OXFORD JOURNAL
OF STUDENT
SCHOLARSHIP

How Can Robotics, Particularly Ai-Enabled and Bionic Systems, Address Productivity Problems Associated With Population Aging?

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ABSTRACT

The world is suffering from several problems, the lack of natural resources, increasing temperature, air pollution etc. But under these natural problems, there is one problem which has no connection to nature, it only connects to humans: fertility decline. This problem brings to an ultimate problem: Aging problem. A workforce decrease caused by an aging population will ultimately lead to decreased productivity and greater pressure on elder care and medical resources (de Meijer et al., 2013; Maestas et al., 2023). Although discussions of future productivity often focus on factors such as resource constraints, changing market conditions, and technological development, demographic change represents another major challenge. Population aging can slow employment growth and labor productivity, thereby reducing economic growth (Maestas et al., 2023).

INTRODUCTION

Although discussions of future productivity often focus on factors such as resource constraints, changing market conditions, and technological development, demographic change represents another major challenge. Population aging can slow employment growth and labor productivity, thereby reducing economic growth (Maestas et al., 2023).

Global fertility has declined substantially over the past several decades. The global fertility rate stood at approximately 2.25 births per woman in 2024, compared with 3.31 in 1990 and much higher levels in previous decades. More than half of countries and areas now have fertility rates below the replacement level of approximately 2.1 births per woman, while nearly one-fifth have fertility rates below 1.4 (United Nations Department of Economic and Social Affairs [UN DESA], 2024) and fertility is exceptionally low in countries such as China and the Republic of Korea. These trends are projected to continue: 76% of countries and territories are expected to have fertility below replacement level by 2050, increasing to 97% by 2100 (GBD 2021 Fertility and Forecasting Collaborators, 2024). The causes of this decline are complex, including economic constraints(see section 3), and lie largely beyond the scope of this review.

Countries like China and Korea are experiencing exceptionally low fertility rates (UN DESA, 2024). The GBD 2021 Fertility and Forecasting Collaborators (2024) predict that 76% of countries and territories will have fertility rates below replacement level by 2050, increasing to 97% by 2100.

Declining fertility influences the labor force and productivity with a time lag, as smaller birth cohorts gradually reach working age (Aksoy et al., 2019; Bloom et al., 2010). The impact is also distributed unevenly across age groups. Middle-aged workers are responsible for much of the physically demanding production work. As smaller cohorts enter the workforce, the supply of these workers contracts, increasing pressure on firms to maintain output with fewer employees (Acemoglu & Restrepo, 2022). Acemoglu and Restrepo contend that this scarcity incentivizes the adoption of technologies that substitute for limited labor or enhance the productivity of remaining workers. Their findings indicate that countries experiencing more rapid population aging adopt industrial robots and other automation technologies more intensively, particularly in industries dependent on middle-aged workers for manual production tasks. This technological response may partially offset the anticipated negative effect of aging on output. This observation does not contradict Maestas et al. (2023), whose estimate for U.S. states reflects a net effect that already incorporates firm-level adjustments made during the study period, whereas Acemoglu and Restrepo specifically identify automation as one such adjustment. The extent to which technology can compensate for the productivity costs of aging remains unresolved, and this review seeks to address that question.

Automation is already being used to address demographic challenges, not just as a future possibility (Acemoglu & Restrepo, 2022). The way automation is implemented is important. Simply replacing workers can lower employment and wages in local labor markets (Acemoglu & Restrepo, 2020). In contrast, combining reskilling with human-robot collaboration aims to boost productivity while keeping workers employed. Research on collaborative robots has looked at how smooth human-cobot interaction affects job performance and satisfaction (Paliga, 2023), as well as how collaborative robots, instead of those that replace workers, influence workers' skills (Dornelles et al., 2023).

This review examines the potential of AI-powered robotics and bionic technologies to mitigate productivity declines associated with an aging workforce. It synthesizes research from three primary domains: the economics of population aging, robotics and artificial intelligence, and occupational exoskeletons. Current evidence indicates that these technologies are more likely to augment workers rather than replace them, primarily through two mechanisms. AI systems can reorganize work by reallocating tasks and redefining job roles, while bionic technologies such as exoskeletons enable individuals to perform existing tasks with reduced physical exertion. For example, a plasterer may continue plastering with less physical strain. Nevertheless, empirical support for both approaches remains limited. Although short-term and laboratory studies yield promising results, there is a lack of long-term field data, and findings regarding exoskeletons are sometimes inconsistent. The broader impact of these technologies on productivity will also depend on their accessibility and affordability for businesses and workers.

The remainder of this paper is organized as follows. Section 2 describes the systematic literature review process used to identify and synthesize relevant research. Section 3 examines the demographic and

economic consequences of population aging, establishing the labor and productivity challenges that motivate the review. Section 4 then examines robotics and recent applications of AI in robotics, with particular attention to industrial automation and human-robot collaboration. Section 5 examines bionic technologies, particularly technologies designed to augment human physical capabilities. Finally, Section 6 integrates the findings across these areas, discusses their implications and limitations, and presents directions for future research.

