cumulative exposure curves show that Jordan lies consistently below Egypt, which in turn lies consistently below Tunisia, indicating that Jordan has a greater concentration of employment in occupations with higher potential AI exposure, across most of the distribution, according to both AIOE_all and AIOE_ILO. Jordan has the largest share of employment at the upper end of the exposure distribution, with almost 30% of workers in 2025 in the highest quintile of exposure (above the 80th percentile).

Once potential complementarily is taken into consideration, these shares fall for all countries, but Jordan's curve remains below those of Egypt and Tunisia at higher exposure levels, indicating a larger concentration of Jordanian employment in occupations with relatively high effective AI exposure even after accounting for potential complementarity. It is worth noting that Egypt's C_AIOE curve is higher than those for the other two countries at low exposure levels, indicating a higher concentration of Egyptian workers at lower levels of complementarity adjusted exposure relative to Jordan and Tunisia. For completeness, Figure A1 in the Appendix shows the same figures for all survey rounds for all countries.

4.2. AI exposure across countries, occupations and industries

We next examine how the distribution of potential AI exposure varies across countries and over time, and how these differences are associated with occupational structure, industry, and worker characteristics. We categorize the AIOE scores into four exposure levels (high, moderately high, moderately low and low exposure) by dividing each AIOE 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 education, gender, age and formality of employment.

The country ordering appears to be driven by differences in occupational structure. Jordan has a relatively high concentration of workers in professional, managerial, and service occupations, which are among those with higher AI exposure and complementarity scores, while Tunisia has a relatively larger share of workers in elementary occupations, which are among the least exposed. Egypt occupies an intermediate position, reflecting its more mixed occupational structure, with a sizable share of employment in agriculture and craft occupations alongside substantial employment in highly exposed white-collar occupations. Thus, the cross-country differences in

aggregate exposure are not simply a reflection of differences in worker characteristics, but also of the types of jobs that dominate each labor market.

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 high and moderately high exposure categories (almost 70% in 2025), with a sharp increase over time, followed by Egypt and then Tunisia[8]. Tunisia has the largest share of workers in the least exposed category as of 2023. It also has the lowest share of highly exposed workers in 2023. Egypt has witnessed a slight increase in highly exposed workers between 2018 and 2023. Figure 5b presents results based on the AIOE-ILO and shows broadly analogous patterns, with only slight differences in shares of low versus moderately low exposure occupations and high and moderately high exposure. Overall similar conclusions apply. Figure 5c presents the results after accounting for AI complementarity (C-AIOE) and shows a substantial reduction in potential 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, reflecting the relatively lower degree of complementarity compared to Jordan and Tunisia.

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), versus those that combine high exposure with low complementarity (LC). We classify occupations as 'HEHC' if both AIOE-all and θ are in the upper two quartiles of their respective pooled distributions, 'HELC' if AIOE-all is in the upper two quartiles but θ is in the lower two quartiles, while 'LE' refers to jobs with AIOE-all in the lower two quartiles. Results are in Figure 6. Results suggest that while Jordan had the highest share of HE jobs overall, most of these were also HC, indicating greater potential for AI complementarity rather than necessarily implying a higher risk of job displacement. In Egypt, a sizable share of employment (25% in 2023) is HELC, suggesting a greater potential for task substitution among highly exposed occupations with relatively low complementarity. 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. This helps explain why Jordan can have the highest overall exposure while not necessarily having the highest share of employment in high-exposure, low-complementarity occupations: its relatively large concentration in highly exposed occupations is accompanied by comparatively high AI complementarity.

The comparison of Egypt, Jordan and Tunisia suggests that differences in AI exposure across middle-income Arab economies are driven primarily by the structure of employment, particularly the occupational composition of jobs, rather than by worker characteristics alone. Countries with larger concentrations of professional, managerial, clerical and service occupations tend to have greater potential exposure, while those with larger shares of elementary, agricultural and craft

[8] 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.

occupations have lower exposure. Nevertheless, potential exposure does not necessarily translate into equivalent potential for task substitution, since the degree of AI complementarity varies substantially across occupations and countries. The cross-country evidence therefore points to the interaction between occupational structure, the skills embedded in jobs, and the capacity to complement AI as the key factors shaping the distributional implications of AI exposure.

To understand these exposure levels better, it is useful to begin by examining the occupational distribution of each country and how it has changed over time. 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, which ultimately drives the overall exposure levels.[9]

Occupations with relatively higher employment shares, such as service and sales, professionals and clerical occupations are also those with relatively higher potential exposure. Crafts, skilled agriculture, machine operators and elementary occupations are least exposed overall. Jordan's workers are concentrated in professional occupations, and sales and services, together accounting for over 50% of employment, which are both highly exposed to AI, contributing to Jordan's higher aggregate exposure. While Egypt has a sizable share of workers in agricultural and craft and related occupations, white-collar occupations (managers, professionals, technicians and clerical occupations) that are highly exposed, together account for over a third of all occupations. Tunisia has relatively more workers in elementary occupations, which accounts for its lower overall AI exposure.

Furthermore, it appears that the decline in Tunisia's overall exposure shares between 2014 and 2023 may have been partially driven by the lower share of crafts workers (from 22% of workers to 14% in 2023) and within that occupation, a sharp reduction in those with the highest exposure levels. The decline in exposure among elementary occupations also appears to contribute to the overall reduction. However, as noted above, changes over time in Tunisia should be interpreted cautiously because of differences in survey and occupational measurement. Figure 7b shows that, while accounting for complementarity reduces the potential exposure substantially in most occupations, one exception is clerical occupations, for which exposure actually rises. This suggests that clerical occupations combine relatively high potential AI exposure with comparatively low complementarity, making them particularly relevant for potential task substitution. In most countries, these occupations make up relatively small shares of employment overall but have high concentrations of female workers (AlAzzawi and Hlasny 2025).

Figure 8 presents results by major industrial group, and the industry groups' relative size within overall employment.10 Commerce, public administration and education and health services

[9] Figure A2 in the appendix depicts the within occupation share of each exposure category.

[10] These industry groups 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.

industries, all relatively large employers, are more highly exposed. Within these industries, 40–60% of workers are in AI-exposed occupations. When AI complementarity is accounted for, exposure falls but within the financial and professional service industries 30-40% of employment remains exposed to AI.

4.3. Exposure and complementarity by worker characteristics

We next examine how exposure and complementarity vary across worker characteristics. Figure 9 shows the distribution of HEHC, HELC and LE employment by education level. Education exhibits the clearest gradient across the worker characteristics considered. Workers with higher education (defined as above secondary/intermediate, university or postgraduate education) are substantially more concentrated in highly exposed occupations than those with lower education, and this pattern is evident across all three countries. In the most recent rounds, the combined share of HEHC and HELC employment among highly educated workers reaches 88% in Egypt, 91% in Jordan and 92% in Tunisia. Importantly, however, the composition of this exposure differs across countries: in Jordan, 41% of highly educated workers are in HELC occupations, compared with 32% in Egypt and 31% in Tunisia, while the share in HEHC occupations is also substantial in all three countries. Thus, higher education is strongly associated with potential AI exposure, but a sizeable portion of this exposure is also associated with high complementarity, particularly among highly educated workers. This finding is consistent with the concentration of educated workers in professional and other cognitive occupations that are more exposed to AI.

Figure 10 presents the corresponding distribution by sex. Women are more likely than men to be in highly exposed occupations, particularly in Egypt and Jordan. In 2023, 73% of employed women in Egypt are in HEHC or HELC occupations, compared with 55% of men; in Jordan in 2025, the corresponding shares are 86% and 66%. The gender difference is also present in Tunisia, although smaller, with 60% of women and 48% of men in highly exposed occupations in 2023. The HELC category is consistently larger among women than men, particularly in Jordan, where 33% of female employment is in HELC occupations compared with 27% of male employment. At the same time, women also have substantial shares of HEHC employment, indicating that higher female exposure does not necessarily imply greater potential for task substitution. The cross-country differences in the gender pattern are likely to reflect differences in the occupational distribution of women, as well as differences in female labor-force participation and selection into employment. In particular, the higher likelihood of women in Jordan being in highly exposed, non-complementary (HELC) occupations, compared with the lower likelihood observed in Tunisia, may reflect differences in the types of occupations in which women who participate in employment are concentrated. Gender differences in AI exposure may thus be shaped not only by individual characteristics, but also by the occupational structures and patterns of female employment specific to each labor market.

Figure 11 shows that formal workers are substantially more concentrated in highly exposed occupations than informal workers across all three countries. [11] In the latest rounds, the combined HEHC and HELC shares among formal workers are 79% in Egypt, 81% in Jordan and 60% in Tunisia, compared with 48%, 41% and 35%, respectively, among informal workers. The difference is particularly pronounced for HEHC employment, which accounts for 49% of formal employment in Egypt and 48% in Jordan, compared with 26% and 30% among informal workers. Formal workers are therefore considerably more exposed to potential AI-related task transformation, but much of this exposure is also associated with high complementarity. These differences are consistent with the concentration of formal employment in more skilled and structured occupations, whereas informal employment is more heavily concentrated in lower-exposure occupations.

Finally, Figure 12 examines differences by age group. The age gradient is less pronounced and less systematic than that observed for education, sex and formality. In Egypt, the share of highly exposed employment increases with age, from 52% among workers aged 15–29 to 62% among those aged 45–64 in 2023. A similar but weaker pattern is observed in Tunisia, where the corresponding shares are 46%, 53% and 51%. In Jordan, by contrast, workers aged 30–44 have the highest combined exposure in 2025, at 73%, compared with 65% among those aged 15–29 and 66% among those aged 45–64. The composition of exposure also varies by age, with HEHC generally accounting for a substantial share of employment across age groups. Overall, the results provide less evidence of a consistent age gradient in potential AI exposure than they do for education, gender or formality.

Taken together, the worker-level patterns suggest that potential AI exposure is concentrated among workers whose employment is more strongly associated with education, formal employment and, in several countries, female employment. Importantly, however, the HEHC/HELC distinction shows that high exposure does not uniformly imply high potential for task substitution. For many groups with high exposure, particularly highly educated and formal workers, a substantial share of employment is also in occupations with high complementarity. This distinction is important for interpreting the distributional implications of AI exposure across workers and labour markets. Jordan has the highest potential AI exposure, but much of this exposure is concentrated in occupations with high potential complementarity; Egypt has a larger concentration of high-exposure, low-complementarity employment; and Tunisia has relatively little high-exposure employment overall.

[11] These results include self-employed and own-account workers where an occupational code is available. The formal/informal distinction is therefore separate from the inclusion of workers in the occupational exposure analysis.

4.4. Socioeconomic correlates of employment in AI-exposed and AI-complementary occupations

Table 1 reports probit regression results for workers' employment in highly AI-exposed, highly AI-complementary, and HELC occupations, conditional on the included individual, employment-status, industry, regional, and survey-round characteristics.[12] The specifications with interactions additionally allow the association of sex with age, education, formality, and employment status to vary across groups; the corresponding specifications without interactions are reported in Table A2. Because the interaction specification is our preferred specification for assessing gender differences, the coefficient on Female should be interpreted as the estimated female–male difference in the underlying index of employment in the relevant AI category, for the reference categories of age, education, formality, and employment status; the interaction coefficients indicate how this difference varies across the corresponding groups. As with any probit specification, these coefficients describe conditional associations rather than causal effects, and do not correspond directly to percentage-point differences in probability. These results are consistent with the descriptive patterns reported in Figures 5–12 regarding the role of worker sex, age, education, broad occupational group, and main economic activity of the job.

The results reveal substantial heterogeneity in the relationship between sex and potential AI exposure and complementarity across countries and worker characteristics. In Egypt, the coefficient on Female is positive but statistically insignificant for high exposure, while it is positive and statistically significant at the 1 percent level for high AI complementarity. The female × medium- and female × high-education interactions are positive and statistically significant for high exposure and are also positive and significant for high complementarity. These results indicate that Egyptian women's relatively higher likelihood of employment in AI-exposed and AI-complementary occupations is concentrated among those with at least a medium level of education, relative to the low-education reference group. For HELC employment, the female × medium-education interaction is positive and significant, whereas the female × high-education interaction is negative and significant, indicating that greater AI exposure among educated Egyptian women does not necessarily translate into a greater likelihood of employment in high-exposure, low-complementarity occupations.

[12] All regressions cluster standard errors at the primary sampling unit (PSU) level to account for the multi-stage, stratified sampling design of the surveys underlying our sample. For the Egypt and Jordan rounds, and for Tunisia's 2014 TLMPS round, the surveys' original PSU identifiers are used directly. The 2022 and 2023 waves of Tunisia's ENPE do not release a PSU identifier in the public-use files; the finest geographic identifiers available for these rounds are region (six categories) and urban/rural locality type. For these two rounds only, we therefore construct a substitute clustering unit from the interaction of region and locality type, using the finest geographic information available in the public-use data to approximate the within-cluster correlation that PSU-level clustering is intended to capture in the other survey rounds. All cluster identifiers are additionally interacted with country and survey round, so that clusters are never pooled across distinct sampling frames. As a robustness check, we re-estimate the Tunisia models with standard errors clustered at the region level alone. Because this specification yields a small number of effective clusters, conventional cluster-robust inference may be unreliable. We therefore use a wild cluster bootstrap following Cameron, Gelbach, and Miller (2008). These results are not reported here for space considerations but are available from the authors upon request.

