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Machine learning and AI technology-induced skill gaps and opportunities for continuous development of middle-skilled employees

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Abstract

Purpose – Based on the sociotechnical systems theory, we examined the human–technology interactions in the context of future works conditioned by machine learning (ML) and artificial intelligence (AI). Skills needed to support career sustainability and the future of the workforce, particularly for the middle-skilled workforce in the contemporary United States America (USA) context, were also studied.

Design/methodology/approach – We conducted a scenario analysis to demonstrate the potential roles that human resource professionals may perform to fill the skill gaps given their expertise in the shaping and skilling processes.

Findings – Assessing the success of the integration of AI and ML into the middle-skilled workforce requires a multi-faceted approach that considers performance metrics, cost-effectiveness, job satisfaction, environmental impact and innovation. Employees with AI skills can be more competitive in the workforce and forward to high-skilled positions.

Research limitations/implications – Empirical research and related studies focusing on evaluations of reskilling and upskilling processes and outcomes would support career sustainability and the future development of middle-skilled workers.

Practical implications – Through a proactive strategic career development plan with AI integration, middle-skilled workers may enhance their career sustainability and be prepared for future higher-skilled work.

Social implications – The economic downturn caused by technology-induced unemployment may be addressed by unleashing middle-skilled workforce potentials for future work created by AI and robotics and sustaining economic competitiveness.

Originality/value – This article offers important implications for human resource development theory-minded researchers and scholarly practitioners.

Keywords Human resource development, Machine learning, Artificial intelligence, Middle-skilled workforce, Human-technology interactions

Paper type Research paper

Introduction

Artificial intelligence (AI) has entered many arenas of everyday life such as smart home applications, self-driving electric vehicles, online shopping and automated customer services. The expanded AI applications in the European Union and the United States of America (USA) have influenced the workforce and the workplace, as it not only can "spur innovations in new

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products and services" but also "lead to discrimination against workers" (The White House, 2022b, p. 3). A vital component of human intelligence is learning from experience. Likewise, a sub-area in the application of AI, known as machine learning (ML), refers to the capability of machines to learn from experience through algorithm training such that their performance can be improved upon acquiring and processing accumulated data over time (Zhou, 2021). As a form of ML, generative AI has emerged with the ability to produce new text, video, images and other types of content based on newly acquired data and information.

While organizations are beginning to utilize AI and automation to address their talent and skills shortages, employers realize that their most challenging skills shortages are in AI adoption, such as new ways to design, develop and maintain these systems as well as other ML-related issues (Schmitt, 2023). The development of AI and ML has led to new employment opportunities that simultaneously challenge the USA workforce differently at all skill levels.

The skill requirements in the workplace can be classified into three general categories: high skills, middle skills and low skills (Autor, 2015). High-skilled positions, known as cognitive non-routine jobs, involve abstract tasks with a college degree and are mostly exposed to AI; middle-skilled positions are routine ones that are cognitive or manual involving precise procedures with an associate degree or certificate and are mostly related to software applications, whereas low-skilled jobs are manual-based non-routine in nature that comprise physical tasks and personal traits with or without a high school diploma and are often exposed to applications of robots (Autor, 2015; Webb, 2020). Contemporary advancements in engineering and technology have created significant employment opportunities demanding high-skilled employees in data science and AI research and application fields. At the same time, the job market has shown an increase in personal services demanding low-skilled workers. This is coupled with an increased tendency of technology-induced unemployment in the middle-skilled workforce (Hughes *et al.*, 2019). This tendency can be rationalized in the following ways and processes.