METHOD: SYSTEMATIC LITERATURE REVIEW PROCESS

This paper uses a systematic literature review to examine how robotics, artificial intelligence, and bionic technologies may help address productivity challenges associated with population aging. The review was organized around three bodies of literature identified as directly relevant to this question: research on the economic and labor-market consequences of population aging; research on robotics and AI-enabled robotics; and research on bionic technologies, particularly occupational exoskeletons. The review process was designed to make the identification, selection, and organization of sources transparent and reproducible, consistent with established guidance for systematic literature reviews (Page et al., 2021; Snyder, 2019).

Literature searches were conducted primarily through Google Scholar and PubMed, supplemented by searches of reference lists and papers that cited particularly relevant articles. Searches were conducted between 12th to 24th July 2026 Because the three areas draw from different academic disciplines, several sets of search terms were used.

For the population-aging literature, searches included combinations of terms such as “population aging productivity,” “aging workforce,” “fertility decline labor force,” “demographic aging economic growth,” “aging manufacturing workforce,” and “aging automation.” For robotics and AI, searches included “industrial robotics,” “human-robot collaboration,” “collaborative robots,” “cobots manufacturing,” “AI for robotics,” “AI-enabled robotics,” “machine learning robotics,” and “robotics manufacturing productivity.” Searches for the bionics literature included terms such as “bionics,” “occupational exoskeleton,” “industrial exoskeleton,” “wearable robotics,” “exoskeleton manufacturing,” “worker augmentation,” and “exoskeleton productivity.”

No single publication-year restriction was imposed across all three literatures. Older studies were retained where they provided important theoretical, economic, or technological foundations. However, greater emphasis was placed on recent publications in AI, robotics, and bionics because the capabilities and applications of these technologies are developing rapidly. Claude was used during the initial sourcing process to suggest potentially relevant keywords and publications. AI-generated suggestions were treated only as leads for further searching. Each source included in the review was independently located and checked through an academic database, journal website, or institutional source before being considered for inclusion. No source was included solely on the basis of an AI-generated recommendation.

The use of AI tools in this review is described in the Declaration of AI Use.

Sources were first assessed based on their titles and abstracts. Studies were retained when they directly contributed to understanding at least one part of the paper's central question: how demographic aging affects labor supply and productivity, how robotics and AI can automate or augment work, or how bionic technologies can extend workers' physical capabilities.

The review primarily included peer-reviewed journal articles, systematic reviews, and empirical studies. Authoritative statistical and policy sources, including publications from organizations such as the United Nations and World Bank, were also included where demographic or labor-market statistics were required. Sources were excluded when they were duplicates, lacked a clear relationship to the research question, consisted primarily of commercial or promotional claims, or discussed a technology without providing evidence relevant to its capabilities, workplace applications, productivity implications, or effects on workers.

For rapidly developing technologies, recent empirical studies and systematic reviews were prioritized. Earlier studies were retained when they were influential or necessary for explaining the development of the literature. This approach allowed the review to capture both established findings and more recent technological developments.

After the initial search, relevant papers were also used for backward and forward citation searching. Their reference lists were examined for earlier studies that may not have appeared in the original keyword searches, while Google Scholar's citation function was used to identify more recent research building on important papers. This process continued until additional searches largely produced sources that were already identified or did not materially extend the themes emerging from the review.

All potentially relevant papers were recorded in a literature-review tracker made in Microsoft Excel, while bibliographic information and available full texts were managed using Zotero. For each paper, the tracker recorded the citation, publication year, research area, research question, study setting, methodology, technology examined, principal findings, relevance to productivity or workforce aging, and major limitations.With Claude AI and Zotero, I can collect sources from different fields and methods. Also, I have 30 backup sources ready to use for any purpose. These sources are closely related to my essays and can be used if I need more detail or additional sources.

The papers were then classified into the three literature groups used to structure the review. The first group examined the demographic and economic consequences of population aging. The second examined robotics, including conventional industrial automation, human-robot collaboration, and recent applications of artificial intelligence to robotics. The third examined bionic technologies, particularly occupational exoskeletons and other wearable technologies intended to augment physical capabilities.

Rather than simply summarizing each article individually, the final synthesis compared findings within and across these three areas. Particular attention was given to evidence concerning labor shortages, productivity, worker capabilities, human-machine collaboration, technological limitations, and the extent to which automation substitutes for or complements human labor.

Before submission, the final review should additionally report: the total number of records initially identified, the number removed as duplicates, the number excluded after title and abstract screening, the number assessed in full text, and the final number of studies included. These numbers can be presented in a simple PRISMA-style flow diagram to make the search and screening process easier to replicate (Page et al., 2021)

The following sections present the findings in the same sequence as the problem addressed by this paper. Section 3 first establishes the problem that the technologies examined later in the review are intended to address. It reviews evidence on declining fertility, population aging, changes in the size and composition of the workforce, and their implications for economic growth and productivity. Establishing these demographic and economic pressures provides the basis for asking what technological responses may become increasingly important as labor becomes scarcer and workforces become older.