Jordan exhibits a similar positive relationship between women's education and potential AI exposure, but with a different pattern across outcomes. The coefficient on Female is positive but statistically insignificant for high AI exposure, and negative but statistically insignificant for high AI complementarity, while the corresponding coefficient for HELC employment is positive but also statistically insignificant. However, these baseline gender differences mask important heterogeneity by education and, to a lesser extent, age. The female × high-education interaction is positive and statistically significant for high exposure and high complementarity, indicating that highly educated women are considerably more likely, relative to comparable men, to be employed in AI-exposed and AI-complementary occupations. For high exposure, the female × medium-education interaction is also positive and significant. For HELC employment, by contrast, the female × high-education interaction is negative and significant- the opposite sign from the other two outcomes- suggesting that the greater exposure of highly educated Jordanian women reflects a stronger association with complementary rather than low-complementarity exposed occupations.

Tunisia presents a markedly different gender pattern. Women are significantly less likely than men to work in high AI-exposure and high AI-complementarity occupations in the reference age and education groups; the corresponding coefficient for HELC employment is also negative but falls short of conventional significance levels. The female × age interactions further reinforce the negative association with exposure among older women: the female × 45–64 interaction is negative and statistically significant for high AI exposure. At the same time, the positive female × medium- and female × high-education interactions for high exposure substantially attenuate the negative baseline gender difference among more educated women. The female × high-education interaction is also positive and significant for high AI complementarity, although the overall female association remains negative and statistically significant. For HELC employment, the female × medium-education interaction is positive and significant, while the female × high-education interaction is not statistically significant.

Taken together, these differences suggest that there is no uniform gender effect across the three labour markets: women's relative likelihood of employment in AI-exposed and AI-complementary occupations depends importantly on their educational attainment and, in some cases, their age and employment status. In particular, the positive and significant interactions between Female and education in the exposure models indicate that women's relative likelihood of employment in potentially AI-exposed occupations rises substantially at higher levels of education. At the same time, the negative female × high-education interaction for HELC employment in Egypt and Jordan suggests that highly educated women who are employed in AI-exposed occupations are relatively more likely to be in occupations that also offer greater potential complementarity, rather than in high-exposure, low-complementarity occupations. These results are consistent with the descriptive evidence in Figures 9–10 and suggest that gender differences in potential AI exposure cannot be adequately characterized by a single female coefficient.

Education itself emerges as one of the strongest correlates of potential AI exposure. In the models without interactions reported in Table A2, medium education is positively and significantly associated with high AI exposure in all three countries, and the association is considerably larger in magnitude for high education, which is likewise significant in all three countries. For high AI complementarity, the relationship with education is weaker and more heterogeneous: high education is positively associated with complementarity in Egypt and Tunisia, but not significantly in Jordan, while medium education is significant only in Jordan and Tunisia. For HELC employment, both medium and high education are positively associated with the outcome in all three countries. The interaction models (Table 1) show that these education gradients also differ by sex, with positive female × education interactions for high exposure in all three countries. Thus, education is strongly associated with potential AI exposure even after conditioning on other socioeconomic characteristics, although its relationship with complementarity and low-complementarity exposure is more heterogeneous.

The education results are broadly consistent with international evidence showing that AI exposure is concentrated in occupations requiring higher levels of cognitive, analytical, and other non-routine skills. They also reinforce the descriptive findings in Figure 9, where highly educated workers account for substantially larger shares of employment in highly exposed occupations. These results indicate that education remains an important correlate of potential AI exposure in these MENA labor markets even after conditioning on employment status, sector, region, and survey round, while its relationship with potential complementarity varies more across countries.

The employment-status results also reveal important gender heterogeneity. Relative to the reference employment-status category (unpaid family workers), employers and self-employed workers are more likely to be in high-exposure and high-complementarity occupations in Egypt, while the associations are generally weaker and not statistically significant in Jordan and Tunisia, with the exception of self-employment, which is positively associated with high exposure in Tunisia, and employer status, which is positively associated with high complementarity in Tunisia. For HELC employment, waged employees, employers and self-employed workers are significantly less likely to be in such occupations in Egypt, as are self-employed workers in Jordan and employers in Tunisia. The interactions with Female indicate that these relationships differ by sex: for example, female self-employed workers are significantly more likely than their male counterparts to be in high-exposure occupations in Egypt and Tunisia, while the female × employer interaction is positive and significant for high exposure and complementarity in Tunisia, in contrast to Egypt and Jordan, where this interaction is negative and significant for high complementarity. These results suggest that the relationship between employment status and potential AI exposure is not gender neutral.

Formality also exhibits a consistent negative association with high AI exposure in the no-interaction specification: informal workers are significantly less likely to be employed in highly

exposed occupations in all three countries. The same pattern generally holds for high complementarity, although the association is not statistically significant in Jordan. For HELC employment, informal workers are significantly less likely to be in HELC occupations in Egypt and Jordan but significantly more likely to be in such occupations in Tunisia. The interaction specification further shows that the gender dimension of informality differs across countries. The female × informal interaction is positive and significant for high exposure in Jordan and Tunisia, for high complementarity in Tunisia, and for HELC employment in Jordan and Tunisia. Thus, while informal employment is generally associated with lower potential exposure, the gender composition of informal employment produces important country-specific differences in the distribution of AI-exposed and low-complementarity occupations.

Across all three countries, rural and urban workers have relatively similar propensities to be employed in highly exposed occupations, although the relationship differs for high complementarity and HELC employment. Urban residence is positively associated with high complementarity in Egypt and with HELC employment in Jordan and Tunisia, while it is negatively associated with HELC employment in Egypt. These results suggest that location is less consistently related to potential AI exposure than education but may matter for the type of exposure, particularly whether exposure is accompanied by potential complementarity.

Regarding economic-activity sectors, the sector coefficients reported in Table A2 indicate substantial heterogeneity. Mining is positively and significantly associated with all three outcomes across all three countries. Manufacturing is also positively associated with high exposure and HELC employment in all three countries but is negatively associated with high complementarity in Tunisia and not significantly associated with high complementarity in Jordan, underscoring that manufacturing employment in these labor markets is more closely tied to automation risk than to AI-complementary augmentation. Workers in commerce, and transportation and communication also tend to have higher propensities to be employed in exposed occupations, although the strength of these associations varies across countries. These patterns are broadly consistent with the descriptive evidence in Figure 8, which shows that industries with relatively large employment shares, including commerce, public administration, and education and health services, contain substantial shares of workers in potentially AI-exposed occupations.

Overall, the regression results reinforce the importance of sectoral structure and worker characteristics in shaping the distribution of potential AI exposure across the three labor markets. Education is a particularly strong correlate of exposure, while gender differences are highly conditional on education and, to a lesser extent, age and employment status. At the same time, exposure should not be interpreted as equivalent to displacement: the distinction between high-exposure/high-complementarity and high-exposure/low-complementarity occupations is important for assessing the potential direction of AI-related labour-market adjustment. The results therefore suggest that the distributional implications of AI in MENA are likely to depend not only

on who is employed in potentially exposed occupations, but also on whether those occupations provide greater scope for complementarity with AI.

5. The workplace digital divide: conditioning AI exposure and complementarity on workplace connectivity

The preceding results identify substantial concentrations of workers in occupations with high potential for AI complementarity, particularly among more highly educated and female workers, but these occupational characteristics do not by themselves indicate whether workers have the digital infrastructure needed to realize such potential. We assess this gap by examining workplace connectivity, defined as using an internet-connected computer at work among workers employed in HC and HEHC occupations (Figure A4 and A5 in the appendix). Across all three economies, aggregate workplace connectivity among HC workers is remarkably low, standing at only 11.9% in Egypt, 22.4% in Jordan, and 16.3% in Tunisia, with only slightly higher shares for HEHC workers. Flipped on its head, this indicates that the vast majority of workers in high-complementarity jobs, ranging from 77.6% in Jordan to 88.1% in Egypt, operate in a state of latent functional obsolescence, possessing the theoretical capacity for AI augmentation but lacking the physical infrastructure to execute it. Descriptively, this digital access gap varies sharply across demographic groups (Figure 13). Educational gradients are particularly stark: workplace connectivity among HC workers is nearly non-existent for those with low education (1% in Egypt, 8% in Jordan, 5% in Tunisia) but rises significantly among highly educated workers, reaching 26% in Egypt, 42% in Jordan, and 50% in Tunisia. Notably, even among Egypt's highly educated workers who are classified as HC, only about 1 in 4 use a computer connected to the internet at work. Gender disparities also emerge, as female HC workers exhibit higher unconditional access rates than their male counterparts across all three countries, most notably in Jordan (47% versus 17%) and Tunisia (27% versus 14%). Spatial divides further compound these gaps, with urban–rural disparities proving pronounced in Egypt (17% versus 8%) and Tunisia (20% versus 7%), though virtually non-existent in Jordan (22% in both areas).

Because these unconditional bivariate patterns cannot determine whether worker characteristics directly drive digital execution or merely reflect underlying sectoral and occupational sorting, an econometric strategy is necessary to formally decompose theoretical task capacity into physical workplace realization. Standard occupational indices evaluate AI complementarity based purely on task structures, implicitly assuming that workers can seamlessly interface with technology, an assumption that risks confusing cognitive potential with practical execution in developing labor markets where infrastructure is unevenly distributed. We address this infrastructural friction by combining the AI exposure and complementarity indices with worker-level survey indicators of internet-connected computer access at work. Specifically, we construct three distinct outcomes: (i) Realized High Complementarity, which identifies workers in high-complementarity occupations who possess the workplace digital connectivity required to leverage AI productivity

gains; (ii) Functional Obsolescence, which captures workers in HC jobs who lack workplace digital tools, thereby isolating their cognitive skills from economic output; and (iii) Realized HEHC, which narrows the focus to workers who simultaneously face high exposure, high potential complementarity, and have the actual digital tools to realize it. By re-estimating our probit models separately across Egypt, Jordan, and Tunisia with these outcomes, we directly evaluate how infrastructural bottlenecks convert theoretical complementarity into unrealized potential.

Table 2 presents the results. Accounting for workplace digital infrastructure reveals that theoretical AI complementarity is heavily constrained by an infrastructural bottleneck across the MENA region. While high-complementarity occupations are common in abstract task-structure models, the sample means for *Realized High Complementarity* (5.4% in Egypt, 9.0% in Jordan, 7.4% in Tunisia) and *Realized HEHC* (5.2% in Egypt, 8.7% in Jordan, 7.3% in Tunisia) represent only a small fraction of workforce employment. In contrast, *Functional Obsolescence*, holding a high-complementarity job without workplace internet and computer access, dominates the distribution, encompassing 32.7% of workers in Egypt, 39.3% in Jordan, and 35.4% in Tunisia. Educational attainment serves as the primary gateway out of this bottleneck: across all three countries, higher education strongly increases the probability of realizing AI complementarity, while simultaneously decreasing baseline functional obsolescence. Similarly, informal employment severely reduces the likelihood of realized complementarity, underscoring how structural informality compounds digital exclusion.

These results uncover a sharp gendered asymmetry in how the digital divide converts potential complementarity into functional obsolescence. Although educated women are disproportionately concentrated in latent high-exposure and high-complementarity occupational profiles, their ability to leverage these cognitive skills is disproportionately blocked at the workplace level. Across all three countries, the interaction terms for Female x High Education in the functional obsolescence specifications are positive, large, and highly statistically significant. This indicates that, holding occupational profile, sector, and background characteristics constant, highly educated women face a far higher risk than their male peers of being trapped in high-complementarity roles without the required digital tools. Consequently, while higher education enables male workers to translate latent task exposure into realized productivity, workplace connectivity deficits act as a gendered mediator, decoupling educated women's human capital from realized returns and leaving them vulnerable to external AI displacement without the compensatory gains of AI augmentation.

6. 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 of AI 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 of robustly identifying 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. Our findings represent estimates of potential exposure based on internationally mapped occupational task profiles; differences between U.S. and MENA task content, especially in informal employment, mean they should not be interpreted as direct measures of the AI exposure of individual workers.

We found substantial cross-country and within-country heterogeneity in the pattern of AI exposure, driven primarily by differences in occupational and sectoral structures rather than worker characteristics alone. Jordan exhibits the highest overall potential AI exposure, but much of this is accompanied by high potential complementarity. Egyptian jobs show a comparatively large concentration of high-exposure, low-complementarity (HELC) employment, 25 percent of workers as of 2023, implying a higher potential for task substitution than in Jordan. Tunisia exhibits the lowest overall exposure, though its temporal pattern warrants caution due to survey instrument changes between 2014 and 2022/2023.