First, technologies have ramifications for both middle-skilled and high-skilled positions. In middle-skilled roles, it excels at automating repetitive and rule-based responsibilities like data entry, report generation and content creation, ultimately amplifying efficiency and minimizing manual labor. This allows workers to concentrate on more intricate and strategic facets of their positions. Second, in professions that require data analysis, generative AI lends its expertise by automating data processing and furnishing insights, thereby empowering more informed decision-making. It equips middle-skilled professionals, including content creators and graphic designers, with tools to expedite content generation and design endeavors. Generative AI can also personalize training content, supporting middle-skilled workers in upskilling and expanding their career horizons. Third, within high-skilled jobs, generative AI proves equally transformative. It aids highly skilled professionals by automating routine and time-consuming tasks, thus enabling them to shift their focus to more complex and strategic elements. In professions that entail data-intensive work, such as data science, it streamlines data analysis and report generation, simplifying the management of extensive datasets and the extraction of valuable insights. Finally, generative AI assists researchers and scientists in modeling experiments, conceiving hypotheses and deciphering vast data sets, thereby expediting the innovation process so that high-skilled experts can harness generative AI to devise custom solutions, designs and prototypes tailored to specific requirements.

Integrating generative AI into middle- and high-skilled roles presents challenges and considerations in innovation-related skills development. Ensuring the quality of AI-generated output, especially in fields that mandate precision and adherence to standards, necessitates rigorous production, monitoring and validation. At a minimum, employees must adapt to these technologies and acquire new skills to collaborate effectively with current and future generative AI systems. However, generative AI technologies, while promising substantial benefits, are not inherently jeopardizing high-skilled jobs. Their impact depends on various factors, including industry dynamics, specific roles and how organizations and professionals adapt to this transformative technology. Rather than jeopardizing these high-skilled jobs, generative AI may enhance efficiency and creativity, allowing professionals to focus on higher value-added aspects of their roles.

At the same time, more workers are progressively feeling insecure, frustrated or at risk in their future employment outlook (Chuang, 2021). For example, using AI in recruitment and selection functions in human resource management created fear of job losses and distrust among recruitment professionals (Ore and Sposato, 2022). Recent research has reported a growing trend of America's middle-skilled workers picking up lower-level or part-time jobs with lower pay to stay in the workplace (Guo, 2022). This may intensify the talent shortage at the high-skill level and add to the severity of the economic downturn if future changes and challenges in the middle-skilled workforce are left unattended. To address the challenges in contemporary organizations caused by environmental complexity, new technology and global competition, we aim to focus on the skill gaps induced by technological advances in ML and AI, particularly for the middle-skilled workforce in the contemporary USA context. The potential solutions are to inform research and practices in improving skills and talent shortages in all other skill levels, regardless of industries or sectors.

In the forthcoming sections, the structure of the paper is as follows: First, we discuss the interrelationship of society (humans) and technology to understand the phenomena of ML and AI technology-induced challenges and opportunities for human workers. Second, we offer a scenario analysis of the impacts of AI and ML in robotics on jobs and the USA workforce. It demonstrates the possibility of upskilling and reskilling the middle-skilled workforce through a proactive strategic career development intervention with AI integration. Finally, implications for human resource research, practice and policy analysis are presented to enhance the career sustainability of the middle-skilled sectoral workforce and the readiness for future higher-skilled positions at the technological advancement frontier.

The interrelationship of people and technology

Today's technological developments empower employees to move from routine tasks to non-routine ones involving complex skills in problem-solving, adaptability and flexibility (Ore and Sposato, 2022). While advances in technology and computers are more productive and cost-effective for organizations and offer opportunities to improve performance and unleash employees' full potential, human-machine integration may create great social and organizational challenges, affecting the continued development of both workplace skills and technology (Chuang, 2024). In this aspect, sociotechnical systems (STS) theory, an idea that originated from Trist and Bamforth's (1951) study on coal miners in England, offers a useful lens to analyze the complexity of the challenges. The conceptual framework of the STS theory explores the interrelationship of the social aspect (human complexity involving supervisory–subordinate interactions, motivation, work culture, occupational role and group dynamics) and technological aspect (including tools, procedures, techniques and associated apparatus that are used to accomplish job tasks within a complex system) for effective performance and organizational success (Walker *et al.*, 2008). When the social and technological aspects work together seamlessly, high-quality outcomes in the form of goods and services and social, organizational and psychological consequences such as job satisfaction and commitment are likely to effectively reach a high degree in workforce structure and resource allocation (Cummings and Worley, 2014). The STS theory recognizes the interactions between human behaviors and societal complex infrastructures in technology and innovative work designs in the workplace and provides insights into the factors influencing AI–human partnership (Chowdhury *et al.*, 2022; Cummings and Worley, 2014). For decades, this framework has been applied to various similar scenarios in the literature (Winter *et al.*, 2014) and is considered highly relevant to the focus of this study.

