Methodology

Literature and measures

This analysis builds on a growing body of research assessing how AI intersects with work. The foundational measure we use—the AI Occupational Exposure (AIOE) score developed by Felten, Raj, and Seamans (2021)—links 10 AI application areas to 52 O*NET occupational abilities to produce a standardized exposure score at the six-digit Standard Occupational Classification (SOC) level. Eloundou et al. (2023) developed an independent measure using O*NET work tasks, finding that roughly 80% of the U.S. workforce has at least some measurable exposure to large language models. The Pew Research Center (2023) produced a typology sorting O*NET work activities into high, medium, and low exposure tiers. These exposure studies converge on the finding that physical, manual, and craft occupations sit at the low end of AI exposure, but leave open whether AI will complement workers or substitute for them in a given role. Pizzinelli et al. (2023) address this by augmenting the AIOE score with a complementarity index (“Theta score”). Most recently, Manning et al. (2026) at Brookings add that even among highly exposed workers, displacement outcomes will vary based on adaptive capacity.

Occupation classification

The present analysis applies the AIOE score and complementarity Theta score to the built environment workforce—a sector that appears consistently at the low-exposure end of existing measures, but has not yet been examined in its own right. We identified 164 built environment occupations—95 “core” occupations directly involved in construction and design (carpenters, civil engineers, architects), and 69 “extended” occupations in materials manufacturing and supporting services—through a two-step process. First, we calculated each occupation’s employment concentration across 45 built environment industries drawn from the Bureau of Labor Statistics’ Occupational Employment and Wage Statistics industry-occupation data, then applied expert review to validate inclusion and enforce boundary decisions.

AI exposure and complementarity matching

Each occupation was matched at the six-digit SOC level to the AIOE score and Theta score. Of the 164 occupations, 16 could not be matched to one or both datasets, leaving 148 occupations as the analytic universe for all exposure and complementarity calculations. We use AIOE = 0 as the low/high exposure cutoff (consistent with the Felten standardization), and the mean of the U.S. occupational theta distribution (0.5725) as the low/high complementarity cutoff.

Wage data

Occupational wage data are drawn from the Bureau of Labor Statistics’ Occupational Employment and Wage Statistics (OEWS) program (bls.gov/oes), which provides annual employment and wage estimates for over 800 occupations across the U.S. economy. We use occupation-level median annual wages, weighted by employment, to characterize the wage distribution.

Statistical validation

A chi-square goodness-of-fit test was applied to assess whether the distribution of built environment occupations across AI exposure and complementarity quadrants differs significantly from what would be expected if built environment occupations were drawn at random from the broader U.S. occupational population. The null hypothesis is that built environment occupations follow the same distribution as U.S. occupations overall. The test strongly rejects this null ($\chi^2 = 38.47$, $p < 0.001$), confirming that the built environment workforce's concentration in lower-exposure, higher-complementarity occupations reflects a statistically meaningful structural difference rather than a product of sampling variation.