At the worker level, education is the single most robust correlate of potential AI exposure, with more educated workers systematically more likely to be employed in highly exposed occupations across all three countries; the relationship between education and AI complementarity is more heterogeneous, being positive and significant in Egypt and Tunisia but not in Jordan. For HELC employment specifically, both medium and high education are positively associated with the outcome in all three countries, indicating that more educated workers also face somewhat greater potential exposure to low-complementarity tasks, though, as noted above, this risk is generally smaller for highly educated women than for highly educated men in Egypt and Jordan.

Across the three countries, gender differences in AI-related labor-market risks and opportunities are present but far from uniform. Descriptively, women in Egypt and Jordan are more likely than men to be employed in highly AI-exposed occupations overall, including complementary ones. The regression results show that this pattern is strongly conditioned by education: highly educated women are considerably more likely than comparable men to be employed in AI-exposed and AI-complementary occupations in all three countries, and in Egypt and Jordan are, if anything, less likely than comparable men to be concentrated specifically in HELC work. Tunisia is the clearest exception to this pattern: women there are significantly less likely than men to be employed in highly exposed or complementary occupations among less-educated workers, although this gap narrows substantially with education. The evidence therefore does not support a single, region-wide narrative of AI-driven gender disadvantage; the direction and magnitude of gender differences depend importantly on educational attainment and, to a lesser extent, on country context.

Extending our empirical strategy to incorporate workplace digital infrastructure reveals that theoretical AI complementarity is severely constrained by an infrastructural bottleneck. While high-complementarity occupations appear widespread in task-based models, realized high complementarity, which requires an internet-connected computer at work, encompasses less than 10 percent of workers in all three countries. Instead, functional obsolescence dominates the distribution, trapping 32.7 percent of Egyptian, 39.3 percent of Jordanian, and 35.4 percent of Tunisian workers who possess the cognitive capacity for AI augmentation but lack the digital tools to execute it.

Education emerges as the primary gateway out of this bottleneck, strongly increasing the likelihood of realized complementarity while reducing baseline functional obsolescence. However, accounting for workplace connectivity uncovers a striking gendered asymmetry: although highly educated women are disproportionately concentrated in latent high-exposure and high-complementarity occupations, they face a severe workplace digital deficit. Holding sector and background constant, highly educated women are significantly more likely than their male peers to experience functional obsolescence across all three countries. Workplace connectivity deficits thus act as a gendered mediator, decoupling educated women's human capital from realized returns and leaving them exposed to external AI displacement without the compensatory productivity gains of AI augmentation. Furthermore, informal employment severely suppresses realized complementarity across all specifications, underscoring how structural informality compounds digital exclusion.

The study's results point to several direct, grounded policy directions. First, policymakers must look beyond worker-side skill supply and directly address the workplace digital divide. Because functional obsolescence affects over a third of the workforce, governments should establish targeted digital capital subsidies and infrastructure incentives for micro, small, and medium enterprises, ensuring that firms supply the requisite hardware and high-speed internet to convert latent human capital into realized AI complementarity.

Second, policy interventions must be tailored to national structural profiles. In Jordan, where latent complementarity is high, but workplace connectivity remains a bottleneck, policy should prioritize firm-level digital infrastructure grants to translate theoretical capacity into realized productivity. In Egypt, where a 25 percent HELC share overlaps with widespread functional obsolescence, policies must combine firm-level digital connectivity with targeted reskilling in AI-complementary skills for medium-educated workers in clerical and manufacturing roles. In Tunisia, where exposure is lower, expanding foundational digital infrastructure and workplace computer access is necessary to prevent technological isolation and enable firms to capture emerging AI opportunities.

Third, governments must address the gendered last-mile bottleneck by ensuring equitable access to digital tools within female-dominated workplaces, particularly in public administration, education, and services. Finally, integrating informal workers into formal digital ecosystems and modernizing labor protections will be essential to prevent structural informality from permanently entrenching AI-driven inequality across the MENA region.

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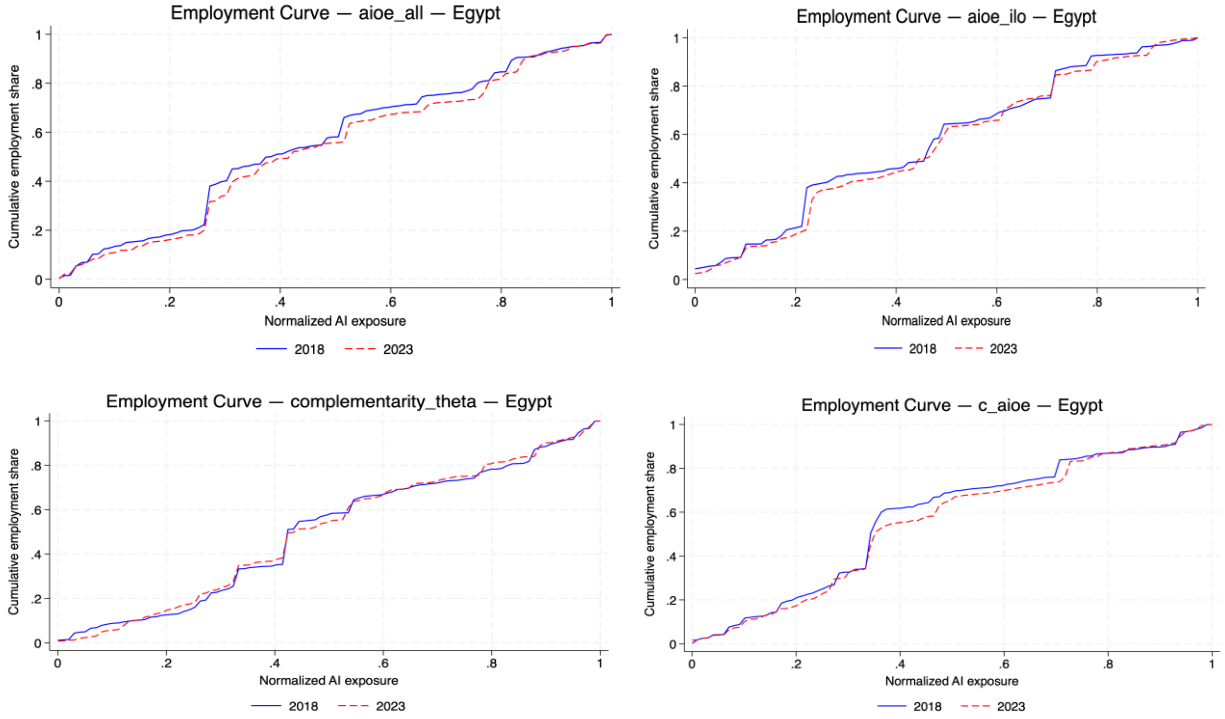
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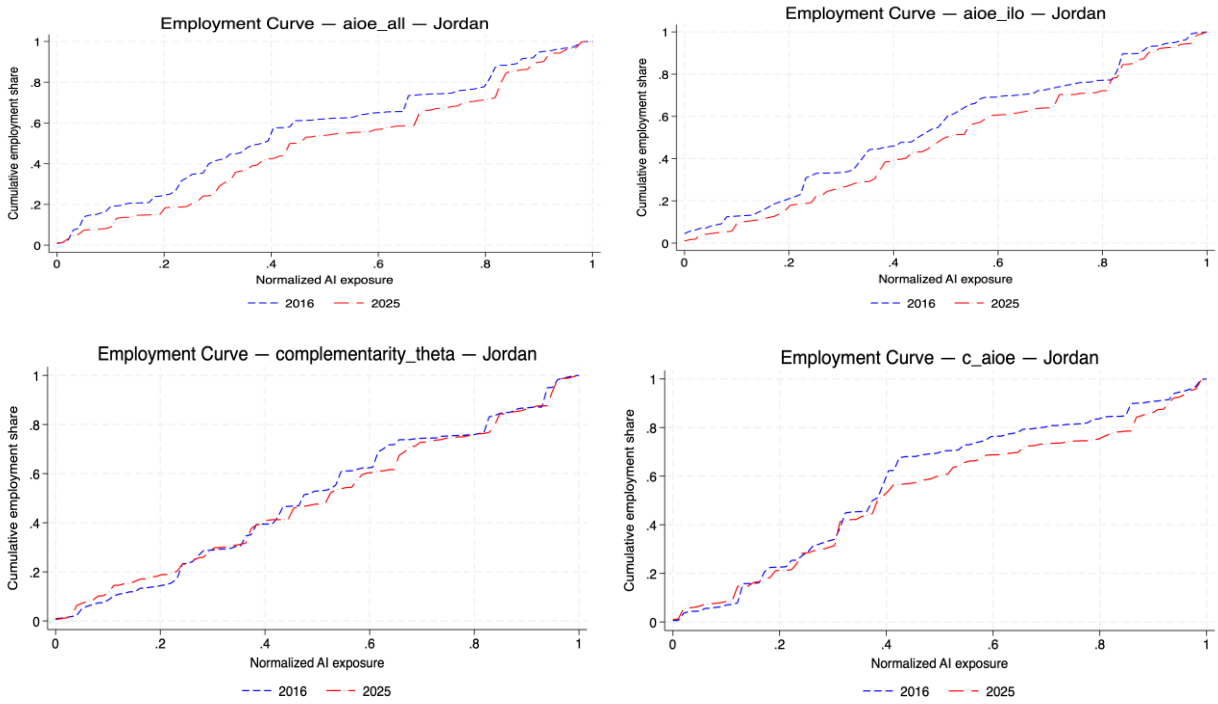
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Figure 1. Egypt AI exposure employment curves, various AIOE indices, 2018-2023



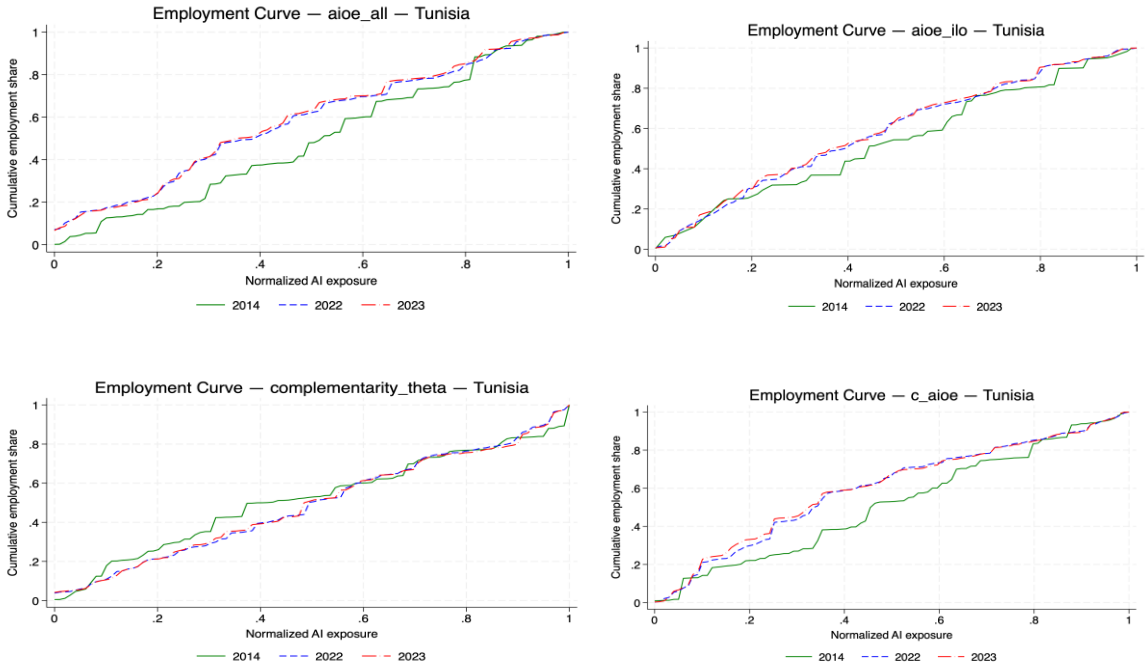
Note: The figures plot the cumulative employment share with respect to each AI index for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the respective index normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