The STS theory emphasizes the freedom of the interface between the STS and the environment to ensure joint optimization from external disruptions and to facilitate information and resource exchanges. The literature on the STS theory advocated the importance of the human aspect in technology innovation at work for sustainable organizational performance (Chowdhury *et al.*, 2022). Because the early literature on STS methods tended to follow a reductionistic analysis approach, David *et al.* (2022) highlighted the importance of considering the principle of bottom-up emergence and micro-level temporal analyses in response to various individual- and team-level inputs and environmental changes and enhancing the applicability of human factors across different domains and complex systems. The STS theory advocates effectively humanizing work and the workplace to optimize the benefits of new technology and improve workforce quality in the 21st century (Guest *et al.*, 2022).

The impacts of AI and ML in robotics in the workplace from a technological aspect

Given the latest developments, AI and ML in robotics may become critical game-changing factors for jobs and the workforce in the foreseeable future. In a study of leadership in the age of AI, Sposato (2024) discussed the implications of AI on leadership and organizational development and proposed that effective leadership behaviors and development programs can be enhanced with AI analytics. To guide organizational leaders through AI-induced transformations, proactive leadership strategies, ethical considerations and talent management are essential (Sposato, 2024). Human resource development (HRD) professionals should embrace what is coming to prepare for proactive strategies to meet new workplace challenges.

Emerging development in technologies and automation

Robotics and automation are expected to advance and integrate into various manufacturing settings and processes (Arinez *et al.*, 2020). AI and ML are also anticipated to be used more frequently for optimizing processes, improving quality and increasing efficiency. Recent advancements in robotics showed the development of more advanced AI algorithms, the creation of more flexible and durable materials for robot construction and the miniaturization of robot components (Wang and Siau, 2022). Some specific examples include the use of learning techniques to improve the perceptions and decision-making capabilities of robots; the development of soft robotics (using flexible materials to create robots that can adapt to their environment and perform tasks beyond the traditional rigid robots) and swarm robotics (involving many relatively simple robots working together to accomplish tasks); the use of robots in hazardous environments for deep sea or disaster zones activities, surgical robots for healthcare sectors, agriculture drones for crop monitoring and personal use for entertainment or home assistants.

One of the most common ways to add AI to robotics is using ML algorithms to train the robot to perform specific tasks, such as object recognition, navigation and grasping (Wang and Siau, 2022). The robot can learn from data and improve its performance over time. Robotics AI can also be leveraged by connecting to a cloud-based AI platform. This platform allows the robot to share sensor data and process it using a cloud-based AI service, providing a more powerful and flexible processing environment. Computer vision technology can enable robots to perceive and interpret their environment for recognizing and tracking objects and interpreting gestures and facial expressions. Natural language processing permits robots to understand and respond to human speech and text, allowing for more natural and intuitive human–robot interactions. AI-based planning and decision-making algorithms can be engaged to enable robots to make decisions and take actions based on their current state and their performance goals. Additionally, expert systems can embed human knowledge and expertise into the robot, allowing it to perform tasks that would otherwise be difficult or impossible to accomplish on its own (Davenport and Kalakota, 2019).