Section 4 then turns from the problem to one potential response by examining developments in robotics and AI-enabled robotics. It considers how robots are currently being used to automate work, how advances in artificial intelligence are expanding what robots can perform, and how human-robot collaboration may allow technology to complement rather than simply replace human workers. Section 5 examines a related but distinct technological response: bionics. Whereas robotics can transfer tasks from humans to machines, bionic technologies such as occupational exoskeletons can directly augment workers' existing capabilities. Together, these three literatures provide the basis for evaluating how technological development may respond to the labor and productivity pressures created by population aging.

THE AGING PROBLEM

People always trust that a solution is made for addressing a problem. The development of automation, in some cases, can be described as a solution for “saving” or “protecting” the world, and the problem is, the aging problem. But what is the aging problem? Statistics from the United Nations indicate that fertility has declined in many countries (United Nations Department of Economic and Social Affairs [UN DESA], 2024). The global population is projected to peak at approximately 10.3 billion in the mid-2080s (up from 8.2 billion in 2024) before slowly declining to around 10.2 billion by the end of the century (UN DESA, 2024). The probability of the global population peaking within this century is estimated at about 80%, up from roughly 30% a decade earlier, driven partly by fertility falling faster than previously expected in several populous countries, including China (UN DESA, 2024). Population aging continues to have major economic effects. Maestas et al. (2023) studied U.S. states from 1980 to 2010 and separated the impact of each state's existing age structure from the effects of younger people moving to faster-growing states. They found that when the share of people aged 60 and over rises by 10%, GDP per capita drops by 5.5%. About two-thirds of this drop comes from slower growth in labor productivity, and the rest is due to slower employment growth. Since demand stays steady even as the population ages, keeping the economy growing with fewer and older workers means finding ways to boost the productivity of those who remain.

Due to the aging problem, the average age of the workforce will increase, and older workers can face greater difficulty with highly physically demanding work because physical work capacity generally declines with age (Kenny et al., 2008). If job demands are not adapted to workers' physical capacity, this can create additional physical strain (Kenny et al., 2008). Newer forms of automation are designed to work with people rather than simply replace them . Those techniques include AI and bionics, which are increasingly being incorporated into human-robot collaboration and worker-assistance technologies (Dhanda et al., 2025; Howard et al., 2020).

AI has already started to influence many different kinds of work. An International Monetary Fund analysis estimates that almost 40% of global employment is exposed to AI (Cazzaniga et al., 2024). This share varies with the level of development: about 60% in advanced economies, where many jobs involve cognitive tasks, compared with 40% in emerging markets and 26% in low-income countries (Cazzaniga et al., 2024). These percentages show how widely AI may affect work, although being exposed to AI does not necessarily mean that a job will be replaced (Cazzaniga et al., 2024).

Bionics draws inspiration from the movement and functionality of living organisms, including both humans and animals (Lu, 2004). In contrast, artificial intelligence (AI) enables robots to perceive, learn, and make decisions (Wang et al., 2024). AI can be conceptualized as the robot's brain, while bionics represents its physical capabilities. The integration of these technologies facilitates collaborative interactions between robots and humans, rather than replacing human workers (Breque et al., 2021; Dhanda et al., 2025). Subsequent sections will examine the mechanisms and benefits of human-robot collaboration in greater detail.

Before talking about automation and robots, the first thing is to analyze the aging problem, as the first paragraph mentions. The fertility rate is dropping in many countries (UN DESA, 2024), contributing to an increase in the average age of their populations over time. But demand won't disappear simply because the population becomes older. That's the reason why society needs to explore automation. As discussed above, Maestas et al. (2023) show that population aging can reduce GDP per person through both slower employment growth and slower labor productivity growth. Society really needs to find more opportunities to increase productivity to meet rising demand and a shrinking workforce and ensure economic growth.

Economic growth is not the only consideration. Automation can create job insecurity among workers who fear that robots or AI may take over some of their tasks or jobs, and these effects may be distributed unequally across workers (Acemoglu & Restrepo, 2020; Cazzaniga et al., 2024). Such concerns matter because unemployment substantially lowers well-being (Clark & Oswald, 1994).

If automation were to be stopped, the productivity gains linked to it would be lost (Autor, 2015), which would constitute a significant problem for those making decisions. A possible solution would be to use automation to supplement workers rather than merely replacing them, though this method does not guarantee that all jobs will be preserved (Acemoglu & Restrepo, 2020; Autor, 2015). At present, robots

are still limited in their ability to adjust, in their perceptual capabilities, and in their capacity to operate safely among humans in changing environments. Progress in artificial intelligence and bionics could help overcome some of these difficulties by allowing robots to interpret situations more effectively, learn from experience, and work together with human workers (Dhanda et al., 2025; Wang et al., 2024).

One approach to addressing an aging population is to promote higher birth rates. Cowan and Wyndham Douds (2022) examined Alaska's Permanent Fund Dividend, which provides annual cash payments to all eligible residents, including children. The payment amount varies each year and is not contingent upon recipients' actions. Their findings indicate that following larger payments, birth rates increased over the subsequent one to two years, particularly among individuals with fewer resources. These results suggest that financial incentives influence reproductive decisions. However, increasing birth rates will not resolve the current labor shortage in the short term, as children born now will not enter the workforce for approximately twenty years. Given the immediacy of the shortage, it is also necessary to implement technologies that enhance the productivity of the existing workforce.