Figure 2. Jordan AI exposure employment curves, various AIOE indices, 2016-2025



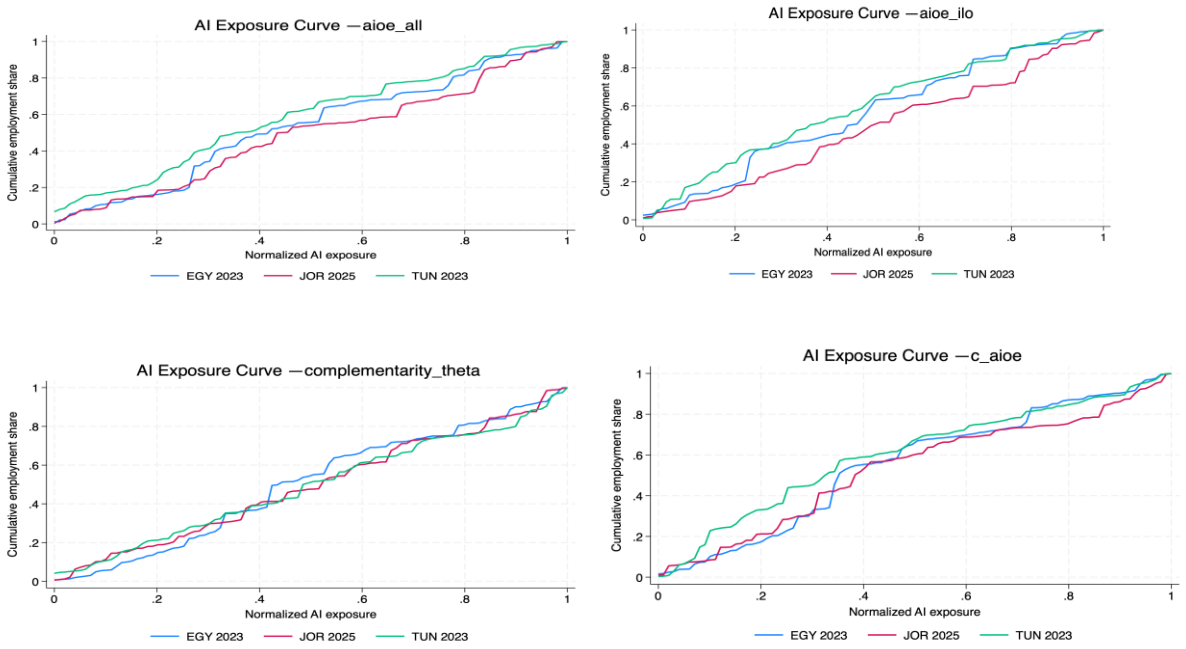
Note: The figures plot the cumulative employment share with respect to each AI index for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the respective index normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

Figure 3. Tunisia AI exposure employment curves, various AIOE indices, 2014-2023



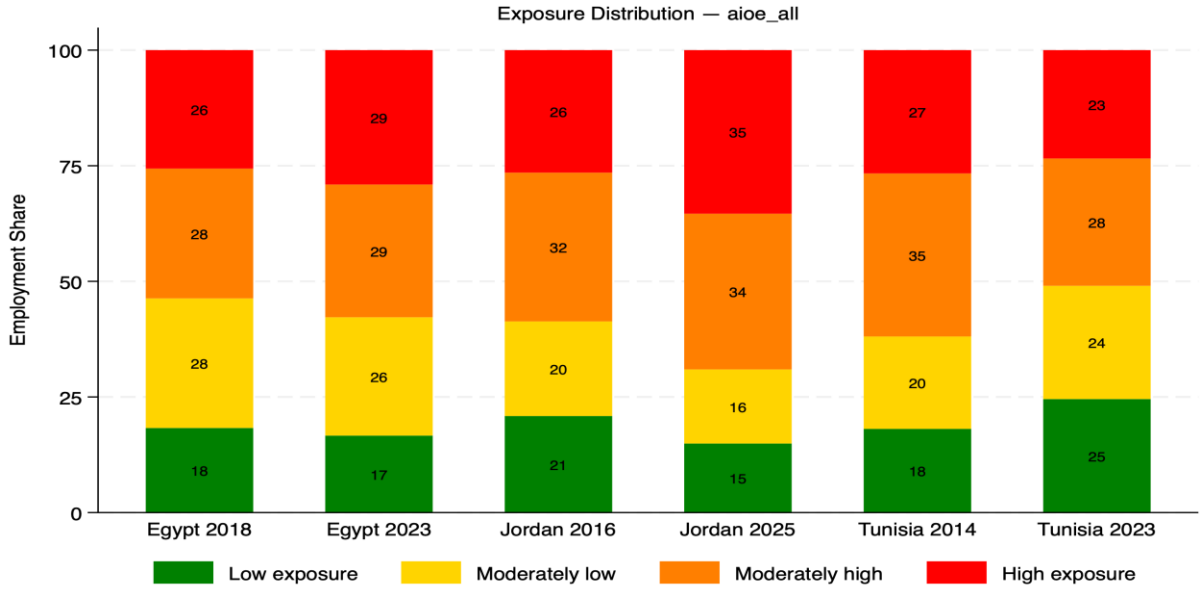
Note: The figures plot the cumulative employment share with respect to each AI index for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the respective index normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

Figure 4. AI Exposure employment curves, various AIOE indices, all countries, latest rounds



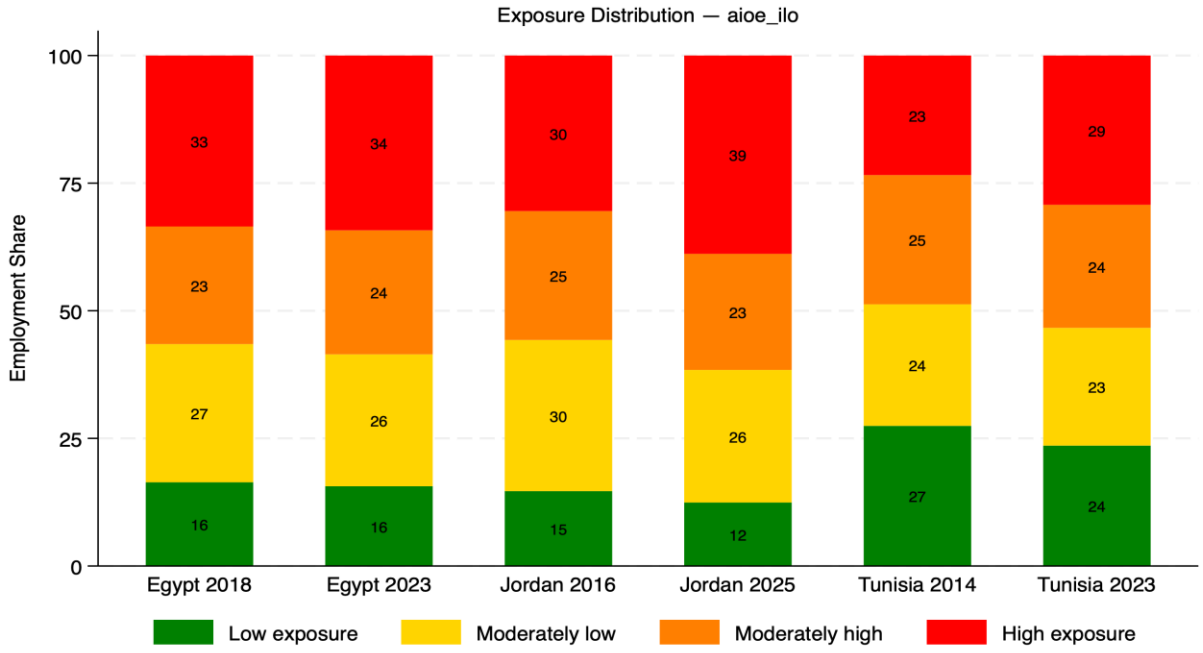
Note: The figures plot the cumulative employment share with respect to each AI index for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the respective index normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

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 32,43,76, using the pooled sample of all countries.

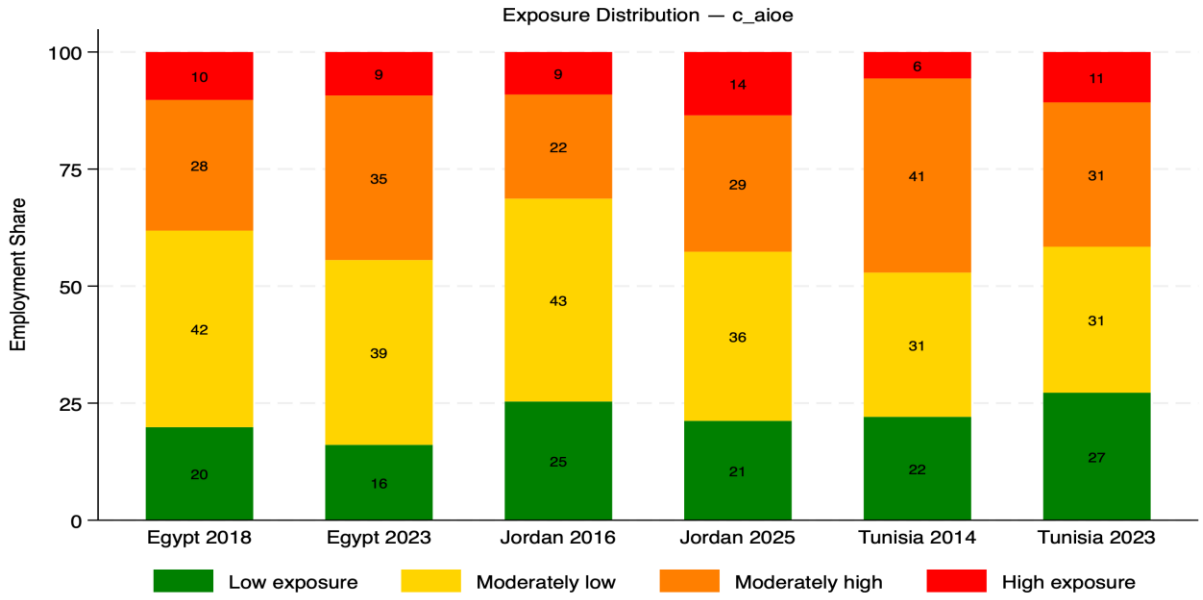
Figure 5b. AI exposure of employment, AIOE-ILO, employment share (percent)



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.

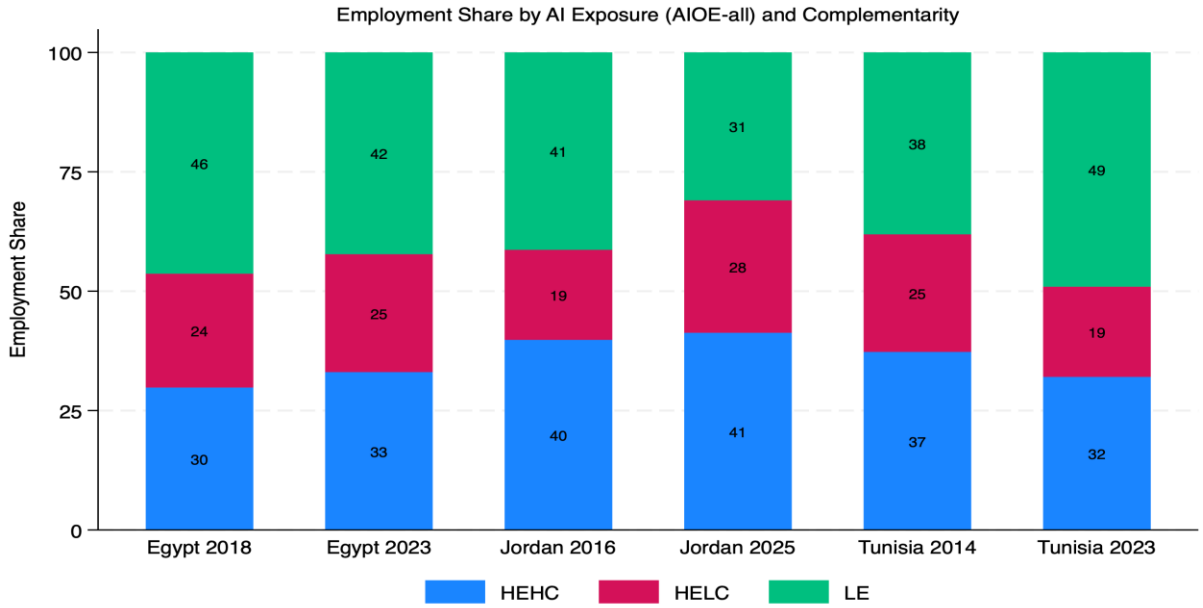
Figure 5c. Complementarity adjusted AI exposure of employment, C-AIOE, employment

share (percent)



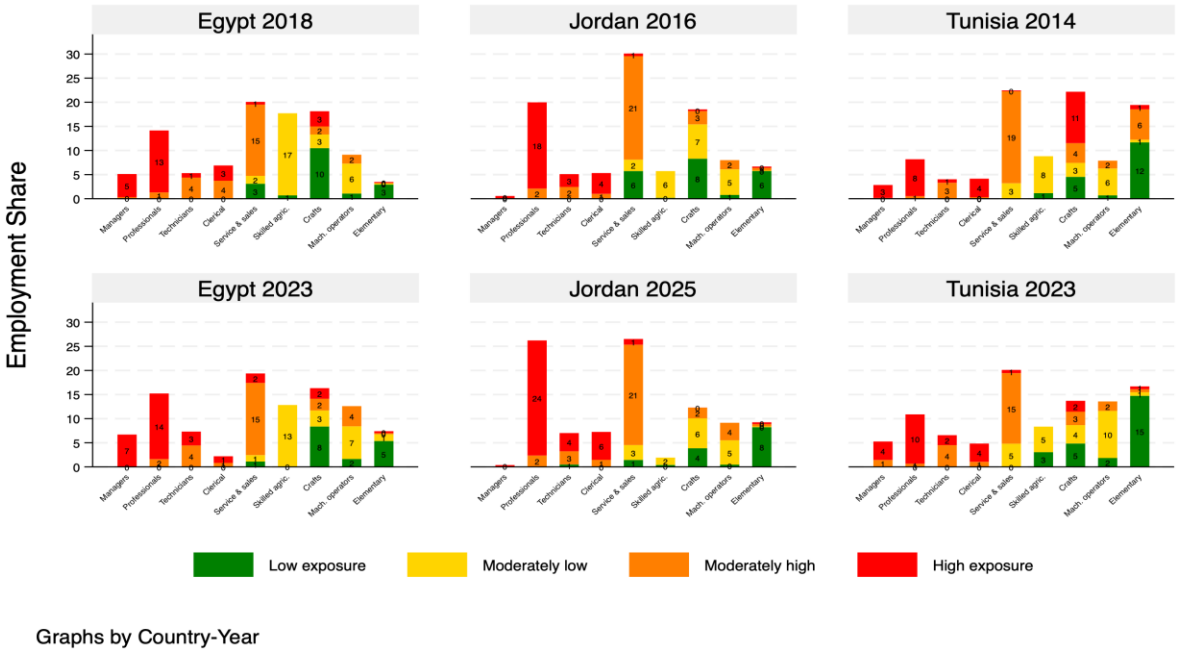
Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and classified using the same pooled thresholds as AIOE-all to facilitate comparison across the two measures.