Human–machine integration in the context of future works

Given AI in mechatronics (an interdisciplinary field of mechanics and electronic engineering) and robotics' capacity to increase productivity and efficiency in manufacturing and application processes, it has led to the creation and advancement of intelligent robotics such as personal robots for home assistants, healthcare robots for surgeries and agricultural robots for autonomous tractors (Davenport and Kalakota, 2019; Gamboa-Montero *et al.*, 2020). Hence, additional workforce upskilling and skills transformation are required for middle-skilled employees in programming, maintaining and repairing AI-powered mechatronic and robotic systems. In the context of future works created by ML and AI, the interactions between humans and technology are evolving and becoming more intertwined. The following are some of the outlooks on human–technology interactions in this context, demonstrating potential skill gaps.

Co-creation. Humans and AI systems are collaborating to create new works. ML and AI algorithms can generate novel ideas, designs or compositions, with humans providing creative input, direction and context (Wu *et al.*, 2021). This collaborative process leverages the strengths of both humans and AI to produce innovative and unique works. The ability to create new works encompasses the harmonious coexistence and collaboration between humans and AI, facilitating their strengths to achieve greater outcomes (Wu *et al.*, 2021).

Enhancing human creativity. AI technologies may further serve as effective tools to augment human creativity. They can assist artists, designers and other creative professionals by providing suggestions, automating tasks or helping to overcome creative blocks (Ali Elfa and Dawood 2023). This is because AI can analyze data and generate insights that humans might have missed, inspiring new ideas and enabling more efficient creative processes. Furthermore, AI technology can provide invaluable insight and inspiration to human designers through its capacity to analyze extensive data and reveal hidden patterns. In the creative process, AI plays an active role in boosting human creativity and fostering innovation by offering data-driven insights, generating fresh concepts and aiding in product finalization (Ali Elfa *et al.*, 2023). Yet, it is crucial to acknowledge that the ultimate decision-making and creative vision remain firmly in the hands of the designer.

Improving efficiency. AI and ML can efficiently automate repetitive and labor-intensive tasks, freeing employees to focus on more complex and creative endeavors. For example, AI algorithms can generate designs based on specific parameters, reducing the time and effort required by human actors (Rajawat *et al.*, 2021). This allows employees to be more productive and explore new possibilities. In sectors traditionally hesitant toward robotics, such as the aerospace industry, a collaborative relationship between humans and robots has emerged to optimize efficiency, conserve resources and energy and enhance working conditions (Rajawat *et al.*, 2021). The human–robot collaboration solution improves efficiency and safety during aerospace development and assembly processes. By harnessing the strength and precision of robots in tandem with human adaptability, manual labor, specialized equipment and time requirements have all been reduced (Rajawat *et al.*, 2021).

Overall, the interactions between humans and technology are characterized by collaboration, augmentation, automation, ethical considerations, new possibilities and the ongoing need for human creativity and interpretation.

Works created by ML and AI

The development of new technologies opens significant employment opportunities that did not previously exist in the workplace. According to Ollero *et al.* (2006), the expertise and skill sets required in robotics cover a wide range of areas, including but not limited to: computer science (programming, algorithm development and computer vision for robots); AI (designing and decision-making algorithms and ML models for autonomous robots); mechanical engineering (design and construction of robots' physical structure); electrical engineering (development of electronic control systems for robots); mechatronics (the integration and synthesis of mechanical and electrical engineering with computer systems in robots); control systems (design of feedback control systems for stable and accurate robot behavior) and human–robot interaction (designing interfaces and experiences that enable effective communication and collaboration between humans and robots). These astounding emerging technological areas and associated requirements in expertise and skill sets have led to significant new job opportunities in fields, such as robotics engineering, automation and robot programming. Specifically, the widespread adoption of Internet of Things technology has shown promising and expanded employment opportunities in fields (Kumar *et al.*, 2019). With the growing capacities of large volumes of data generation induced by ML, automation and AI technologies, the need for experts who can understand and handle these data has grown at an ever-increased pace in the areas of data engineering, data visualization and data analysis (Johnson *et al.*, 2021). Coupled with all the demand in the new employment trend, other associated fields are also required to create new positions at high-skill levels related to data science, ML engineering and AI research (Arinez *et al.*, 2020).