ROBOTICS

A way of dealing with population ageing is to increase fertility. Cowan and Wyndham Douds (2022) looked into the Alaska Permanent Fund Dividend, which is an annual cash payment given to all eligible residents, including children, and the amount paid each year is not linked to the recipients' actions. They discovered that fertility increased in the year or two following bigger payments, with the most significant increases being seen among socioeconomically disadvantaged groups, indicating that financial constraints do affect the decision to have children. Nevertheless, boosting fertility cannot address the labour shortage mentioned above in the short term since a child born today will not begin working for about twenty years, while the shortage of working-age labour is already occurring. Technologies that improve the productivity of the current workforce are therefore a necessary complement.

In manufacturing, a central aim of current robotics is collaboration with human workers (Dhanda et al., 2025). Robots can now take over some of the dangerous, heavy, or highly repetitive tasks that workers once performed (Dhanda et al., 2025). The rise of robotics can address worker scarcity, but it can also displace some tasks and jobs, so its employment effects are not entirely one-sided (Autor, 2015; Acemoglu & Restrepo, 2020). Dhanda et al. (2025) describe human-robot collaboration as combining human flexibility and decision-making with robotic precision, consistency, and repeatability. In this sense, humans and robots can be complementary rather than simply competing. In many settings, companies still rely on human capabilities that are difficult to automate fully, particularly adaptability, problem solving, and judgment (Autor, 2015).

Robots can raise productivity and output, which may lower costs and expand demand. However, whether this creates additional jobs depends on whether these productivity and scale effects are large enough to offset the tasks displaced by automation (Autor, 2015; Acemoglu & Restrepo, 2020). Mechanization began in British textile production in the late eighteenth century (Allen, 2009) and later spread to

industries like iron and automobile manufacturing. Each time, it replaced some jobs but also created new ones (Autor, 2015), while improving output and helping companies reach more markets. Autor (2015), for example, describes how ATMs reduced the number of tellers required in each bank branch, but lower operating costs also contributed to banks opening more branches. Teller jobs did not simply disappear; the work increasingly shifted toward customer-facing tasks. The example shows how automation can change the kind of work people do rather than simply eliminate it.

As automation spreads, many manual jobs are being redesigned. In the human-robot collaboration model described by Dhanda et al. (2025), workers concentrate on tasks that require judgment and creativity and intervene when robots need adaptation or when high-precision or complex work requires supervision (Autor, 2015; Dhanda et al., 2025).

There is no single answer to which kind of robot or assistive technology is best for cooperating with human workers. Take an exoskeleton as an example. According to de Vries' research, exoskeletons take an important role in plastering work. When workers perform plastering with an exoskeleton, their shoulder muscle activity and subjective fatigue are lower than before, meaning they use less energy to finish work they previously expended more energy on (de Vries et al., 2021). This suggests that an arm-support exoskeleton can make some physically demanding plastering tasks easier to perform. But other research by Kim tested exoskeletons on automotive assembly workers across nine manufacturing facilities. Across the facilities, the exoskeleton and control groups did not differ significantly in overall perceived work intensity or musculoskeletal discomfort, although some facility-specific improvements appeared (Kim et al., 2021). This suggests that positive short-term results do not automatically translate into consistent long-term effects in real workplaces (Howard et al., 2020; Kim et al., 2021). So the function of the exoskeleton is still being examined through long-term work, and how to use it remains questionable. But, no doubt, an exoskeleton can have an effect in certain circumstances.

4.1. AI in Robotics

As a human, what are the three main parts that are extremely important for our body? arms, legs, and of course, brain. The human brain controls basically all the actions humans make; receives all messages and information both within the body and outside the body; controls every aspect of our life. Now, the arms and legs have already been introduced in the previous part. It's time to talk about the brain.

Traditional industrial robots are really good at handling repetitive, routine tasks with clear instructions (Autor, 2015). But when things get unpredictable, they kinda struggle. To handle more complex stuff, robots need to be adaptable, not just follow preset commands. AI helps make robots more flexible when it comes to sensing, learning, and making decisions (Dhanda et al., 2025; Wang et al., 2024).

AI enables robots to learn from demonstrated actions rather than only execute pre-programmed sequences, so humans can demonstrate a task and turn this into data that a robot can learn from rather than

specify every step of it (Argall et al., 2009). Using this data, the robot can then learn to complete complicated actions on its own. AI can also receive feedback on every task it performs. This feedback-based learning is central to reinforcement learning, in which an agent learns behavior through rewards or other feedback from its actions (Kober et al., 2013). The key difference is that humans need to experience something, and from then, process that experience before they are able to learn it. Humans then undergo this learning process in a slow, experience-by-experience manner.