Figure 6. Employment share by AIOE and complementarity



Note: The figure plots the share of employment in each group of occupations for each country. HEHC denotes occupations in the upper two quartiles of the pooled AIOE-all and complementarity θ distributions; HELC denotes occupations in the upper two quartiles of AIOE-all and lower two quartiles of θ; and LE denotes occupations in the lower two quartiles of the pooled AIOE-all distribution.

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



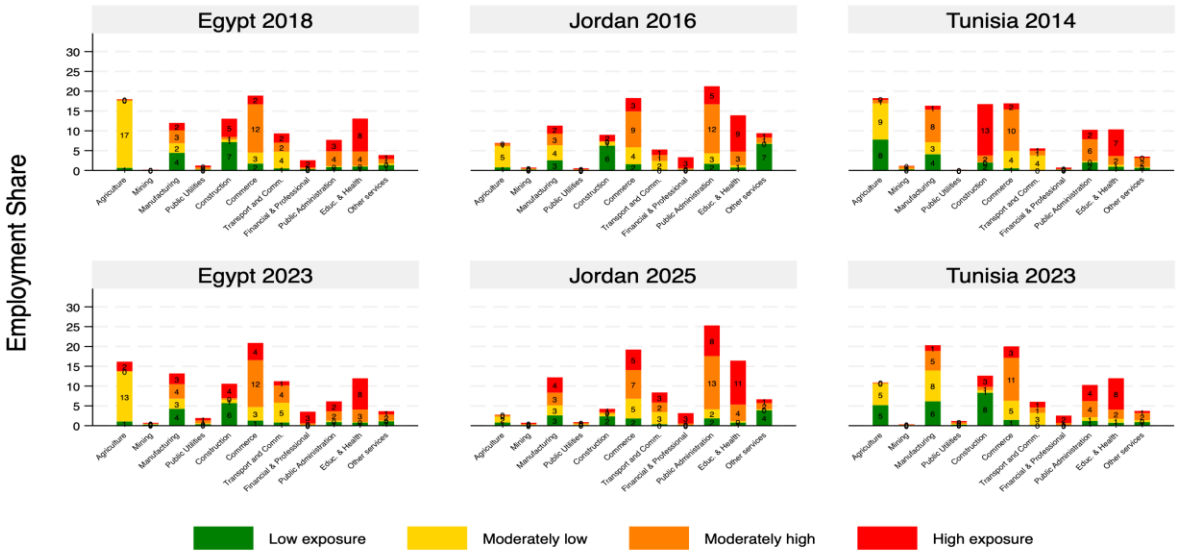
Note: Population weighted employment shares for workers aged 16-64. AIOE-all was normalized to 0-100 and divided into quartiles, with cutoffs at 32,43,76, using the pooled sample of all countries

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



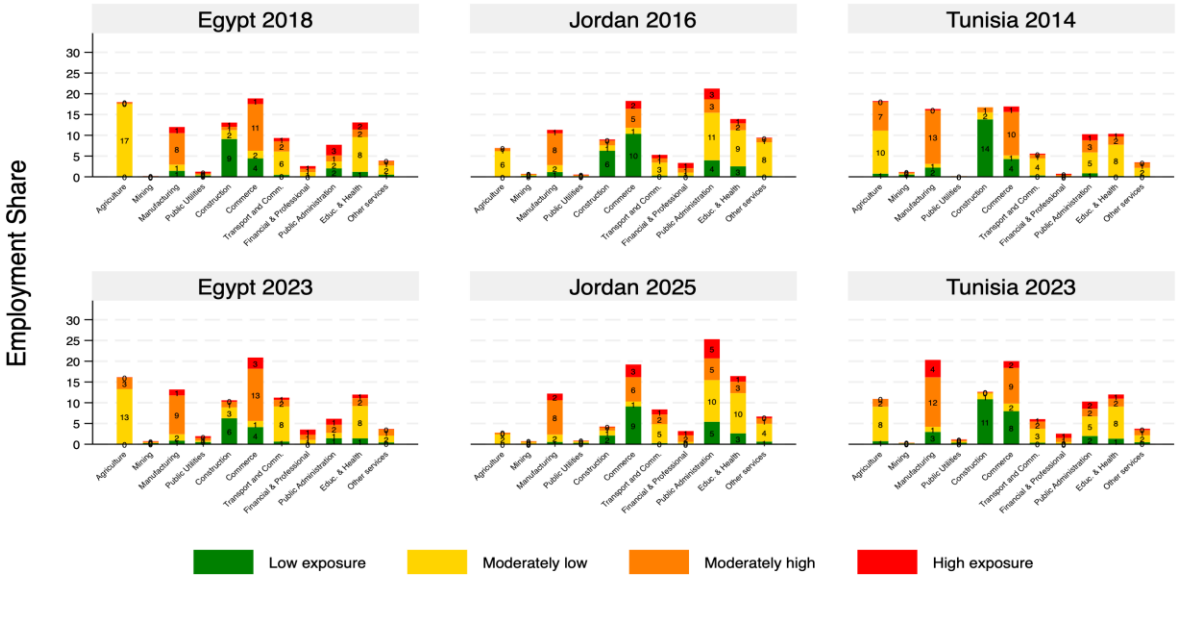
Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and classified using the same pooled thresholds as AIOE-all to facilitate comparison across the two measures.

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



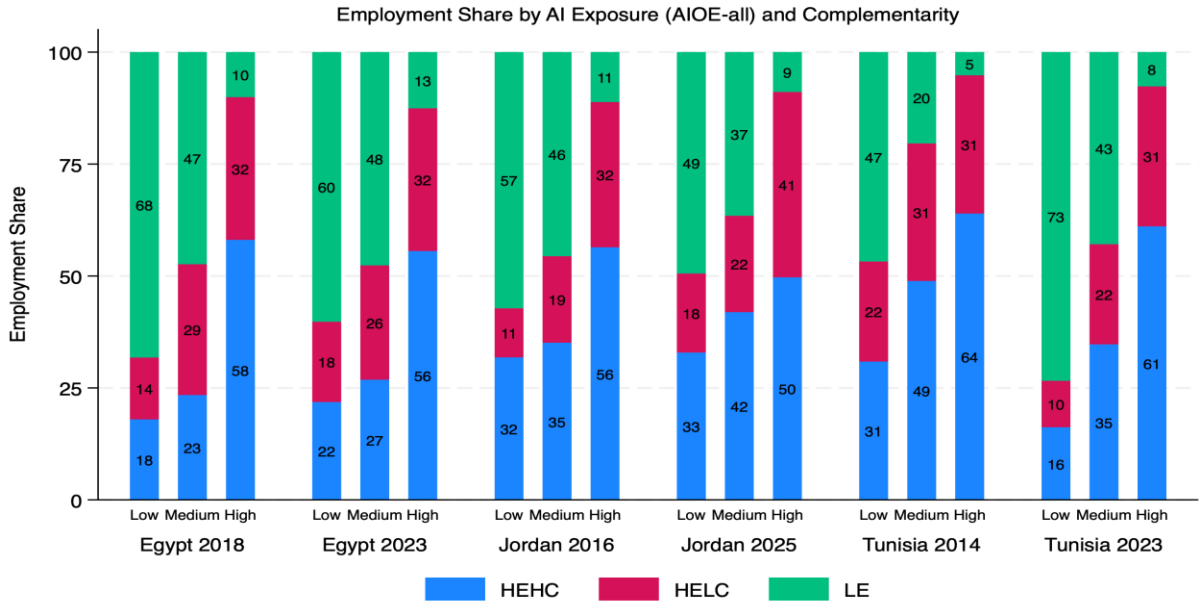
Note: Population weighted employment shares for workers aged 16-64. AIOE-all was normalized to 0-100 and divided into quartiles, with cutoffs at 32,43,76, using the pooled sample of all countries.

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



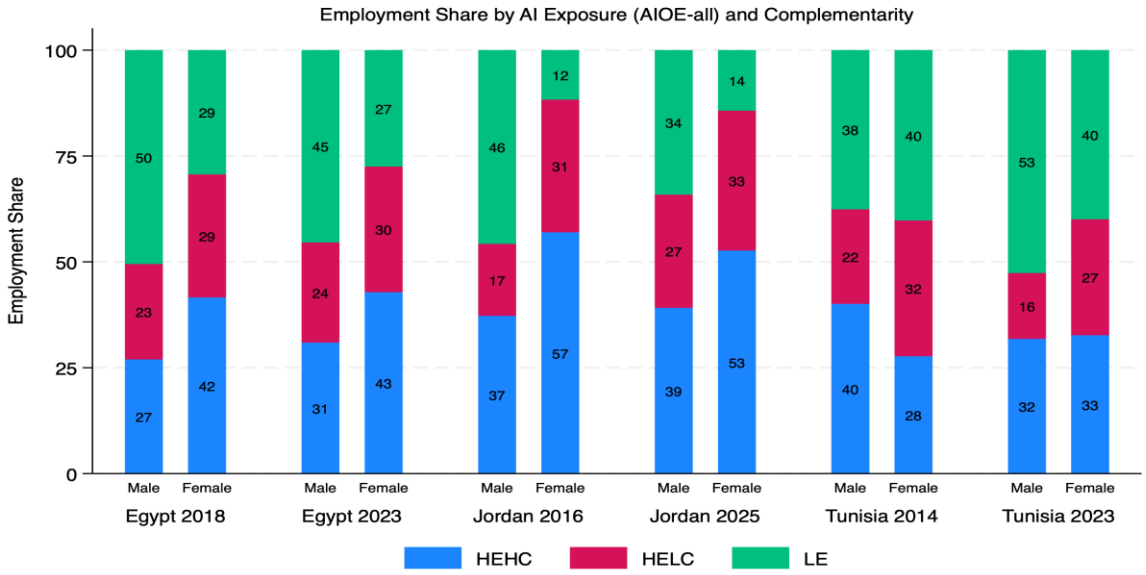
Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and classified using the same pooled thresholds as AIOE-all to facilitate comparison across the two measures.

Figure 9. Employment share by AI exposure and complementarity, by education level



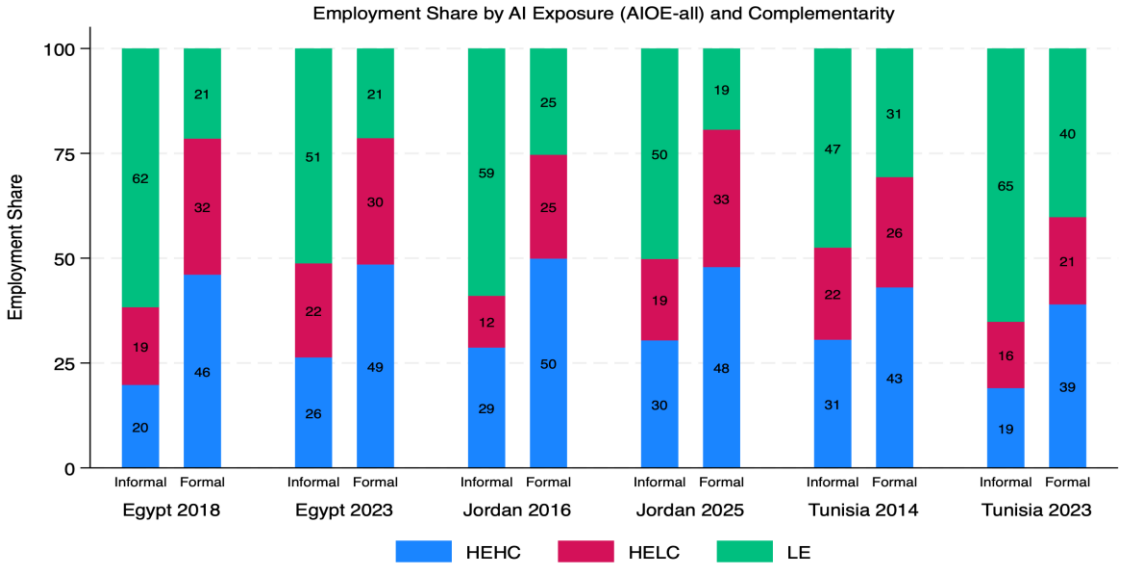
Note: The figure plots the share of employment in each group of occupations for each country. HEHC denotes occupations in the upper two quartiles of the pooled AIOE-all and complementarity θ distributions; HELC denotes occupations in the upper two quartiles of AIOE-all and lower two quartiles of θ; and LE denotes occupations in the lower two quartiles of the pooled AIOE-all distribution.

