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The future of the labor force: higher cognition and more skills

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Skills can be categorized into two types: social-cognitive and sensory-physical. Sensory-physical skills, governed by explicit rules and transparent rationales, can be effectively executed through meticulous programming, with humans spontaneously trusting machines to perform these skills. In contrast, social-cognitive skills entail open interpretations reliant on personal opinions or intuition and are contextually and problem-dependent. The inherent complexity and subjectivity of social-cognitive skills, underscored by Polanyi's paradox and algorithm aversion, render machines less capable of replicating these skills. Thus, automation exerts differential impacts on these two skill sets. Moreover, the specialization of machines leads to expensive setup costs when switching tasks, whereas humans switch tasks with much less effort. The versatility in skills enables workers to adapt to a wide array of tasks, making them less prone to automation. Our empirical research, utilizing skill score data from O*NET and employment data from Employment and Wage Statistics (OEWS), validated the attributes of labor resistant to automation: the higher the scores of cognitive skills in a job, the lower its susceptibility to automation; workers endowed with a diverse array of skills experience an increase in their employment share. Conversely, jobs focusing on sensory-physical skills are more likely to be supplanted by machines. Therefore, workers can adopt two strategies to maintain a competitive edge. First, they can enhance cognitive skills, such as creativity and critical thinking. Second, they can develop diverse skills, encompassing both social-cognitive and sensory-physical skills. Specializing in a specific sensory-physical skill does not offer an advantage. Fostering a workforce proficient in cognitive skills and equipped with multifaceted skills, that is, flexible workers, becomes imperative. Our investigation represents the inaugural effort to empirically affirm the differential impact of automation on sensory-physical versus social-cognitive skills, thereby delineating the characteristics of irreplaceable labor. This analysis offers critical insights for individual career development and the strategic planning of national educational systems.

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Introduction

Automation and digitization are precipitating the displacement and evolution of occupations. Certain conventional occupations confront the peril of obsolescence, exemplified by Insurance Underwriters and Data Entry Keyers (Frey and Osborne, 2017). Burgeoning occupations, such as Blockchain Engineers, Digital Forensics Analysts, and Information Security Engineers, are flourishing. Lin (2011) observes that the designations of newly introduced Census occupations predominantly aggregate into two categories: those entailing avant-garde technologies, such as Web Developers or Database Administrators, and those about innovative personal services. Tasks in existing occupations are transforming due to the deconstruction of complex production processes, where automation supplants certain human-performed tasks while simultaneously engendering novel tasks necessitating human execution (Acemoglu et al., 2022). Rather than supplanting human labor, automation technology mainly seeks to augment and synergize with the human workforce by capitalizing on human comparative advantages (Igami, 2020; Acemoglu et al., 2022; Autor, 2015; Acemoglu and Restrepo, 2018). For example, a new trend is emerging among some middle-skill workers, who are integrating routine technical tasks with various non-routine tasks where workers exhibit comparative strengths, such as interpersonal interaction, flexibility, adaptability, and problem-solving acumen (Autor, 2015). These modern workers are referred to as "new artisans" (Holzer, 2015). Therefore, organizations and individuals should not fear the rise of machines but regard them as tools for enhancing productivity and forging the human–machine alliance (Moritz and Kate, 2022).

New tasks emerge as certain tasks are automated, altering the requisite skills. Two strategies exist for measuring labor skills. The human capital approach perceives education and training as investments in skill acquisition, yielding returns in the form of elevated wages. Owing to data accessibility, education proxy is extensively employed, yet it has faced substantial criticism for the assumption of static skills. Some scholars use wages as a proxy for skills, positing that occupations with high wages are deemed to be skill-intensive. However, such a coarse-grained distinction may overlook critical relationships between skills (Alabdulkareem et al., 2018). Focusing on job content offers an alternative measurement, suggesting that an individual's tasks should reflect their skill level. Therefore, the skill level is contingent upon the nature and content of the tasks required for the occupation (Martinaitis et al., 2021; Autor and Dorn, 2013; Autor et al., 2003). Autor and Dorn (2013) classify tasks into routine, manual, and abstract tasks to calculate routine task intensity, illustrating that the substitution of routine tasks by computers leads to the reassignment of a majority of middle-skill labor primarily engaged in routine tasks to lower-skilled service occupations, elucidating the employment polarization and growth of low-skilled service occupations in the United States from 1980 to 2005. Based on task manual flexibility and cognition, Gong (2023) builds a machine endowment cost model to examine the economic allocation of tasks between humans and machines. Alabdulkareem et al. (2018) further dissect tasks into skills, utilizing the O*NET data on the importance of workplace skills, knowledge, abilities, and some generalized work activities and employing unsupervised clustering techniques from network science. They discover that skills bifurcate into social-cognitive and sensory-physical sets, providing a new interpretation of the employment polarization at a fine-grain level. Building upon the insights of Alabdulkareem et al. (2018), our inquiry centers on discerning the directional shifts in workers' skills within the United States in the context of the ongoing technological revolution.