Robots do not learn instantaneously, and reinforcement learning in physical systems can require large amounts of training and careful attention to safety. However, training can sometimes be accelerated through simulation and repeated trials before a learned policy is transferred to a physical robot (Kober et al., 2013; Kaufmann et al., 2023). This can make some forms of robotic learning more scalable than relying only on physical trial-and-error. Thus, for robots that leverage artificial intelligence, remembering and analyzing feedback can help them avoid repeating unsuccessful actions and make better predictions next time (Kober et al., 2013). Therefore, the addition of AI to robotics can bring enormous improvements in automation.

The cooperation between AI and robots has already produced strong results in some specific tasks. Kaufmann et al. (2023) show how their system, Swift, learned to fly a racing drone using deep reinforcement learning. They trained Swift mostly in simulation before testing it on a real drone, which helped lower costs and risks from trial and error. In head-to-head races, Swift beat three human champions, including two world champions, and set the fastest race time on the track (Kaufmann et al., 2023).

However, this result only shows what is possible in a very specific and controlled task. Although it proves that learned control can match or beat expert humans, it does not directly show that AI improves productivity in real workplaces. There is still little evidence that AI-powered robots boost productivity in actual manufacturing, so later applications should be considered with this in mind.

AI is not only useful for operating robots through fixed code. In some tightly defined perception and control tasks, learning-based systems can operate at very high speed and accuracy (Kaufmann et al., 2023; Salinas-Martínez et al., 2024). Dhanda et al. (2025) argue that AI-enabled perception and decision systems can support human-robot collaboration in manufacturing by allowing robots to respond more flexibly to changing tasks and human actions. The robot shows the advantages of AI in high-speed work. This can reduce the amount of continuous monitoring and calculation that workers need to perform, although the effect depends on how the system is designed and used (Dhanda et al., 2025). This not only shows cooperation among humans, robots, and AI but also demonstrates advances in the field of cognition. With high-speed real-time computation, robots can enhance the efficiency of collaborative work. It means workers do not need to spend all of their time and energy on becoming the robot's brain. AI is particularly useful where rapid, repeated computation is required, while human workers retain strengths in judgment, flexibility, and adaptation (Autor, 2015; Dhanda et al., 2025).

Efficiency is not merely a function of the capabilities of robots but also depends on how tasks are divided between robots and people. Gao et al. (2025) have proposed a dynamic task-allocation system which makes use of human body modeling and motion recognition in order to monitor workers, estimate the amount of work they are doing, and modify task assignments as the situation changes. Incorporating AI into the allocation process can help to balance productivity with ergonomic safety. For instance, Baratta et al. (2025) found that when both ergonomic and productivity factors were taken into account in making task decisions, this resulted in better task times and an improvement in ergonomic safety.

Salinas-Martínez and colleagues in 2024 examined a decentralised human-machine interaction platform designed for use in the manufacture of printed circuit boards (PCBs). The system incorporated two gesture-recognition devices (the Leap Motion and the Tap Strap), a voice-recognition system (Cellya), and biometric multi-user access control. In this case study, both of the two gesture devices achieved an average recognition accuracy of 95% or higher. In contrast, the reliability of voice recognition was lower, with a word error rate of approximately 22%. Therefore, in this situation, gesture input is much more reliable than voice input.

The fourth modality, physiological sensing, is different in kind from the first three. Physiological sensing can detect workers' physiological signals and estimate their internal status. Common indicators include electromyography (EMG, muscle activity and fatigue), heart-rate measures, eye movement, and electroencephalography (EEG) (Wang et al., 2024). Visual, auditory, and haptic channels primarily rely on human workers to actively convey information, such as gestures or spoken instructions. Physiological perception enables robots to infer some worker states more passively. It doesn't require human workers to pay the same amount of extra attention to communicating with the robot. Wang et al. (2024) place these modalities within a perception-cognition-action framework and argue that combining multiple modalities can support safer and more effective human-robot interaction.

The benefits of this difference are that it changes the directionality of human-machine communication. In the past, human workers had to give orders to the robot and let it execute them. But robots equipped with physiological sensing can increasingly be designed to detect indicators such as worker fatigue or cognitive load and adjust their behavior in response (Wang et al., 2024). Wearable sensing research also shows that workers’ physical fatigue can be estimated using multimodal sensor data and machine-learning models (Mohapatra et al., 2024). The direction is therefore toward robots that adapt more to the worker's state, rather than requiring the worker to adapt entirely to the robot.

Last but not least, the job redesign. Kaasinen introduced a concept called Operator 4.0. Operator 4.0 aims to let robots strengthen human workers but not replace them. It advocates that human workers can be developed and strengthened by high-tech skills. Instead of letting robots purely replace human workers and create a huge unemployment population, Operator 4.0 redesigns human workers' jobs toward an enhanced operator. This is not merely a conceptual proposal. Kaasinen et al. (2019) had three Operator 4.0 solutions assessed by 118 shop stewards from different factories, and the results showed high expectations toward a participatory-design solution that allowed workers to take an active role in shaping their work and training (Kaasinen et al., 2019).