Figure 10. Employment share by AI exposure and complementarity, by sex



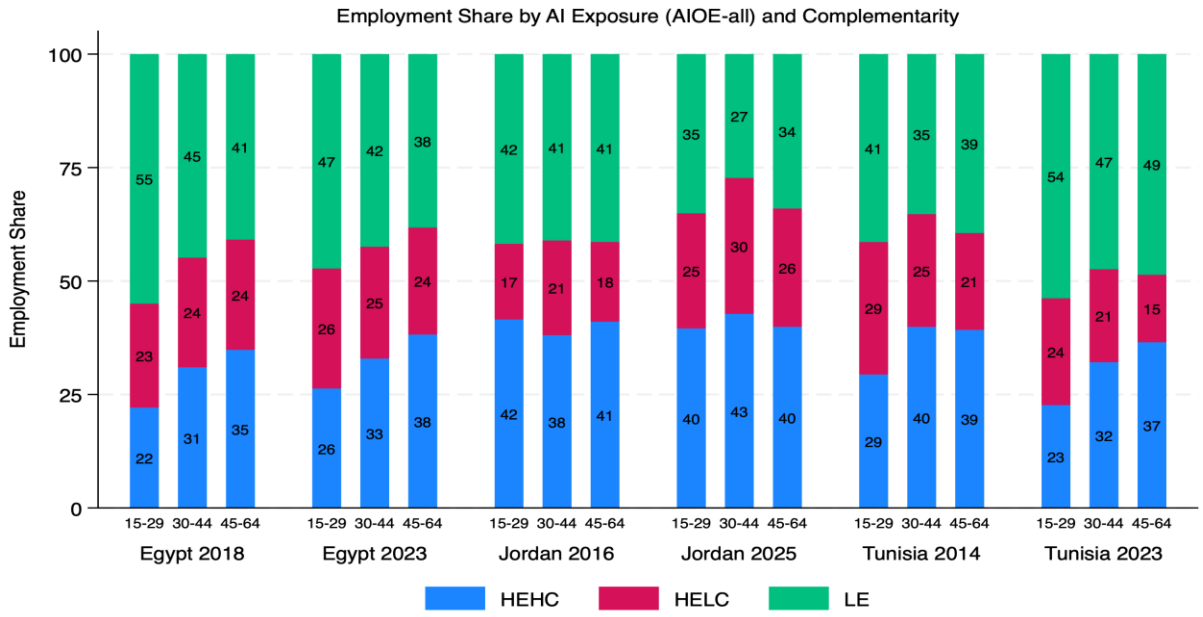
Note: The figure plots the share of employment in each group of occupations for each country. HEHC denotes occupations in the upper two quartiles of the pooled AIOE-all and complementarity θ distributions; HELC denotes occupations in the upper two quartiles of AIOE-all and lower two quartiles of θ; and LE denotes occupations in the lower two quartiles of the pooled AIOE-all distribution.

Figure 11. Employment share by AI exposure and complementarity, by formality of employment



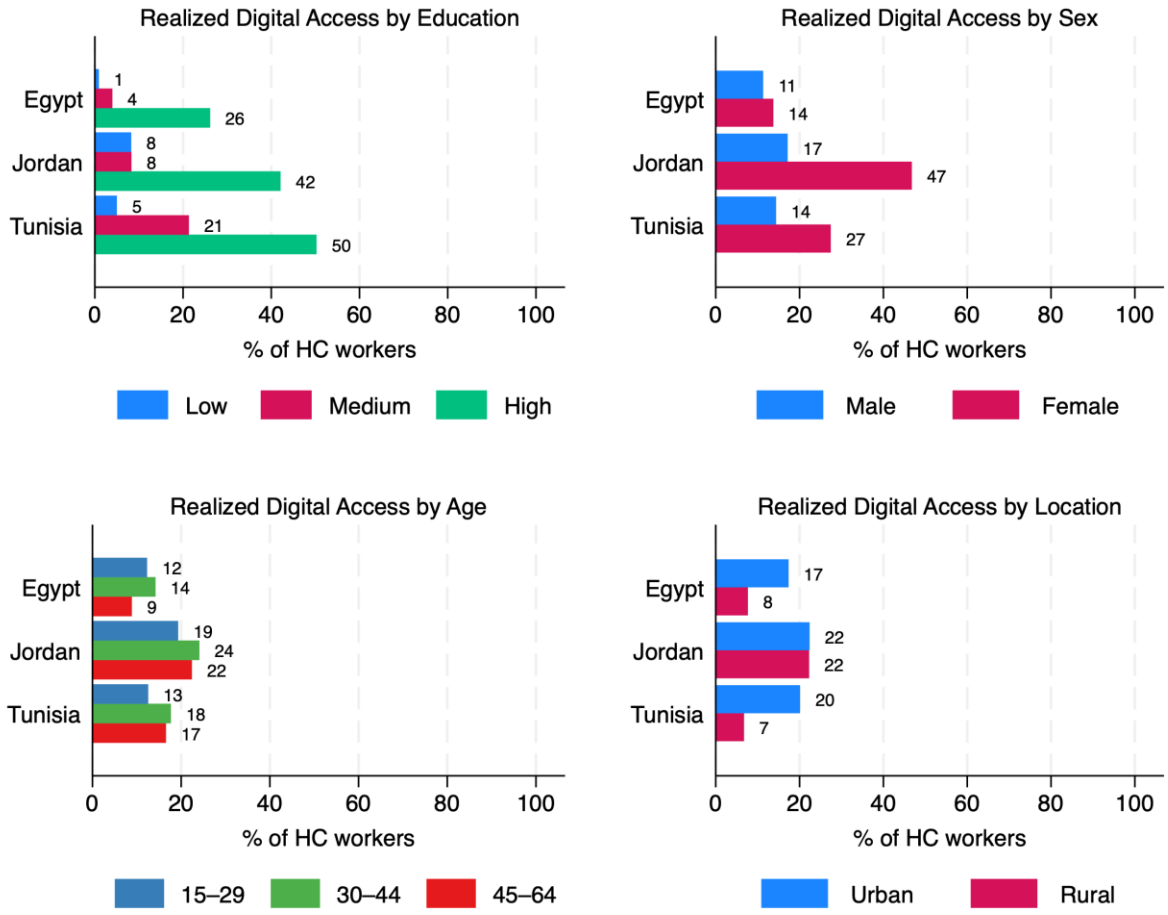
Note: The figure plots the share of employment in each group of occupations for each country. HEHC denotes occupations in the upper two quartiles of the pooled AIOE-all and complementarity θ distributions; HELC denotes occupations in the upper two quartiles of AIOE-all and lower two quartiles of θ; and LE denotes occupations in the lower two quartiles of the pooled AIOE-all distribution.

Figure 12. Employment share by AI exposure and complementarity, by age group



Note: The figure plots the share of employment in each group of occupations for each country. HEHC denotes occupations in the upper two quartiles of the pooled AIOE-all and complementarity θ distributions; HELC denotes occupations in the upper two quartiles of AIOE-all and lower two quartiles of θ; and LE denotes occupations in the lower two quartiles of the pooled AIOE-all distribution.

Figure 13. Realized digital access by worker characteristics for high complementarity workers



Sample restricted to workers in high-complementarity (HC) occupations.
Realized access = uses a computer connected to the internet at work.
Egypt: 2023; Jordan: 2025; Tunisia: 2014. Population-weighted estimates.

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

	High AI Exposure			High AI Complementarity			High Exposure and Low Complementarity		
	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia
Female	0.142	0.54	-0.921***	1.040***	-0.268	-0.859***	0.271	0.473	-0.523
	-0.191	-0.657	-0.335	-0.16	-0.541	-0.234	-0.172	-0.712	-0.321
Age: 30-44	-0.041	0.074	0.088	-0.016	-0.055	0.076	-0.017	0.106	0.053
	-0.033	-0.061	-0.069	-0.029	-0.056	-0.078	-0.036	-0.071	-0.08
Age: 45-64	0.106**	0.077	0.151**	0.038	-0.089	0.061	0.055	0.098	0.039
	-0.054	-0.082	-0.068	-0.045	-0.075	-0.061	-0.045	-0.103	-0.078
Female # 30-44	-0.083	0.333	-0.048	0.002	-0.116	-0.057	-0.072	0.222*	-0.12
	-0.093	-0.209	-0.16	-0.075	-0.132	-0.11	-0.09	-0.124	-0.168
Female # 45-64	0.02	0.031	-0.223**	-0.063	-0.186	0.076	0.023	0.175	-0.167
	-0.105	-0.225	-0.107	-0.09	-0.166	-0.127	-0.098	-0.163	-0.112
Medium education	0.232***	0.136**	0.460***	-0.004	0.156*	0.179***	0.342***	0.166*	0.170***
	-0.034	-0.062	-0.055	-0.032	-0.09	-0.044	-0.037	-0.086	-0.06
High education	1.039***	1.080***	1.337***	0.307***	-0.133**	0.386***	0.580***	0.941***	0.572***
	-0.077	-0.082	-0.108	-0.05	-0.068	-0.061	-0.044	-0.06	-0.088
Female # Medium educ.	0.624***	0.547**	0.467***	0.167**	0.581**	0.234**	0.257***	-0.062	0.483***
	-0.104	-0.231	-0.094	-0.084	-0.232	-0.102	-0.087	-0.256	-0.111
Female # High educ.	0.612***	1.124***	0.451***	0.828***	1.618***	0.779***	-0.658***	-0.950***	0.04
	-0.149	-0.225	-0.146	-0.107	-0.2	-0.128	-0.105	-0.249	-0.13
Urban	0.121	-0.006	0.004	1.538***	-0.062	0.008	-0.900**	0.133**	0.125
	-0.142	-0.067	-0.056	-0.271	-0.061	-0.051	-0.372	-0.058	-0.077
Informal	-0.404***	-0.302***	-0.252***	-0.163***	-0.054	-0.388***	-0.263***	-0.325***	0.122**
	-0.044	-0.078	-0.057	-0.04	-0.061	-0.052	-0.04	-0.061	-0.058
Female # Informal	-0.097	0.890***	0.462***	-0.05	0.111	0.339**	0.052	0.585***	0.283***
	-0.11	-0.229	-0.103	-0.084	-0.181	-0.168	-0.091	-0.159	-0.106
Waged employee	0.011	0.026	-0.324*	0.358***	0.106	0.099	-0.210*	-0.337	-0.234
	-0.1	-0.353	-0.166	-0.086	-0.321	-0.18	-0.111	-0.299	-0.189
Employer	1.253***	0.54	-0.064	1.601***	0.217	0.505**	-1.027***	0.043	-0.838***
	-0.119	-0.374	-0.181	-0.097	-0.345	-0.245	-0.122	-0.379	-0.274
Self-employed	0.366***	0.17	-0.048	0.844***	0.387	0.1	-0.363***	-0.607*	-0.256
	-0.107	-0.363	-0.143	-0.088	-0.32	-0.207	-0.115	-0.315	-0.22
Female # Waged employee	-0.092	-1.135*	0.610**	-1.607***	-1.039*	-0.212	0.267*	0.177	0.758***
	-0.136	-0.616	-0.304	-0.131	-0.565	-0.216	-0.143	-0.701	-0.276
Female # Employer	0.317	-1.216	1.564***	-0.883***	-1.244*	0.740***	-0.084	0.199	0.694*
	-0.211	-0.968	-0.326	-0.174	-0.64	-0.259	-0.226	-0.885	-0.365
Female # Self-employed	0.650***	-0.866	1.396***	-0.798***	-0.555	0.952***	0.329*	0.224	0.327
	-0.149	-0.652	-0.305	-0.137	-0.59	-0.214	-0.18	-0.736	-0.28
Constant	-1.821***	-1.209***	-1.307***	-3.321***	-0.641	-0.598**	-0.974**	-1.965***	-1.723***
	-0.17	-0.402	-0.169	-0.285	-0.394	-0.264	-0.388	-0.377	-0.199
Observations	32489	13213	20355	32489	13213	20355	32388	13196	20125
Clusters	2285	740	262	2285	740	262	2282	740	261
Mean of dep. var.	0.538	0.675	0.476	0.38	0.516	0.427	0.225	0.231	0.163
Wald chi2	5912.32	1246.48	1931.51	3208.48	1047.15	2137.16	3390.63	1237.33	1882.02
Prob > chi2	0	0	0	0	0	0	0	0	0
Pseudo R2	0.352	0.308	0.299	0.193	0.142	0.179	0.249	0.172	0.184