Literature review and research hypotheses

The advancements in automation are poised to disrupt the labor market substantially (Dahlin, 2019). The application of technology may lead to the displacement of some workers while concurrently engendering new employment opportunities and demands, necessitating other workers to develop, maintain, and innovate these technologies. Hence, the consequences of technology are multifaceted. There are three predominant perspectives: deskilling, upskilling, and reskilling.

The deskilling perspective contends that the decomposition and delegation of originally complex production tasks to robots simplifies these tasks for laborers over time, resulting in a decline in worker skills (Manyika et al., 2017; Noble, 2017). The upskilling perspective holds that technological transformation motivates workers to enhance their skills. Technology favor skilled labor (e.g., those with higher education, abilities, and experience) over unskilled labor. Reskilling posits that technology spurs workers to learn new skills to adapt to automation requirements. The deskilling and upskilling are not mutually exclusive. In a report for the European Parliament, the Panel for the Future of Science and Technology (STOA) (2021) underscores that technology impacts the distribution of tasks within jobs. While technology may aid in skill enhancement and elevate the quality of work, it can also lead to deskilling, creating low-paid and low-autonomy work. The deconstruction of originally complex production tasks, now performed by robots, liberates workers from tedious, repetitive routine tasks, redirecting them to more flexible positions, which demand higher non-routine skills (Ge, Sun, and Zhao, 2021; Downey, 2021). Therefore, from the perspective of task routineness, technology leads to deskilling in routine tasks and upskilling in non-routine tasks. Using unsupervised clustering techniques, Alabdulkareem et al. (2018) discover two skill sets: sensory-physical and social-cognitive. We summarize the characteristics of sensory-physical skills and social-cognitive skills in Table 1. Our investigation seeks to explore the impacts of automation on these two skill sets.

Table 1 Key characteristics of sensory-physical and social-cognitive skills.

Skill sets	Characteristics	Description
Sensory-Physical Skills	Physical Interaction	Engaging in direct operation and control of physical objects, such as machines, tools, and equipment.
	Sensory Sensitivity	Utilizing senses like vision, hearing, and touch to gather information and respond.
	Precision Control	Requiring high control accuracy and hand-eye coordination during task execution.
	Physical Capabilities	Including strength, endurance, and balance.
Social-Cognitive Skills	Cognitive Processing	Involving understanding, analyzing, evaluating, and utilizing information.
	Interpersonal Interaction	Emphasizing effective communication, collaboration, and negotiation with others.
	Problem Solving	Requiring creative and critical thinking to address complex problems.
	Resource Management	Involving the efficient management of time, materials, and personnel resources.
	Learning Ability	Including active learning and applying learning strategies to adapt to new information and environments.

A skill becomes a candidate for automation when it entails repeatable actions or following some logical sequence. For instance, control precision relies on controls' rapid and recurrent adjustment. The repetitive nature of this ability suggests it is readily codifiable, and machines hold a comparative advantage in speed of execution (Josten and Lordan, 2022). Sensory-physical skills primarily involve direct interaction with the physical world. Tasks utilizing these skills are predominantly objective tasks that can be repetitively executed through precise programmatic design and machine operation. For example, haptic feedback for upper limb prostheses restores the sense of touch by relaying force, pressure, and slip measurements to the user. These devices use vibrotactile feedback and artificial impedance feedback to improve the user's interaction with their environment, enhancing their grasp success and dexterity and reducing the need for visual attention during manipulation. Significant advancements in technology, such as vision aids for the blind, auditory aids for the deaf, sensory augmentation, and identifying important sensory feedback, demonstrate that sensory-physical skills like vision, hearing, and motor abilities can be replaced by machines (Shull and Damian, 2015; Yu et al., 2023). Additionally, people exhibit varying preferences for machines performing different tasks and skills (Castelo et al., 2019). Based on clear rules and transparent reasons, sensory-physical skills engender spontaneous human trust in machines to execute tasks that require these skills (Bonnefon and Rahwan, 2020; Castelo et al. 2019). Lastly, skills are enhanced through education, experience or training, and the anticipated returns for a skilled worker are usually higher than those for unskilled workers (Acemoglu, 1998; Autor et al., 2003; Autor and Handel, 2013; Krueger, 1993; Card, 2001). From a cost perspective, the higher the wages, the stronger the motivation to automate such tasks under technological feasibility and human trust. Considering these three factors: technical feasibility of automation, human algorithmic trust, and cost factors, with the decreasing costs of computers, enterprises are increasingly likely to employ automation to replace occupations requiring high sensory-physical skills. The deskilling of machines reduce the sensory-physical skill requirements for workers. Based on this, we propose our first hypothesis:

H1: The higher the sensory-physical skill requirement of workers, the more likely they are to be replaced by machines.