A related broader idea introduced by the European Commission is Industry 5.0, which emphasizes three main principles: human-centricity, sustainability, and resilience (Breque et al., 2021). Compared with Industry 4.0's strong focus on digitalization and production efficiency, Industry 5.0 places greater emphasis on worker well-being and on designing technology around human needs (Breque et al., 2021). In this vision, robots take on repetitive work while humans concentrate on more creative tasks (Autor, 2015; Breque et al., 2021).

4.2. Bionics

As mentioned in Section 3, bionics uses biological structures and functions (Lu, 2004). It has many applications, such as bio-inspired robots and wearable devices that help the human body, like exoskeletons and prostheses. Bionics works together with AI. While AI learns behavior from data and training, bionics offers physical structures and mechanisms that have already been shaped by evolution. Because human movement is well suited to many manufacturing tasks, copying human actions is a logical place to start.

Bionics are not limited to mimicking only humans. As Lu (2004) point out, living systems, having developed over billions of years through evolution, offer a far broader range of proven designs than those which have been created by humans. Rather than starting from scratch, bionic design makes use of structures and mechanisms that nature has already tested. Exoskeletons apply this same principle by replicating the structure of the bodies they are intended to assist. The following section examines exoskeletons that are used for work.

Industrial exoskeletons are one of the most developed applications of wearable robotics for physically demanding work (de Looze et al., 2016; Howard et al., 2020). According to the European Agency for Safety and Health at Work, roughly three out of five EU workers report some form of musculoskeletal complaint, making musculoskeletal disorders one of the most common work-related health problems in Europe (European Agency for Safety and Health at Work [EU-OSHA], 2019). These problems are particularly relevant to physically demanding work involving repetitive movement, heavy loads, or awkward postures (EU-OSHA, 2019). This is one reason industrial exoskeletons are being explored as a way to reduce physical loading in demanding tasks (de Looze et al., 2016; Howard et al., 2020).

The most compelling evidence regarding its benefits comes from studies focused on specific tasks. For instance, de Vries et al. (2021) found that using a passive arm support exoskeleton could reduce the intensity of shoulder muscle activity and alleviate fatigue during plastering work. However, the results of long-term studies are less promising. Kim et al. (2021) conducted a 18-month follow-up survey of automotive assembly workers in nine factories who were performing heavy lifting tasks and using arm support exoskeletons. The results showed that there was no significant difference in feedback regarding the degree of physical effort or musculoskeletal discomfort between workers using the exoskeleton and those not using it. Although some minor improvements were observed in certain factories. This indicates

that in actual working environments, short-term positive effects do not necessarily translate into lasting benefits (Howard et al., 2020; Kim et al., 2021).

So far, research on older workers has focused on their expectations instead of actual results. In an online survey of manual workers aged 55 and above, Khanpour et al. (2024) found that learning about exoskeletons led to a small, but not statistically significant, increase in their confidence at work. Since the study looked at expectations rather than real use, it points to possible acceptance of exoskeletons among older workers, but not necessarily better work ability.

A key practical question is which types of work exoskeletons actually improve (de Vries et al., 2021). In a Delphi study with 18 experts from academia, industry, and government who had knowledge in business, technology, organization, policy and regulation, ergonomics and safety, and end use, Mahmud et al. (2022) examined the challenges and possible solutions for adopting exoskeletons in construction.

The issue of using exoskeletons is divided into several parts. First, the price: each exoskeleton can cost between 5,000 and 100,000 dollars (Mahmud et al., 2022). It's definitely not affordable for most individual workers, and it can also be difficult for companies to buy exoskeletons for many workers because they have to cover the purchase cost as well as repairs and maintenance (Mahmud et al., 2022). Second, the privacy problem also becomes one of the main issues. Sensor-equipped wearable robots can collect movement, performance, and potentially health-related data about the user, creating questions about how this information is stored, shared, and protected (Kapeller et al., 2020). These stats can be sensitive and need to be secure. How to use, share, and protect this data and information is therefore a concern that requires further consideration (Kapeller et al., 2020).

AI makes it possible to redesign jobs. The Operator 4.0 concept uses technology to support and improve human workers, not replace them. It focuses on expanding workers' abilities with digital and robotic tools. Kaasinen et al. (2019) put this idea into practice by asking 118 shop stewards from different factories to evaluate three Operator 4.0 solutions. The respondents were especially interested in a participatory design based on a virtual factory, which lets workers help shape their own work environment.

To address these problems, Golabchi et al. (2023) developed a six-stage adoption framework through a focus group involving eight research experts and eight industry professionals. This six-stage adoption framework addresses many of the problems stated before. The first stage is feasibility assessment. The framework argues that exoskeletons can be considered similar to personal protective equipment and that higher-level controls, such as eliminating or redesigning the hazardous task, should therefore be considered before exoskeleton adoption (Golabchi et al., 2023). Even if a company wants to accept and use an exoskeleton, the decision about which workers should use it also matters. Golabchi points out that if no one can correctly identify which project can truly benefit from using an exoskeleton, financial and resource misallocation can cause significant damage (Golabchi et al., 2023).

It is important to assess feasibility because the return on investing in exoskeletons is not always clear. While companies may hope for long-term gains from this advanced technology, they also need to see a reasonable short-term payback. This risk can be especially challenging for small businesses.

