Motivation

Advances in artificial intelligence (AI) and automation are changing which abilities production requires. At the same time, population aging is changing which abilities are available. Fertility has fallen across almost all economies: the global total fertility rate declined from 3.3 births per woman in 1990 to 2.25 in 2024, and more than half of all countries now have fertility below the replacement level of 2.1 (United Nations 2024). In about one in five countries, including China, Italy, Spain, and Japan, fertility is below 1.4; South Korea's rate fell to 0.72 in 2023, and the U.S. rate to 1.62. Combined with longer lives, the age structure of the workforce will also change unevenly across countries, i.e., employers in different places face very different supplies of younger and older workers.

A large literature shows that demographic change affects growth, productivity, firm entry, and firm dynamics (Maestas, Mullen, and Powell 2023; Hopenhayn, Neira, and Singhania 2022; Karahan, Pugsley, and Şahin 2024; Peters and Walsh 2026; Acemoglu et al. 2026). Acemoglu and Restrepo (2022) show that aging spurs the development and adoption of automation technologies, and Lehr (2023) studies innovation in an aging economy. We ask a broader question: does population aging change what firms invent, not only how much they automate?

Our starting point is that technological change is not age-neutral. Workers' abilities vary systematically with age, so aging shifts the relative supply of abilities. Firms may respond by directing invention toward technologies that complement abilities becoming more abundant, or that substitute for abilities becoming scarce. We call the resulting pattern age-biased technological change (ABTC). The question is timely for digital technologies: recent evidence suggests that generative AI affects workers differently across career stages (Brynjolfsson, Chandar, and Chen 2025; Lichtinger and Hosseini Maasoum 2025). We ask whether age-differentiated technological change also reflects a longer-run response of invention to demographic change.

Framework and Measurement

Measuring ABTC requires two objects: how the productivity of each ability changes with age, and how closely each invention draws on those abilities.

Ability age gradients. We build a Roy-type occupational choice model with Fréchet-distributed idiosyncratic productivity. An occupation's age-specific productivity combines the age-specific productivities of O*NET's 52 cognitive, sensory, psychomotor, and physical abilities, weighted by their importance to the occupation. Workers value both wages and the non-monetary benefits of a good match. Occupations with higher age-specific productivity therefore attract workers with weaker idiosyncratic draws, so naive age-by-ability wage gradients confound productivity with selection. The model maps the age-by-ability coefficients of a pooled wage regression into ability-specific age productivity, scaled by the weight on wages. Two further moments identify the remaining parameters for each age group: the cross-occupation relationship between employment

shares and average wages, and the dispersion of residual log wages within occupations. Together they deliver sorting-corrected age gradients for each ability.

Patent age bias. We embed the text of each U.S. utility patent (title, abstract, and first independent claim) and the 52 ability descriptions with PatentSBERTa. A patent's age bias (AB) weights its similarity to each ability by that ability's estimated age gradient. Higher AB indicates closer alignment with abilities whose relative productivity rises more, or falls less, with age.

Automation and augmentation. An invention aligned with older workers' abilities could complement those abilities or replace tasks that use them. We therefore measure age orientation separately from automation and augmentation. Building on the task–title distinction in Autor et al. (2024), automation scores capture how concentrated a patent's textual similarity is on historical occupational task descriptions (DOT and O*NET), and augmentation scores capture its concentration on historical Census occupational titles. Both are ranked within application year, so they measure relative orientation rather than aggregate trends, and both can coexist within one invention.

Data and Empirical Design

O*NET abilities link the worker and patent data. CPS-ASEC (2000–2024) provides about 1.47 million full-time wage earners aged 20 and older in 454 detailed occupations. USPTO PatentsView provides roughly 7.5 million utility patents with application years 1974–2022 and disambiguated inventors and assignees. The UN World Population Prospects 2024 provides country median age, which we assign to each patent by application year, separately for the inventor's and the assignee's country.

We relate AB, automation, and augmentation to country median age. All specifications include CPC subclass-by-application-year fixed effects. We pair assignee-country age with assignee fixed effects and inventor-country age with inventor fixed effects; the most demanding specification adds assignee-by-year effects. This compares patents by the same inventor and by the same patent owner in a given year. We also relate AB to automation and augmentation conditional on country age, and report citation-weighted estimates.

Preliminary Findings

Four patterns emerge.

1. Correcting for sorting matters. Accounting for occupational selection changes estimated ability age profiles, sometimes reversing their sign. Reasoning and communication abilities follow different patterns from some sensory and physical abilities, but the results do not reduce to a simple cognitive–physical split.
2. Aging is associated with invention aligned with older worker’s abilities. Patents invented or owned in older countries have higher AB. The association becomes smaller but persists

within inventors and within assignee-years, and the more recent 2004–2022 sample points in the same direction.

3. Age bias is distinct from automation. The aging–automation association does not survive the most demanding specification, whereas augmentation remains positively associated with aging. Inventions aligned with older workers' abilities can carry both task-replacement and augmentation orientations, so age bias needs to be measured on its own.
4. Demand may pull in the opposite direction. Industries that serve older households most intensively, such as health care, household and property services, and construction and building maintenance, employ relatively young workers. If aging shifts spending toward these industries, demand may offset incentives to adapt technology to older workers.

Next Steps and Contribution

We are extending the analysis in three directions. First, we examine how age bias relates to specific technologies such as AI and robots: whether these inventions are more or less aligned with older workers' abilities than other technologies, and whether population aging shifts their age orientation. Second, we study what age-biased technological change implies for productivity, growth, and inequality, including how exposure to these technologies is distributed across workers by age, education, and occupational pay. Third, we instrument country median age with past fertility, which shapes today's age structure but is predetermined relative to current invention, to move from conditional associations toward causal estimates.

The paper makes three contributions. First, it provides a sorting-corrected measure of how the productivity of each ability varies with age. Second, it measures the age content of invention across five decades of U.S. patents, shifting attention from the amount of innovation to its direction. Third, it separates the age orientation of technology from its automation and augmentation orientation. Because most of our evidence predates generative AI, it lets us examine demographic change as a longer-run force that may shape the direction of technology, against which the recent age-differentiated effects of AI can be assessed.

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