Social-cognitive skills, which involve responding to others (in nursing or teaching occupations), performing services (mechanics or high-end restaurant servers) or engaging in agile or creative thinking (in leadership or knowledge work), are open interpretations based on personal opinions or intuition. In essence, social-cognitive skills are abstract. Frey and Osborne (2017) estimates that 47% of total US employment is at risk of automation, noting that jobs requiring high social intelligence and creativity are less likely to be automated despite some studies suggesting an overestimation of automation risks due to an occupation-based approach (Arntz et al., 2016; Nedelkoska and Quintini, 2018). Automation impacts sensory-physical and social-cognitive skills differently. For instance, the da Vinci Surgical System precisely controls instruments during procedures like prostatectomies, automating incisions, tissue cutting, and suturing tasks, thereby reducing bleeding and recovery time. However, planning surgery, interpreting patient responses, and making intraoperative decisions still require a doctor's direct involvement, underscoring the importance of social-cognitive skills. This difference is due to two factors.

Firstly, the technical challenge in automating social-cognitive skills lies in the Polanyi paradox—"we know more than we can tell". People can implicitly understand and complete tasks that require social-cognitive skills, but neither computer programmers nor anyone else can elucidate the vague "rules" or procedures (Autor, 2015). As Jordan (2019) points out AI focuses on humans' high-level or cognitive capability to reason and think. Sixty years later, however, high-level reasoning and thought remain elusive. In recent years, due to advances in machine learning technology, some people have come to believe that utilizing massive data can capture the implicit and opaque heuristic-based mode. However, technical feasibility does not mean that such tasks will be automated. An algorithm can only be applied if it is trusted. Humans do not trust machines to undertake subjective tasks requiring social-cognitive skills (Castelo et al., 2019). People tend to think that machines lack essential human emotions or emotional abilities (that is, they lack emotions similar to humans) (Haslam et al., 2008; Gray et al., 2007), so they are skeptical of machines performing socio-cognitive skills. For example, a Parature (2014) survey found that 60% of customers prefer interacting with a live customer service agent. Even though intelligent customer service can provide quick and immediate responses, people often wait or press the right sequence of numbers to talk to someone who can solve their issue, because human agents can offer more personalized and empathetic services (Brown, 2019). In the medical domain, medical imaging enhanced by AI systems may surpass human doctors in disease identification, yet this does not render doctors superfluous. Instead, integrating such technology allows physicians to devote more attention to designing treatment plans and fostering doctor-patient relationships because medicine requires a combination of skills, including critical thinking, problem-solving, empathy, and communication skills, which machines lack. The Polanyi paradox and algorithm aversion in cognitive skills determine that the substitution of machines for these skills presents considerable challenges., i.e., the "upskilling" characteristic of machines, which will expand the scores of workers' cognitive skills. This view is consistent with current studies indicating the difficulty of replacing high cognitive tasks with machines (Autor 2015; Autor and Dorn 2013; Gong 2023). Based on the above analysis, we propose our second hypothesis:

H2: The higher a worker's social-cognitive skills, the less likely they are to be replaced by machines.

Machines can be programmed to perform specific tasks efficiently, yet they cannot execute multiple tasks that necessitate a combination of skills. This is because transitioning between diverse tasks incurs expensive setup costs. Although complex tasks can be decomposed into simpler ones, some occur infrequently and need to achieve economies of scale, thus rendering machines not cost-effective. Gong et al. (2022) argue that in future smart factories, humans will primarily be responsible for setup tasks requiring workers to have various skills and production tasks will be delegated to machines. Machines excel in repetitive tasks, thereby assigning work demanding flexibility to humans. The emergence of new tasks imposes new demands on humans. Addressing new tasks and problems with automation technology necessitates collaborative expertise across multiple disciplines, departments, and fields. Thus, the more diverse the workforce's skills, the smoother their transition to new roles. In other words, automation motivates workers to 'reskill'. The World Economic Forum estimates that by 2025, 50% of employees will require retraining due to adopting new technologies. Five years later, over two-thirds of the skills currently deemed important in job requirements will change (Li, 2022). Workers need to acquire diversified skills to cope with task optimization and upgrades brought about by technological advancements. Based on this, we propose our third hypothesis:

H3: The greater the number of skills a worker possesses, the less susceptible they are to being replaced by machines.

Our research contributes by conducting the first empirical investigation into the differential impacts of machines on sensory-physical skills and social-cognitive skills, affirming the characteristics of irreplaceable labor. This provides valuable insights for individual career planning and the development of national educational systems.

Data sources, models, and measurements

Data sources. This study used the O*NET and OEWS databases under the Standard Occupational Classification (SOC) system. There are three versions of SOC, namely SOC2000, SOC2010, and SOC2018. It is necessary to establish crosswalks to compare the occupations under different SOC systems. Therefore, we aggregated some occupations to form SOC2010dd based on SOC2010. Appendix S.1 shows the necessity and detailed process of establishing SOC2010dd.