Second, task identification directly answers the question of who should be prioritized. The most direct tool is the REBA scoring system, which combines factors such as the number of workers exposed to risk, the level and quantity of risk associated with the task itself, energy expenditure, workload, and posture (Golabchi et al., 2023). Workers themselves are involved in this scoring process, since they have the most familiarity with their daily tasks and are best positioned to identify where the risk actually lies (Golabchi et al., 2023). At the same time, existing reports of worker discomfort or injury, Physical Demand Analysis (PDA) reports, and records of workers' pre-existing medical conditions are reviewed, with an ergonomics expert consulted if necessary (Golabchi et al., 2023).

Beyond task intensity, frequency is the other criterion used to determine priority. The more physically demanding a task is, the less time is needed to justify considering exoskeleton use, because concentration of forces on the body contributes to work-related musculoskeletal disorders. But even a task that is not especially strenuous can still justify consideration if it is repeated often enough, since prolonged repetitive movement can also contribute to these disorders (Golabchi et al., 2023). Frequency is easier to calculate for cyclic tasks, such as those in manufacturing, but harder to pin down in more dynamic environments like construction, where the mix of tasks changes from day to day (Golabchi et al., 2023).

Third is the choice of exoskeleton. Although the general purpose is physical assistance, the body part that needs support varies depending on the job. This ranges from the specific body part to be supported, such as the lower back, shoulders, or lower limbs, to the choice between active and passive systems. Active systems provide powered assistance but are generally more complicated, whereas passive systems rely on mechanical structures and can be lighter and simpler to use (de Looze et al., 2016). Also, after finishing choosing the type of exoskeleton, the company needs to measure its size to make sure it fits and is easy to wear. The device should match workers' body dimensions and existing health conditions, and Golabchi et al. (2023) recommend consulting occupational-health professionals where necessary.

Last but not least. Even after a task is deemed high priority, individual workers may still be screened out if the exoskeleton does not match their body measurements or would aggravate an existing condition such as back pain or joint problems, adding a layer of individual-level exclusion on top of task-level prioritization. And when the number of exoskeletons available does not cover every worker who could benefit, companies are left to work out a shared-use schedule, turning access itself into something that has to be rationed and managed rather than guaranteed (Golabchi et al., 2023).This benefit goes beyond just helping people work with robots. It can also help workers who might otherwise leave physically demanding jobs.

Talking about how bionics help increase the workforce. The development of bionics, especially exoskeletons, not only has the potential to bring workers into physically demanding jobs but may also increase the length of each worker’s working life. Valentin mentions that with the development of bionics,

many older workers start to rethink their retirement age. Valentin and Choi (2022) found that older workers in physically demanding jobs reported higher expected retirement ages and stronger intentions to delay retirement when told that exoskeleton assistance could be available. The reaction of workers shows that the development of automation, especially when combined with bionics, may help mitigate some effects of workforce aging, although the study measures workers' intentions rather than actual retirement behavior.

These findings point to two separate dimensions of redesign: the physical cost of the task (de Vries et al., 2021) and the worker's own sense of capability and commitment to staying in the job (Khanpour et al., 2024; Valentin & Choi, 2022). It is worth keeping them distinct rather than treating exoskeleton use as a single, uniform improvement. Neither dimension changes what the job actually consists of: the plasterer is still plastering, the manual laborer is still doing manual labor. This is a narrower form of job redesign than the one AI enables elsewhere in this paper. Kaasinen's (2019) Operator 4.0 concept reshapes work by reallocating or supporting tasks so that workers can take on more active, supervisory, or developmental roles. Bionic technologies like exoskeletons do not reallocate tasks in this way; they redesign the same job by lowering its physical and psychological cost, rather than changing its content.

DISCUSSION AND CONCLUSION

This paper has been concerned with how AI and bionics can reduce some of the effects of population aging on labor shortages while also creating more valuable forms of work. The aim of development automation is not to replace humans and create a huge unemployment gap. The argument developed here is instead that automation can be designed to support and cooperate with human workers. Both AI and bionics reach this purpose but the methods are different.

AI and bionics have the same objective, but they achieve it in different ways (Table 2). AI systems alter the way work is carried out by redistributing the tasks. For instance, dynamic task allocation makes use of information concerning the workers and the production process to modify workloads (Baratta et al., 2025; Gao et al., 2025). The Operator 4.0 solutions, as investigated by Kaasinen et al. (2019), modify the roles of workers so that they can carry out more active, supervisory, or developmental tasks. In contrast, bionic technologies do not involve transferring tasks between people; instead they alter the job in two main ways: they reduce the physical effort required, since exoskeletons can decrease muscle usage and make certain tasks seem easier (de Vries et al., 2021), and they can enhance the sense of capability and commitment that workers have towards remaining in their jobs (Khanpour et al., 2024; Valentin & Choi, 2022). Nevertheless, these changes do not affect the essential nature of the job. For example, a plasterer still plasters and a manual labourer still performs manual labour. Therefore, "augmentation rather than replacement" can mean two things: it can refer to changing how tasks are shared, or to making the tasks less physically and mentally demanding.