Technological advances in ML and AI automation have created tremendous job opportunities in areas requiring highly skilled expertise. However, the scenarios in the middle-skilled workforce displayed a different picture, also influenced by technological advances.

The impacts of AI and ML in robotics in the workplace from social aspect

In general, advanced technologies have changed the nature of work and the workforce structure and replaced middle-skill workers with complementing high-skill positions because of skill polarization in the workplace. For example, it is estimated that approximately 47% of all positions in transportation and logistics, office and administrative support and manufacturing will be replaced by computerization, automation, robots or machines between 2010 and 2030 in the USA (Frey and Osborne, 2017). Although Handel (2022) found little support for this view of massive disruption in the United States Bureau of Labor Statistics data, a few small occupations were confirmed to decline by 30% or more over 10 years.

It has been observed in the literature that a skill polarization tendency in the workplace has been and will continue to take place, that is, a growing concentration in high-skilled cognitive non-routine jobs and low-skilled manual non-routine jobs coupled with a decreasing middle-skilled routine manual and cognitive jobs (The White House, 2022b; Webb, 2020). Consequently, there is a coexistence of technology-induced unemployment for middle-skilled workers and an increased demand for, but a shortage of, high-skilled employees (Chuang, 2021). This phenomenon has caused technology-induced unemployment and created a U-shaped workforce structure, as illustrated in Figure 1. Autor (2015) noted that workforce polarization could be reshaped when middle-skill jobs continually demand a mixture of tasks that combine routine and non-routine tasks.

According to research from the American Workforce Policy Advisory Board, nearly 7 million USA workers, both employed and unemployed, seek career development and reskilling opportunities to remain employable after automation impacts their industry (Alonso, 2021). Human capital development has not been catching up with the speed of technological development. The changes in employment, work structures and the workplace require additional focused attention to employees' transitions into the technological era. Along with the effect of the declining fertility rate and the retirement of baby boomers, organizations are facing greater challenges in talent shortage and are forced to rely on AI and robots to meet their business needs. Thus, reskilling and upskilling middle-skilled employees for higher-skill jobs created by advanced technology are critical to meeting economic and social challenges induced by technological unemployment, talent shortages, declining fertility rate and the exit of baby boomers. Employees need to embrace technological changes and continually develop high-level skills to remain competitive in the workforce.

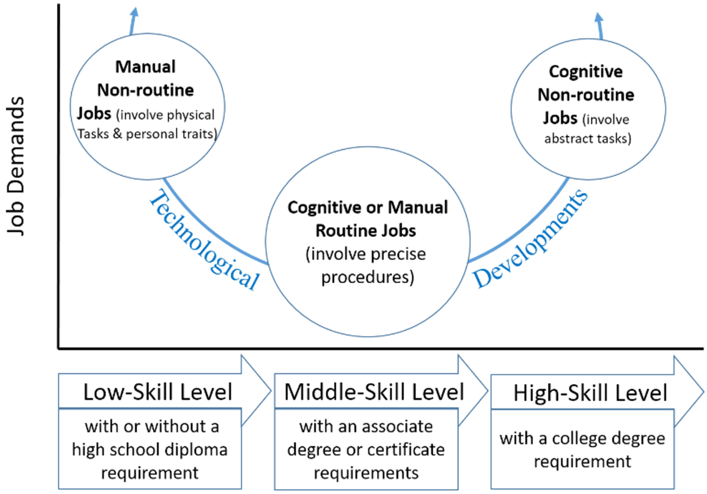

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Figure 1. Technological impacts on the workforce