The O*NET program by the U.S. Department of Labor annually produces the publicly available database detailing the importance and the level of 118 workplace skills, knowledge, and abilities (these three categories are collectively referred to as skills) for the 923 occupations. The time range of database is 1998–2023, and we selected data from 2003 to 2022 because the data from 1998–2002 is Transitional Databases. O*NET encourages researchers conducting longitudinal data studies to use the O*NET 5.0(2003) database as a starting point. The latest employment data is for 2022 in OEWS. O*NET has the O*NET-SOC Taxonomy based on the SOC system. Generally speaking, O*NET-SOC is more detailed than the SOC. For example, The O*NET-SOC 2019 taxonomy structure is based on the 2018 SOC. The former includes 1016 occupational titles, 867 of which in 2018 SOC. In order to map O*NET databases to the corresponding SOC system, we reviewed and summarized the Taxonomy History from 2003 to 2022 and identified the O*NET SOC on which the data is based. Then, the occupational classification of each year was mapped to the SOC system. Table 2 summarizes the O*NET-SOC taxonomy and its corresponding SOC system.

The OEWS program produces employment and wage estimates annually for ~830 occupations. These estimates are available for the nation, individual states, and metropolitan and nonmetropolitan areas. After mapping O*NET and OEWS to the SOC system, we used a crosswalk between SOC2000/2010/2018 and SOC2010dd to map databases to the unified system SOC2010dd (see Fig.1). The processed data can be used for time series research and cross-sectional analysis. After processing, we obtained panel data on occupations from 2003 to 2022.

Model. Based on the panel data from 2003 to 2022, we examined the direction of occupational transitions induced by automation technology from three factors: scores of sensory-physical skills, scores of social-cognitive skills, and the number of skills mastered by workers.

$$\Delta GES_{j,t} = \alpha_0 + \alpha_1 Phy_{j,t-10} + \alpha_2 Cog_{j,t-10} + \alpha_3 NS_{j,t-10} + \alpha_4 OI_{j,t-10} + \alpha_5 \Delta Wage_{j,t} + \varepsilon_j$$

$\Delta GES_{j,t}$ represents the Box-Cox transformation of the growth rate of employment share in occupation j at year t. The impact of machines on employment is long-term; thus, following Autor and Dorn (2013), we used a decade as a period to provide a longer-term perspective. $Phy_{j,t-10}$ and $Cog_{j,t-10}$ represents the scores of sensory-physical and social-cognitive skills of occupation j ten years ago, respectively. $NS_{j,t-10}$ is the number of skills mastered by workers. $OI_{j,t-10}$ is the offshorability index of occupation j at year $t-10$. $\Delta Wage_{j,t}$ measures the change in the 90th percentile of annual wages from year $t-10$ to t. We controlled for occupation fixed effects and year fixed effects and used heteroskedasticity-robust standard errors.

Variable measurements. To stabilize variance and normalize the distribution of the dependent variable, we applied the Box-Cox transformation as follows:

$$\Delta GES_{j,t} = \begin{cases} \frac{\text{Growth of employment share}^{\lambda} - 1}{\lambda} & ,\lambda \neq 0 \\ \ln(\text{Growth of employment share}) & ,\lambda = 0 \end{cases}$$

The Growth of employment share measures the rate of growth in the labor share between periods $t-10$ and t. The parameter λ, obtained through maximum likelihood estimation, was found to be $\lambda = -1.092$.

Table 2 Taxonomy and SOC systems for OEWS and O*NET databases.

OEWS	OEWS SOC	SOC	O*NET	O*NET SOC	SOC
2022May	SOC2018	2018	O*NET 26.3 May 2022	2019	2018
2021May	SOC2018	2018	O*NET 25.3 May 2021	2019	2018
2020May	OES2019	2018	O*NET 24.3 May 2020	2010	2010
2019May	OES2019	2018	O*NET 23.3 May 2019	2010	2010
2018May	OES2018	2010	O*NET 22.3 May 2018	2010	2010
2017May	OES2018	2010	O*NET 21.3 May 2017	2010	2010
2016May	SOC2010	2010	O*NET 20.3 April 2016	2010	2010
2015May	SOC2010	2010	O*NET 20.0 August 2015	2010	2010
2014May	SOC2010	2010	O*NET 19.0 July 2014	2010	2010
2013May	SOC2010	2010	O*NET 18.0 July 2013	2010	2010
2012May	SOC2010	2010	O*NET 17.0 July 2012	2010	2010
2011May	OES2010	2010	O*NET 16.0 July 2011	2010	2010
2010May	OES2010	2010	O*NET 15.0 July 2010	2009	2000
2009May	SOC2000	2000	O*NET 14.0 June 2009	2009	2000
2008May	SOC2000	2000	O*NET 13.0 June 2008	2006	2000
2007May	SOC2000	2000	O*NET 12.0 June 2007	2006	2000
2006May	SOC2000	2000	O*NET 10.0 June 2006	2006	2000
2005May	SOC2000	2000	O*NET 8.0 June 2005	2000	2000
2004May	SOC2000	2000	O*NET 6.0 July 2004	2000	2000
2003May	SOC2000	2000	O*NET 5.0 April 2003	2000	2000