*Notes: Probit coefficients are reported, with standard errors clustered at the survey cluster/PSU level. The reference categories are age 15–29, low education, male, rural residence, formal employment, and unpaid family worker; country-specific regional and survey-round fixed effects, as well as industry fixed effects, are included but not reported. In the interaction specification, the coefficient on Female represents the female–male difference for the reference categories, while the interaction coefficients indicate how this difference varies across age, education, formality, and employment-status groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2. Probit regression results for realized complementarity, functional obsolescence and realized HEHC, by country

	Realized High Comp (High Comp + Work Computer & Internet)			Functional Obsolescence (High Comp Job without Work Computer & Internet)			Realized HEHC (High Exposure, High Comp + Work Computer & Internet)		
	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia	Egypt	Jordan	Tunisia
Female	0.147	-1.301**	0.022	0.927***	0.035	-0.704	0.219	-1.328**	0.179
	-0.365	-0.631	-0.708	-0.157	-0.562	-0.654	-0.367	-0.643	-0.709
Age: 30-44	0.008	-0.022	0.078	-0.006	-0.053	0.365**	0.015	-0.035	0.055
	-0.06	-0.09	-0.236	-0.029	-0.05	-0.143	-0.062	-0.086	-0.243
Age: 45-64	-0.004	0.072	0.357	0.055	-0.107	0.145	0.016	0.063	0.395
	-0.071	-0.102	-0.253	-0.042	-0.077	-0.125	-0.072	-0.107	-0.258
Female # 30-44	-0.089	0.031	0.293	0.011	-0.122	-0.514**	-0.104	0.046	0.308
	-0.109	-0.138	-0.318	-0.073	-0.129	-0.239	-0.11	-0.135	-0.321
Female # 45-64	-0.182	-0.379**	-0.706	-0.019	0.063	-0.158	-0.202	-0.362**	-0.74
	-0.125	-0.156	-0.475	-0.086	-0.171	-0.255	-0.125	-0.154	-0.477
Medium education	0.638***	0.225**	0.797***	-0.03	0.124	0.007	0.623***	0.237**	0.816***
	-0.101	-0.108	-0.241	-0.032	-0.089	-0.134	-0.108	-0.115	-0.255
High education	1.546***	0.807***	1.454***	-0.086*	-0.422***	-0.377**	1.547***	0.856***	1.488***
	-0.1	-0.083	-0.257	-0.047	-0.073	-0.182	-0.105	-0.085	-0.27
Female # Medium	-0.113	0.177	0.488	0.216***	0.577**	0.857***	-0.118	0.151	0.484
	-0.288	-0.398	-0.547	-0.082	-0.242	-0.262	-0.291	-0.394	-0.553
Female # High	-0.07	0.746*	0.184	0.759***	1.127***	1.316***	-0.097	0.697	0.186
	-0.284	-0.426	-0.492	-0.098	-0.226	-0.273	-0.287	-0.425	-0.5
Informal	-0.428***	-0.643***	-1.237***	-0.041	0.096	-0.228**	-0.445***	-0.697***	-1.339***
	-0.056	-0.126	-0.278	-0.039	-0.066	-0.096	-0.059	-0.123	-0.311
Female # Informal	0.043	0.814***	0	0.041	-0.153	0.101	0.064	0.881***	0
	-0.117	-0.286	(.)	-0.08	-0.212	-0.277	-0.118	-0.292	(.)
Waged employee	-0.144	0.191	-0.088	0.384***	0.074	0.272	0.005	0.14	0.059
	-0.241	-0.774	-0.316	-0.09	-0.328	-0.341	-0.249	-0.775	-0.333
Employer	0.234	0.408	-0.042	1.563***	0.162	0.206	0.394	0.431	-0.014
	-0.253	-0.81	-0.358	-0.102	-0.344	-0.368	-0.259	-0.81	-0.382
Self-employed	-0.295	0.483	0	0.894***	0.302	-0.101	-0.162	0.493	0
	-0.256	-0.746	(.)	-0.092	-0.323	-0.337	-0.262	-0.747	(.)
Female # Waged employee	-0.05	0.784**	-0.587	-1.507***	-1.166**	-0.429	-0.084	0.854***	-0.735
	-0.198	-0.324	-0.626	-0.131	-0.54	-0.578	-0.201	-0.33	-0.615
Female # Employer	-0.188	0.673	0	-0.947***	-1.367**	0.509	-0.22	0.666	0
	-0.324	-0.639	(.)	-0.175	-0.63	-0.858	-0.326	-0.634	(.)
Female # Self-employed	0	0	0	-0.847***	-0.604	1.618***	0	0	0
	(.)	(.)	(.)	-0.14	-0.552	-0.574	(.)	(.)	(.)
Constant	-2.955***	-2.722***	-1.137**	-2.058***	-0.742*	-1.537***	-3.120***	-2.668***	-1.292***
	-0.281	-0.896	-0.459	-0.11	-0.411	-0.35	-0.293	-0.9	-0.475
Observations	31388	13162	1786	32453	13192	2717	31388	13162	1786
Clusters	2282	740	248	2285	740	250	2282	740	248
Mean of dep. var.	0.054	0.09	0.074	0.327	0.393	0.354	0.052	0.087	0.073
Wald chi2	1190.32	1058	163.75	2253.63	539.87	677.4	1153.03	1067.85	151.71
Prob > chi2	0	0	0	0	0	0	0	0	0
Pseudo R2	0.273	0.234	0.306	0.152	0.102	0.285	0.279	0.246	0.315

*Notes: Probit coefficients are reported, with standard errors clustered at the survey cluster/PSU level. The reference categories are age 15–29, low education, male, formal employment, and unpaid family worker; country-specific regional and survey-round fixed effects, as well as industry fixed effects, are included but not reported. In the interaction specification, the coefficient on Female represents the female–male difference for the reference categories, while the interaction coefficients indicate how this difference varies across age, education, formality, and employment-status groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

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	
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 Augmented AII	873 8-digit SOC 2010 occup. groups 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)

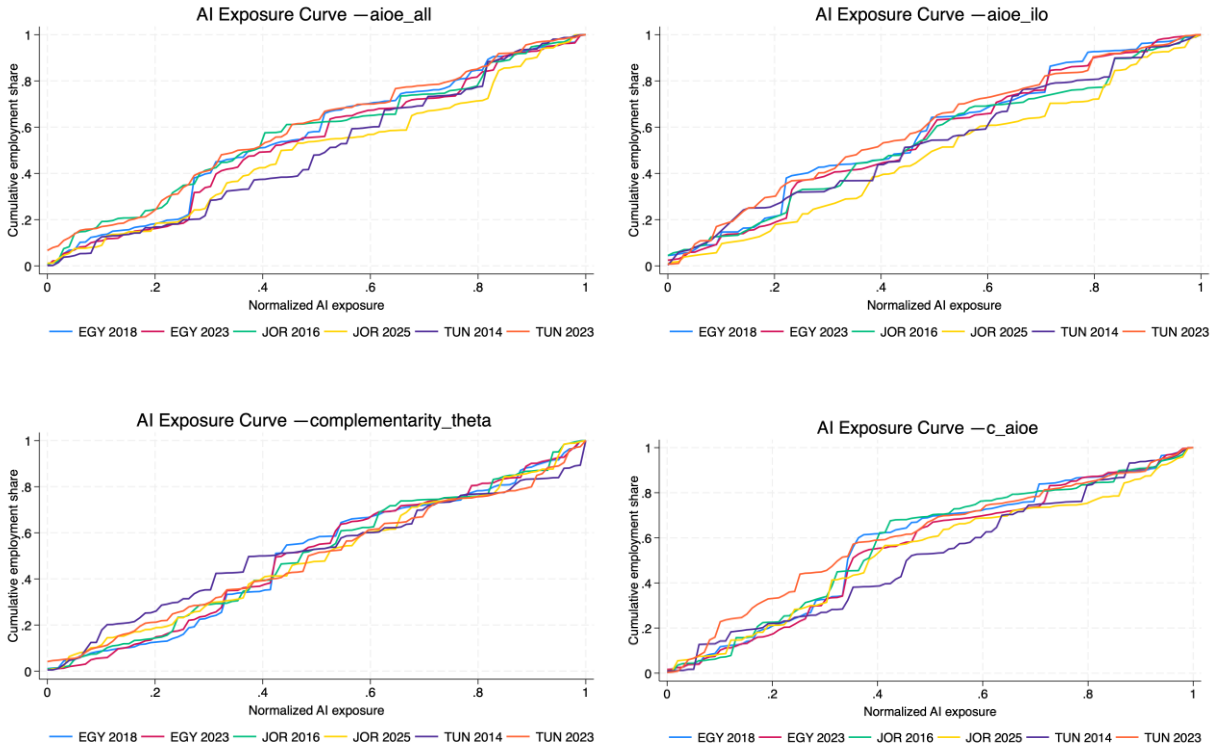
Source: Compiled by authors.

Table A2. 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

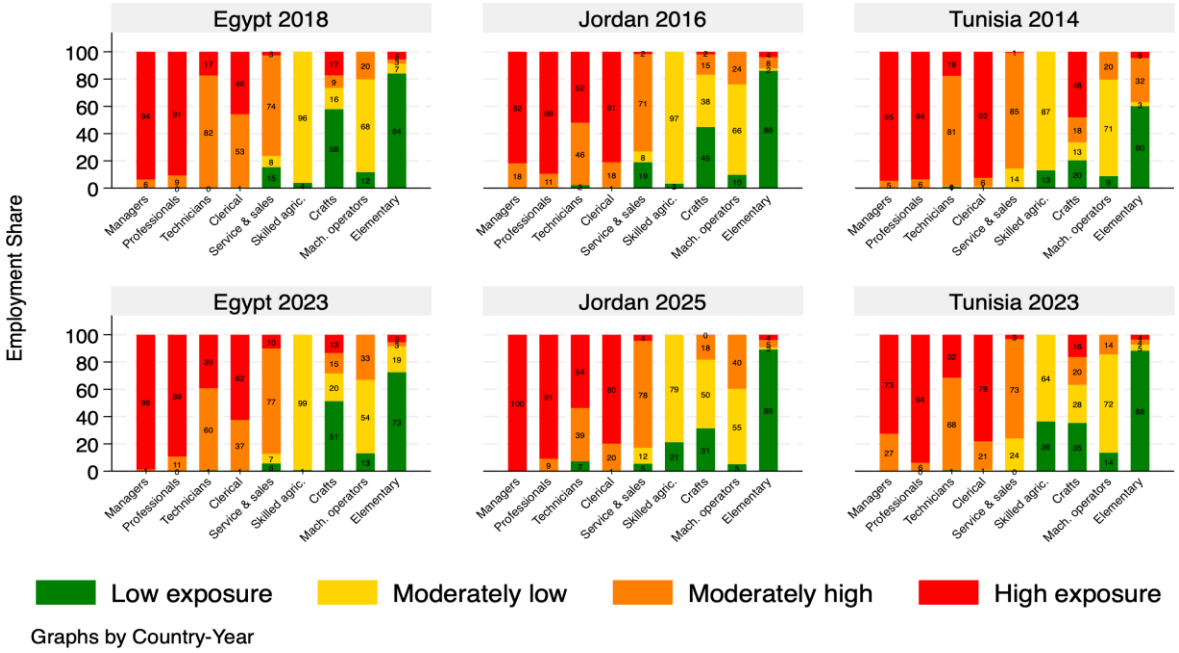
*Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Some variables are excluded from particular regressions for incidental perfect collinearity or perfect prediction of the dependent variable. Regression for Tunisia also includes a binary indicator for the y2022 round, but this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