Middle-skilled workers can be developed into a high-skilled workforce with the right HRD strategies. ML and AI have the potential to significantly improve the work of middle-skilled workers by reducing manual labor, providing real-time insights and automating tasks (Wang and Siau, 2022). For example, middle-skilled jobs in mechatronics typically involve the application and integration of mechanical, electrical and computer systems in the design and development of mechatronic systems, including robots (Nnodim *et al.*, 2021). Some examples of middle-skilled jobs in mechatronics include installing, maintaining and repairing mechatronic systems and equipment, control systems (e.g. sensors and actuators) and robots and related equipment. With necessary upskilling, these employees can use AI algorithms for designing and developing mechatronic systems, including robots and automation systems, to monitor mechatronic systems and proactively address systems' problems or inspect and evaluate the quality of products produced by mechatronic systems, helping identify and resolve any defects, among other tasks (Nnodim *et al.*, 2021).

Methodology

To demonstrate the potential roles that HRD may play in developing the middle-skilled workforce for reskilling and upskilling, we conducted a scenario analysis informed by Chermack (2022). We selected some technological-based fields with skill levels between middle- and high-skilled in computer systems, mechatronics and robotics. We also selected some middle-level positions in electro-mechanical and mechatronic technology and computer numerical control for the following reasons: (1) these positions meet the definition of middle-skill level work and have declined in growth rate on employment, and (2) the positions have related work activities to the corresponding high-skilled positions in computer systems, mechatronics and robotics, which have a bright employment outlook and tend to be the seed talent for data scientist occupation. We collected data from O*NET OnLine, a database of over 900 occupational information sponsored by the US Department of Labor, and the *Occupational Outlook Handbook*, a publication of the US Department of Labor's Bureau of Labor Statistics, which describes what workers do on the job, working conditions, the training and education needed, earnings and expected job prospects. The projected growth or decline in employment is an estimated change in total employment over the projected period from 2021 to 2031.

Results analysis

The O*NET Online (2023c) data showed that data scientists, a higher-skilled occupation with 113,300 employees in 2021, have a much faster projected growth rate than the average, 11% or higher between 2021 and 2031. It has 13,500 projected job openings with median hourly wages of $49.76 or $103,500 annually. It is classified as a bright outlook occupation and is expected to grow rapidly in the next several years (O*NET Online, 2023c). Data scientists: (1) develop and implement a set of techniques or analytics applications to transform raw data into meaningful information using data-oriented programming languages and visualization software; (2) apply data mining, data modeling, natural language processing and ML to extract and analyze information from large structured and unstructured datasets and (3) visualize, interpret and report data findings (O*NET Online, 2023c).

Other jobs created by AI and ML in data science, ML engineering and AI research fields, such as computer systems engineers/architects, computer systems analysts, robotics engineers, mechatronics engineers and computer numerically controlled (CNC) tool programmers, are high-skill-level jobs with a bright outlook. These are expected to grow faster than average at an 8% or higher growth rate in 2021–2031 per O*NET and have large numbers of job openings as new and emerging occupations. Table 1 lists some related lower-skilled occupations that may become seed talent for data scientist positions. The fact that many of these occupations have a bright outlook in the job market highlights the importance of analyzing data scientist positions.

The number of open positions in data science continues to grow in the USA (Janssen, 2022). To address the talent shortage and skill gaps, electro-mechanical and mechatronics (EMM) technologists and technicians and CNC tool operators, as two middle-skilled occupations, are expected to decline in growth rate at 2% or lower in 2021–2031 (O*NET Online, 2023a, d). Employees in these positions may be reskilled and upskilled with a strategic career development plan to become future data scientists rather than being replaced by AI and robots with obsolete or incompatible skills in the organization. These professions usually require a high school diploma, an associate degree or a post-secondary certificate and involve operating electro-mechanical/robotic machines and CNC machines. Based on the familiarity of middle-skilled workers in these technical areas, it is logical to upskill them with the programming of CNC machines to enter the positions in CNC tool programmers that have a