OES2019 means that OEWS data collected under two different structures were combined to create a “hybrid” structure based on SOC2010&2018 for the May 2019 and 2020 estimates. Similarly, OES2018 is used for the May 2017 and 2018 estimates collected under SOC 2010. OES2010 based on SOC2000&2010 is used for the May 2010 and 2021 estimates.

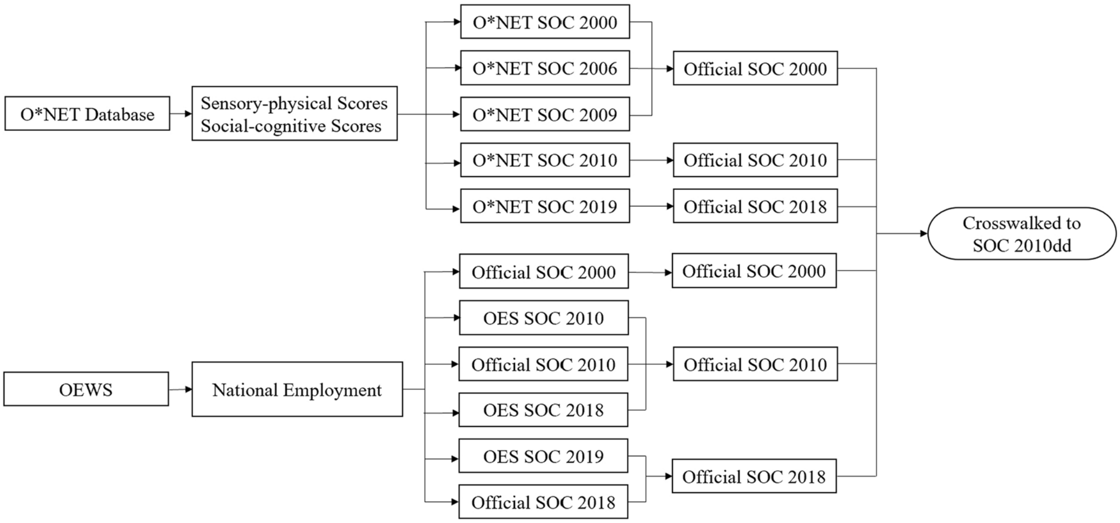

Fig. 1 Crosswalk O*NET and OEWS database to SOC2010dd. The figure presents the methodology for harmonizing the O*NET and OEWS databases with the hybrid occupational classification standard, SOC2010dd. At the top of the diagram, the process begins with the extraction of sensory-physical and social-cognitive scores from the O*NET database, categorized according to O*NET SOC 2000/2006/2009/2010/2019. The bottom portion of the figure outlines the acquisition of national employment data from the OEWS database based on Official SOC 2000/2010/2018 and OES SOC 2010/2018/2019. The central area of the figure illustrates the crosswalk procedure, demonstrating how data from each source is crosswalked to SOC2010dd, which enables the comparative analysis across the databases and years.

Task execution necessitates skills. We utilized the importance of skill in O*NET denoted by $onet(j, s)$ to construct variables of interest. Importance is rated on a scale of five, with a higher score indicating the skill's greater importance. Alabdulkareem et al. (2018) and Xu et al. (2021) note that raw O*NET data do not control for ubiquitous skills, such as "Identifying Objects" and "Communicating with Supervisors and Peers" and they focus on skills that are overexpressed in an occupation, a distinct characteristic that differentiates one occupation from others. Accordingly, we calculated the revealed comparative advantage (RCA) of each skill in an occupation using the following formula:

$$RCA(j,s) = \frac{onet(j,s)/\sum_{s'\in S} onet(j,s')}{\sum_{j'\in J} onet(j',s)/\sum_{j'\in J, s'\in S} onet(j',s')}$$

$onet(j, s)$ is the importance of skill $s \in S$ to occupation $j \in J$. $RCA(j,s)$ quantifies the comparative advantage of skill s in occupation j relative to the overall distribution of that skill across all occupations. We denote effective use of a skill using $e(j,s) = 1$ if $RCA(j,s)>1$, and $e(j,s) = 0$ otherwise.