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



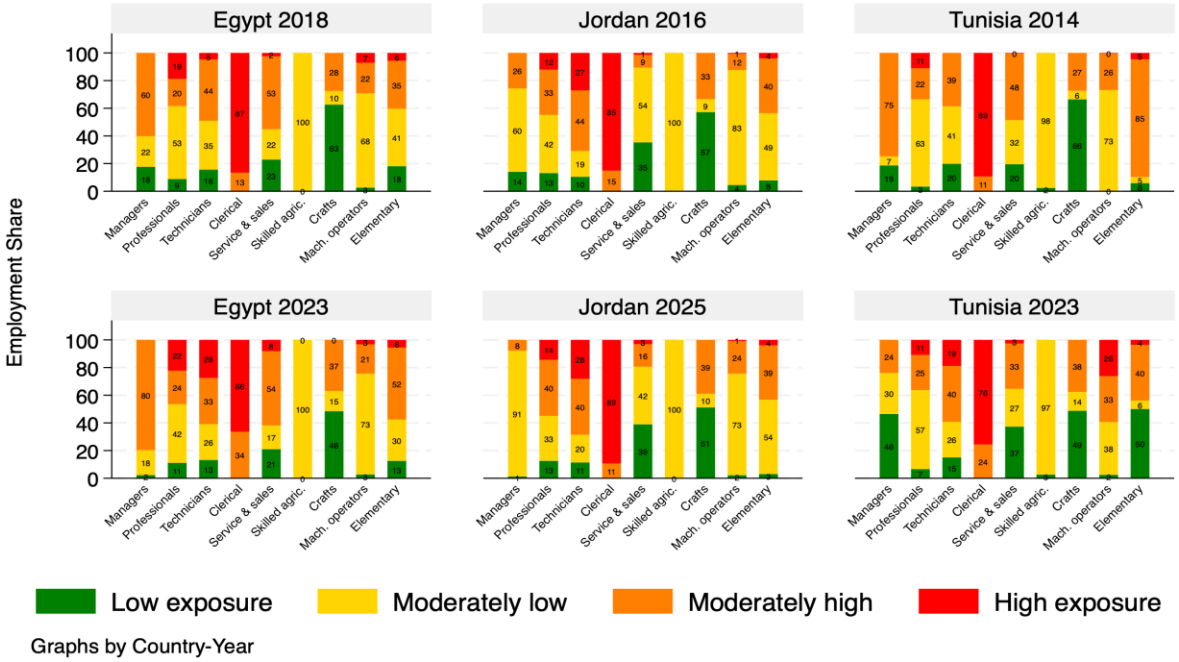
Note: The figures plot the cumulative employment share with respect to each AI index for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the respective index normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

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



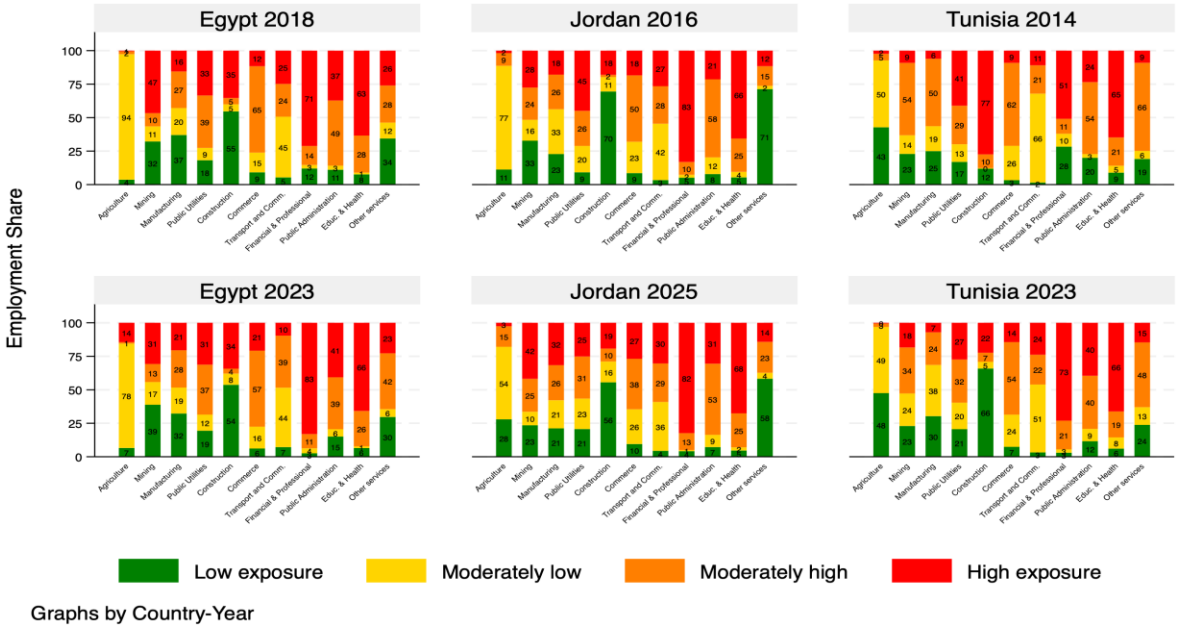
Note: Population weighted employment shares for workers aged 16-64. AIOE-all was normalized to 0-100 and divided into quartiles, with cutoffs at 32,43,76, using the pooled sample of all countries

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



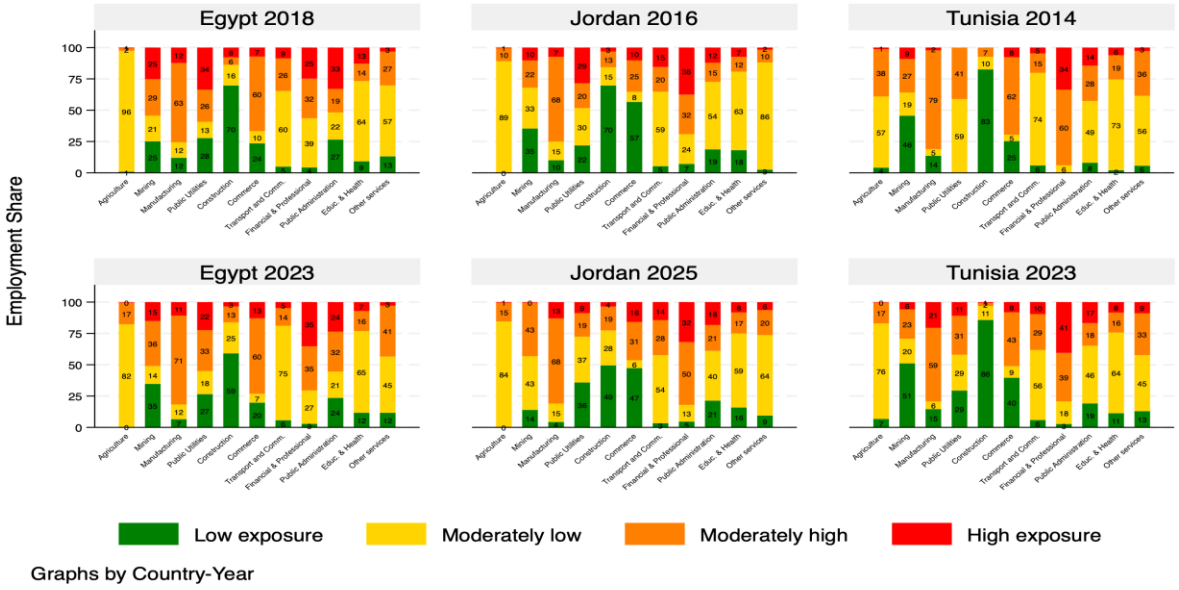
Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and classified using the same pooled thresholds as AIOE-all to facilitate comparison across the two measures.

Figure A3a. AI exposure by main industry: AIOE-all



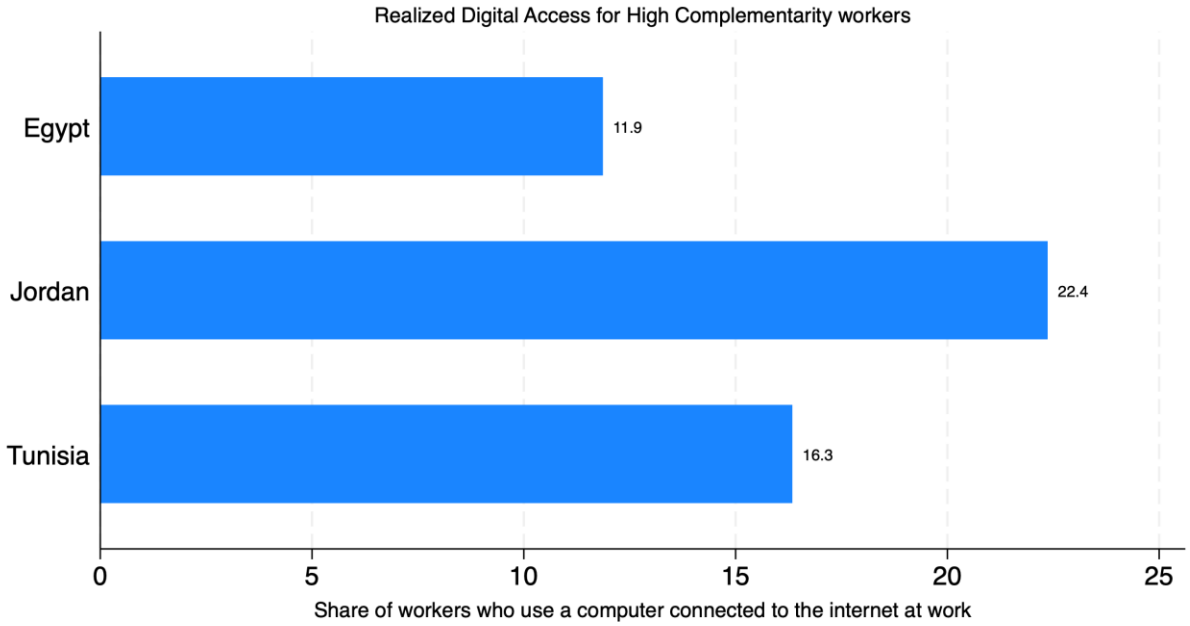
Note: Population weighted employment shares for workers aged 16-64. AIOE-all was normalized to 0-100 and divided into quartiles, with cutoffs at 32,43,76, using the pooled sample of all countries

Figure A3b. AI exposure by main industry: C-AIOE



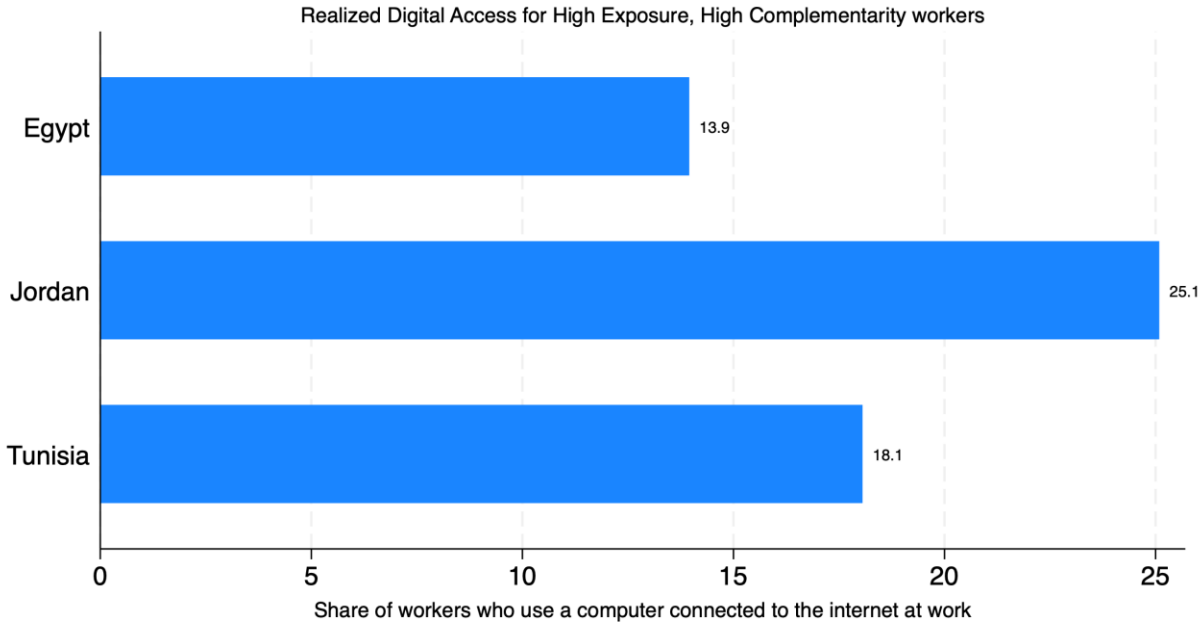
Note: Population weighted employment shares for workers aged 16-64. C-AIOE was normalized to 0-100 and classified using the same pooled thresholds as AIOE-all to facilitate comparison across the two measures.

Figure A4. Realized Digital access by country for High Complementarity workers



Sample restricted to workers in high-complementarity (HC) occupations.
Realized access = uses a computer connected to the internet at work.
Egypt: 2023; Jordan: 2025; Tunisia: 2014. Population-weighted estimates.

Figure A5. Realized digital access by country for high exposure, high complementarity workers



Sample restricted to workers in high exposure, high-complementarity (HEHC) occupations.
Realized access = uses a computer connected to the internet at work.
Egypt: 2023; Jordan: 2025; Tunisia: 2014. Population-weighted estimates.