Table 1. Occupations closely related to data scientists in robotics

Occupations	Projected Growth (2021-2031)	Projected Job Openings (2021-2031)	Bright Outlook	Education Required
Computer Systems Analysts	Faster than average (8% to 10%)	44,500		MS 14% BS 33% AS 29%
Computer Systems Engineers/Architects	Faster than average (8% to 10%)	34,700		MS 17% BS 57%
Robotics Engineering	Little or no change	10,800		MS 17% BS 50% AS 17%
Mechatronics Engineers	Little or no change	10,800		BS 66% AS 10%
Computer Numerically Controlled (CNC) Tool Programmers	Much faster than average (11% or higher)	3,600		AS 19% PSC 41% HSD 24%

Note(s): MS = Master's degree; BS = Bachelor's degree; AS = Associate's degree; PSC = Post-secondary certificate; HSD = High school diploma or equivalent

Source(s): Table created by authors using O*NET database bright outlook with faster than average growth rate at 11% or higher during 2021–2031 (O*NET Online, 2023b). Entering positions as a CNC tool programmer provides them with job security, as not only is this field expected to have fast growth but also it ranks high as an area where organizations have difficulty in talent acquisition (San Diego Workforce Partnership, 2015). This upskilling also significantly improves the earning potential of these employees from the median annual salary of $46,760 for CNC tool operators to $60,800 for CNC tool programmers (O*NET Online, 2023a, b).

It is worth noting that, although this first step of upskilling provides the workforce with job security, they are still middle-skilled. However, since this first step of upskilling has introduced computer programming concepts and they already have knowledge about CNC and electro-mechanical machines, this upskilling provides the opportunity to further upskill themselves to the higher-skilled positions of robotics engineering, mechatronics engineering, computer systems engineering and computer systems analyst. This second level of upskilling introduces them to the knowledge of mathematics, engineering and technology, as well as skills in complex problem-solving, decision-making and critical thinking. After acquiring these skills and knowledge, they can enter the next level of high-skilled positions in data science and AI, which have bright outlooks with expected growth, as illustrated in Figure 2. Data scientist occupation involves analyzing, manipulating and processing data, leading to data-driven decisions (Qin and Chiang, 2019). ML utilizes data analysis to predict trends (Zhou, 2021). AI utilizes continuous data input to learn and improve decision-making.

Based on the STS theory, as technology progresses, the disruptive change in the existing skill sets results in an intense and urgent need to focus on continuous learning and upskilling for the middle-skilled workforce. For employees, upskilling and reskilling in these areas can help them acquire new skills and knowledge to increase their employability and earning potential. Upskilling and reskilling middle-skilled workers in AI and robotics can also help close the skills gaps and increase the competitiveness of organizations in the global economy.

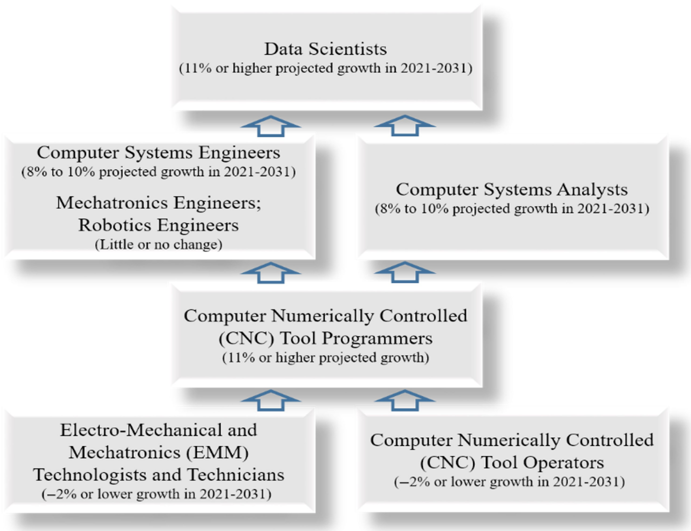

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Figure 2. Career path for middle-skill workforce in EMM technologists and technicians and CNC tool operators to high-skill workforce in data scientists

In short, our scenario analysis showed that by upskilling and reskilling the middle-skilled workforce through a proactive strategic career development intervention with AI integration, this middle-skilled sectoral workforce could enhance their career sustainability and be prepared for future higher-skilled positions at the technological advancement frontier.