We calculated the scores of skills using the average importance scores of effectively utilized skills. The formulas are as follows:

$$Phy_j = \frac{\sum_{s'\in P} onet(j,s') \cdot e(j,s')}{\sum_{s'\in P} e(j,s')}$$

$$Cog_j = \frac{\sum_{s'\in C} onet(j,s') \cdot e(j,s')}{\sum_{s'\in C} e(j,s')}$$

P represents sensory-physical skills, and C represents social-cognitive skills, as categorized by Alabdulkareem et al. (2018) (refer to Appendix S.3 online). Their paper conducted a cluster analysis on 161 workplace skills, knowledge, abilities, and generalized work activities. Since a subset of skills from the generalized work activities was utilized to construct the OI variable in this study, we employed 118 skills, knowledge, and abilities to construct the variables Phy_j and Cog_j, in which we are interested. These variables, representing the scores of sensory-physical and social-cognitive skills, were log-transformed.

In the O*NET database, if $onet(j,s) = 1$, the skill s is unimportant for occupation j; if $onet(j,s)>1$, the skill is somewhat important. We calculated the number of important skills for each occupation where $onet(j,s)>1$. Occupations with a skill number greater than the average were assigned a value of 1, while those with a skill number less than or equal to the average were assigned a value of 0, thus the number of skills mastered by workers (NS) was generated.

Our study focuses on the impact of machines on the workforce. However, job offshoring might produce effects similar to those of machines. Literature suggests that tasks suitable for offshoring can be effectively performed without needing physical proximity to customers or specific job locations (Firpo et al., 2011; Autor and Dorn, 2013). Sensory-physical skills involving physical actions can be easily offshored. In contrast, cognitive occupations often require high interpersonal interaction between workers and clients, making them less susceptible to offshoring. This reasoning indicates that offshoring can partially explain the increase in social-cognitive skills and the decrease in sensory-physical skills. Following Autor (2015), we incorporated the offshorability of jobs into our analysis. Occupational offshoring is not included in national accounts and is thus largely unmeasured (Autor and Dorn, 2013). Firpo et al. (2011) and Autor and Dorn (2013) measure the offshoring potential (offshorability) of jobs rather than actual offshoring. Referring to their study, we used a simple average of two aggregate variables: direct interpersonal interaction and proximity to a specific work location (face-to-face contact and on-site job), then reversed the sign of the resulting variable so that it measures offshorability instead of non-offshorability. The offshorability index was then log-transformed to obtain OI. The correspondence between non-offshorability and O*NET codes is shown in Table 3.

To capture shifts in wage structure, we utilized changes in the annual 90th percentile wage, as suggested by Autor and Dorn (2013). Then the changes in wages were log-transformed to obtain the variable $\Delta Wage$.

Results and analysis

Main results. Table 4 presents the regression results. The coefficient of Phy α_1 is -3.480 (t value is -2.54). After reverse

Table 3 Characteristics linked to non-offshorability.

	Element ID	Element name
Face-to-Face	4.C.1.a.2.l	Face-to-Face Discussions
	4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships
	4.A.4.a.5	Assisting and Caring for Others
	4.A.4.a.8	Performing for or Working Directly with the Public
	4.A.4.b.5	Coaching and Developing Others
On-Site Job	4.A.1.b.2	Inspecting Equipment, Structures, or Material
	4.A.3.a.2	Handling and Moving Objects
	4.A.3.a.3	Controlling Machines and Processes
	4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
	4.A.3.b.4	Repairing and Maintaining Mechanical Equipment
	4.A.3.b.5	Repairing and Maintaining Electronic Equipment

Table 4 Scores and number of skills on the growth of employment share Dependent variable: 100X Box-Cox transformed annual growth in employment share between 2003 and 2022.

Variables	
$Phy_{j,t-10}$	−3.480**
	(−2.54)
$Cog_{j,t-10}$	6.361***
	(4.36)
$NS_{j,t-10}$	0.509**
	(2.35)
$OI_{j,t-10}$	−3.205***
	(−4.51)
$\Delta Wage_{j,t}$	1.781***
	(3.02)
Constant	25.676***
	(4.30)
Observations	6,295
Adjusted R-squared	0.140
Occupation FE	YES
Year FE	YES

To linearize relationships, we applied the Box-Cox transformation ($\lambda = -1.092$) to the growth rate of employment share in occupations. However, this means that effects on the original scale are no longer linear, which poses a challenge for the interpretation of our coefficients. The relationship between the original scale and those after the transformation (α_i) is discussed in Appendix S.2. The heteroskedasticity-robust standard errors are shown in parentheses and the coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