But, the conclusion is limited and can't be used as a final conclusion, because the sources and information provided in this passage are preliminary and waiting for further discussion. The findings regarding self-efficacy reported by Khanpour et al. (2024) did not reach statistical significance. An 18-month field study by Kim et al. (2021) on arm-support exoskeletons used in automotive assembly lines found no consistent overall long-term differences between users and non-users, despite the positive short-term results reported in studies such as de Vries et al. (2021). This difference between promising short-term studies and limited long-term field evidence has also been identified as an important weakness in the wider industrial-exoskeleton literature (Howard et al., 2020). The claim that "bionic technology can reliably improve worker conditions" is therefore best understood as a hypothesis supported by early evidence, rather than a proven conclusion.

The allocation of resources and jobs during this passage needs further consideration. The price of an exoskeleton is expensive, ranging from approximately $5,000 to $100,000 depending on the system (Mahmud et al., 2022). However, it is incorrect to say that 91% of U.S. companies cannot afford an exoskeleton. Mahmud et al. (2022) instead report that around 91% of U.S. construction businesses have fewer than 20 employees, which helps explain why high purchase and maintenance costs can create a particularly large adoption barrier for smaller companies. It's hard to allocate the exoskeleton without further planning. Exoskeletons may therefore flow first to large enterprises capable of bearing the upfront costs, and within those enterprises, they may be directed toward the specific workers or tasks prioritized for implementation. The adoption framework proposed by Golabchi et al. (2023) offers a partial solution by using ergonomic risk assessment and participatory decision-making to systematically, rather than arbitrarily, allocate exoskeletons. However, the adoption of a systematic framework still hinges on organizational willingness; it does not resolve the underlying cost barriers (Golabchi et al., 2023; Mahmud et al., 2022). To ensure the benefits of bionic augmentation truly reach a broader population, cost-reduction mechanisms and standardized allocation criteria must be prioritized from the outset, rather than being treated as secondary issues.

This paper still has several limitations. Many conclusions concerning attitudes, confidence, and other self-reported outcomes come from small samples or short-term investigations. The case study on prosthetics (Schweitzer et al., 2018) involved only a single user and cannot be generalized. Most of the sources are directly from North America and Europe, and many of the applications reviewed are concentrated in manufacturing, construction, and automotive settings. Therefore, the extent to which these conclusions generalize to other regions, industries, and labor markets remains uncertain. Long-term real-world data such as those presented by Kim et al. (2021) remain scarce (Howard et al., 2020), limiting the extent to which the conclusions of this paper can be confidently generalized to long-term workforce planning.

Future research should first focus on obtaining more data from long-term, real-life experiments because this is one of the largest gaps in the current evidence (Howard et al., 2020). The field which still needs to be investigated is whether cost-reduction models such as subscription services alter adoption patterns among small and medium-sized enterprises, and whether the allocation framework proposed by Golabchi et al. (2023) can truly transform, in practice rather than merely in principle, who stands to benefit from

bionic technologies. Another thing worth exploring is inspired by the findings of Mohapatra et al. (2024), who found that their fatigue-prediction models performed better for workers represented in the training data and performed less accurately when predicting fatigue for new individuals. This raises the question of whether personalization mechanisms built into new sensing systems might give rise to a novel form of unequal benefit: one based not on income or firm size, but on whose data the organization has already collected.

The population aging described at the beginning of this article is not a distant prediction; demographic aging is already underway, and evidence suggests that it can reduce both employment growth and labor productivity (Maestas et al., 2023; UN DESA, 2024). The response cannot simply be to replace the workers who have left the workforce. The evidence reviewed here suggests that AI and bionics offer two distinct yet complementary approaches: AI does so by reorganizing task allocation and the nature of human-machine interaction, while bionics reduces the physical demands of tasks that still require human execution (Dhanda et al., 2025; de Vries et al., 2021; Gao et al., 2025). Neither path eliminates the need for workers. Instead, both can potentially contribute to making human work more productive and sustainable, although the strength of the evidence differs substantially across technologies and applications. However, this outcome is not guaranteed by technology alone. It hinges on evidence that is currently only partial and on distributional choices regarding costs, access, and allocation that have so far been made only incompletely. Realizing the productivity and societal benefits described here requires not only continued technological advancement but also careful attention to who actually has access to these technologies, rather than focusing solely on their efficacy.

Declaration of AI Use

Claude (Anthropic) was used at two stages of this work. During the literature search in July 2026, it suggested potential keywords and publications. These suggestions were treated only as leads: every source was independently located and checked through an academic database, journal website, or institutional source before being considered for inclusion, and no source was included solely on the basis of an AI-generated recommendation. During revision in September 2026, Claude was used to check cited claims against source abstracts. The author rewrote or reviewed all suggested text and made all decisions about screening, inclusion, data extraction, synthesis, and interpretation. Every citation in the final manuscript was checked by the author against its source document.

Acknowledgments

The author thanks Sam Nelberto Nicholas Quinto for research mentorship, detailed feedback on the argument and structure of this paper, and suggested revisions and sources, and Tessa Smith for careful feedback on the writing.

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