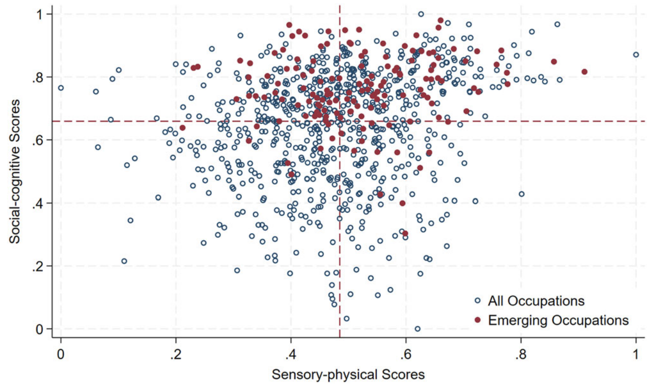

Fig. 2 Skill scores of emerging occupations and all occupations. The scatter plot represents the distribution of normalized sensory-physical and social-cognitive scores across all occupations, depicted as blue hollow circles, and emerging occupations, shown as red solid circles. Two intersecting red lines indicate the mean values of the respective scores, dividing the plot into quadrants and providing a reference point to ascertain the relative positioning of emerging occupations in comparison to the overall job market. The clustering of red solid circles suggests that emerging occupations possess cognitive score characteristics when contrasted with the broader landscape of all occupations.

transformation, the coefficient is −3.357%, indicating that a 100% increase in the sensory-physical scores leads to a 3.357% decrease in employment share. Hypothesis 1 is supported. The coefficient of the variable *Cog* α_2 is 6.361 (t value is 4.36), and the coefficient on the original scale is 6.815%. This suggests a 6.815% increase in employment share for every 100% increase in social-cognitive scores. Hypothesis 2 is supported. Moreover, since α_2 is greater than α_1, it implies that the impact of *Cog* is dominant. The coefficient of *NS* α_3 is 0.509 (t value is 2.35); after reverse transformation, the coefficient is 0.512%. This means that compared to the group with a lower number of skills, the group with a higher number of skills has a 0.512% higher employment share. The coefficients of *OI* and *ΔWage* are as expected.

Emerging occupations. The discussion above does not encompass emerging occupations. Between 2000 and 2023, a total of 150 new occupations have been identified. We analyzed the skill scores of these 150 emerging occupations to discern their distinctive characteristics (refer to Fig. 2). The mean values of the two scores bisect the graph into four quadrants. Most new occupations cluster in the first and second quadrants, suggesting a predominant orientation towards social-cognitive skills. Some occupations in the fourth quadrant exhibit high sensory-physical scores and low social-cognitive scores. Only a handful of occupations reside in the upper right corner of the third quadrant, indicative of "sunset occupations" with low cognitive and physical skills.

In line with the OEWS occupational classification standards, the 150 emerging occupations can be categorized into eight principal groups. As Table 5 illustrates, the most significant emergence of new occupations is seen in Computer, Engineering, and Science Occupations, encompassing roles such as Blockchain Engineers, Human Factors Engineers and Ergonomists, and Bioinformatics Scientists. Breaking this major occupation down further reveals that Computer and Mathematical Occupations and Life, Physical, and Social Science Occupations demand considerably more social-cognitive skills than sensory-physical skills. Time Management Architecture and Engineering Occupations exhibit a balanced social-cognitive and sensory-physical skills requirement. Healthcare Practitioners and Technical Occupations and Management, Business, and Financial

Table 5 The major category of emerging occupations.

Major occupations	Number of emerging occupations	%
Computer, Engineering, & Science Occupations	54	36
Healthcare Practitioners and Technical Occupations	38	25.33
Management, Business, & Financial Occupations	34	22.67
Natural Resources, Construction, & Maintenance Occupations	7	4.67
Service Occupations	7	4.67
Production, Transportation, & Material Moving Occupation	5	3.33
Education, Legal, Community Service, & Arts Occupations	3	2
Sales & Office Occupations	2	1.33
Total	150	100

Table 6 Robustness test Dependent variable: 100 X Box-Cox transformed annual growth in employment share.

Variables	(1) Time period is limited to 2003–2007 and 2013–2017	(2) *Phy* and *Cog* based on the Classification of O*NET	(3) Handling missing values of the 90th percentile wage
$Phy_{j,t-10}$	−9.708***	−3.755***	−3.310**
	(−5.18)	(−2.91)	(−2.47)
$Cog_{j,t-10}$	6.042***	3.943***	6.120***
	(3.13)	(2.81)	(4.18)
$NS_{j,t-10}$	0.795***	0.381*	0.606***
	(2.62)	(1.76)	(2.84)
$OI_{j,t-10}$	−4.462***	−4.094***	−3.197***
	(−4.29)	(−6.31)	(−4.57)
$\Delta Wage_{j,t}$	3.059***	1.991***	1.172**
	(5.58)	(3.48)	(2.00)
Constant	24.620***	28.265***	32.309***
	(4.34)	(4.62)	(5.40)
Observations	3083	6277	6650
Adjusted R-squared	0.184	0.136	0.132
Occupation FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Occupations also show activity. These three major categories are termed "sunrise occupations" and are poised for rapid employment growth in the future.

Robustness test. To mitigate the impact of the financial crisis and COVID-19, we kept data between 2003–2007 and 2013–2017, yielding our first robustness test (as shown in the first column of Table 6). In the main regression, *Phy* and *Cog* were constructed based on the skill classification by Alabdulkareem et al. (2018). They categorize skills into two clusters: social-cognitive skills and sensory-physical skills. Our second robustness test used different skill classification to construct *Phy* and *Cog*. The O*NET content model divides 52 abilities into four categories: Cognitive Abilities, Psychomotor Abilities, Physical Abilities, and Sensor Abilities (refer to Appendix S.4 online). Cognitive Abilities were utilized to form *Cog*, while the remaining three skill categories were used to develop *Phy* (refer to the second column of Table 6). Due to the missing of the 90th percentile wage for 355 observations, the third robustness test supplemented these missing values with the average wage. Initially, we identified occupations without missing and calculated the multiplier of the 90th percentile wage to the average wage, denoted as $p90p50$. We then obtained the average of $p90p50$ for the same major occupation category (at the two-digit level). Subsequently, we filled in the missing values by multiplying the average wage by the average value of $p90p50$ (refer to the third column of Table 6).

The three columns of Table 6 display the robustness tests 1–3, respectively. The results align with our main findings. *Cog* and *NS* exert a significantly positive influence on employment share, which suggests that higher cognitive skills and a broader skillset decrease the likelihood of being replaced by machines. Higher sensory-physical skills increase the likelihood of machine replacement. The results from the robustness tests corroborate our hypothesis.

Conclusion

As technology advances, innovations like machine learning extend automation into previously thought irreplaceable domains: autonomous vehicles, legal document analysis, and agricultural field labor (Autor, 2015), seemingly overcoming the Polanyi Paradox. In early 2023, OpenAI released GPT-4, a large-scale language model whose primary function is to comprehend and generate language by analyzing and learning from extensive text data. This poses a challenge to the unique understanding, creativity, and decision-making abilities of humans. However, the job replacement by machines is determined by technological capabilities and human acceptance of the technology. Humans exhibit distinctly different attitudes towards sensory-physical and social-cognitive skills. There is a spontaneous trust in machines to perform tasks requiring sensory-physical skills, as such operations are based on clear rules and transparent reasons. Additionally, the higher the sensory-physical skills required, the more training or experience accumulation is needed by workers, and employers pay higher wages, hence motivating businesses to introduce machines to replace such labor. Cognitive skills, on the other hand, often involve open interpretations based on personal opinions or intuition. There is an algorithm aversion regarding machines undertaking these tasks, as people tend to think machines lack essential human emotions or emotional abilities. Using skill importance scores from the O*NET database and occupational wage and employment data from the OEWS database, we empirically studied for the first time the differential impacts of machines on sensory-physical skills and social-cognitive skills. The study finds that low sensory-physical skills, high social-cognitive skills, and a wide array of skills characterize occupations less likely to be replaced by machines.

A key advantage of humans over machines is the flexibility and adaptability. Cognitive flexibility permits the appropriate adjustment of thoughts and behaviors in response to changing environmental demands (Yeo et al., 2015; Uddin, 2021). This capability involves creative thinking, critical reasoning, and analyzing problems from multiple perspectives. Drawing from the definition of cognitive flexibility, we conceptualize worker flexibility as the ability to adapt and switch between multiple and varied tasks. In our paper, worker flexibility encompasses cognitive flexibility and the number of mastered skills. Cognitive flexibility allows for adjusting cognitive functions in response to varying cognitive demands, facilitating adaptation to complex and changing task requirements (Yeo et al., 2015). Consequently, higher cognitive capabilities correlate with greater flexibility. Similarly, the more skills a worker possesses, the easier it becomes for them to switch between diverse tasks, enhancing their flexibility. Thus, workers with high cognitive skills and diverse abilities can collectively be termed as "flexible workers." The future require flexible workers. Therefore, workers should focus on enhancing cognitive skills, such as creativity and critical thinking, developing diverse skills encompassing both social-cognitive and sensory-physical skills, and emphasizing lifelong learning to adapt to technological changes. National education should underscore cognitive skills and interdisciplinary learning and offer lifelong education and professional retraining opportunities.

A limitation of our study is that the O*NET database are based on collection methodology featuring job incumbent, occupational expert, big data, and other sources, which carry a degree of subjectivity. Scholars might consider developing objective ways to measure skill scores in the future.

Data availability

All data generated or analyzed during this study are included in this published article and its supplementary material files.

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Concept: QG and K-hL; resources and data preparation: WZ; visualization and plotting: WZ; writing—original draft preparation: WZ; writing—review and editing: QG and K-hL; supervision: QG and K-hL. All authors have read and agreed to the published version of the paper.

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The authors declare no competing interests.

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This article does not contain any studies with human participants performed by any of the authors.

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