Implications for human resource research, practice and policy analysis

Reskilling and upskilling middle-skilled workers have important implications for human resource research, practices and federal and state policies on workforce development fronts. While technological advancement may have important impacts on the labor market with various employment opportunities, HRD as a field of practice and research can offer unique contributions to improve and optimize the workforce structure through reskilling and upskilling, as well as empirical research. Such efforts also offer important implications for workforce development policies at the national, state and local levels.

Implications for research in workforce development

It must be noted that the technological advances in AI and ML demonstrated unequivocal impact on, and challenges in, HRD theory research. Given the emerging trends and challenges, empirical research and related studies focusing on the evaluation of reskilling and upskilling processes and outcomes, especially in particular industries, are limited and inadequate. Such research is needed to support career sustainability and the future development of middle-skilled workers (e.g. Frady, 2021). To support the nation's technology infrastructure and capacity for innovation-related upskilling initiatives, research in workforce development may need to devote efforts to the following areas:

(1) Develop a finer-grained understanding of middle-skilled workforce job context, outlook and skill gaps based on changes in technologies and associated workforce structure created by AI and robotics and future technology development.

(2) Promote the human–technology interactions of middle-skilled workers through upskilling and reskilling pathways as a part of mindset-shaping awareness at the community, regional and national levels to alert the urgency of technological changes and skill gap challenges.

(3) Develop a career development framework or pathway to guide middle-skilled workers whose jobs are potentially at risk due to technological advancement by offering information resources and guidelines and providing training and development resources and opportunities in their respective specializations.

The above areas are related to empirical research that may add significant value to the development of middle-skilled workers and allow them to be aware of future career possibilities and potentials. Such research may also derive HRD theorizing research opportunities to better understand the relationships between contemporary works, the workplace and the workforce concerning technological advancement (Chowdhury *et al.*, 2022).

It must be noted that technologies also present potential challenges such as gender bias in AI systems, especially in workforce development areas. This is because that AI systems may unintentionally reinforce existing biases (Ahn *et al.*, 2022; Leong and Sung, 2024), leading to unequal opportunities for women and underrepresented groups. Addressing this challenge is essential to ensure equitable reskilling and career advancement. Future research may consider identifying and mitigating gender bias in AI-driven HRD practices to promote a more inclusive and equitable workforce.

Implications for HRD practice

The delivery of HRD interventions can be advanced due to new learning technologies that make remote virtual learning possible. Yet, technologies can never change the essence of HRD (Wang and Doty, 2022). In other words, technologies only make HRD research and practice more efficient across the board or advance the HRD interventions related to delivery channels but cannot replace or change HRD's core functions and attributes. As HRD is defined and identified in two major functions – shaping and skilling – at both organizational and national levels (Wang and Doty, 2022), human resource professionals in the related industries, sectors and workforce development communities may be engaged in associated initiatives and activities. Essentially, shaping technological advancement in the contemporary workplace context means developing employees' mindsets and motivating career development aspirations toward the direction and trend consistent with the technological advances and frontiers.

One way to upskill and reskill middle-skilled workers is through training programs focusing on specific areas of AI and robotics. These programs can be delivered through various formats, including online learning, in-person training and apprenticeships. Another way to upskill and reskill middle-skilled workers is to initiate on-the-job training (OJT) and mentoring opportunities. This may involve working alongside more experienced senior employees who are already proficient in AI and robotics or participating in projects that use these technologies.

It is also important for organizations to provide ongoing support for employees engaged in the reskilling and upskilling process, including access to resources and tools in the form of software, books, tutorials and online communities to help them continue to develop their skills. AI can be used to upskill middle-skilled workers in a variety of ways. For example, human resource professionals can use AI-powered learning platforms to personalize training and development programs to meet the specific learning needs of individual employees. These platforms can use data and analytics to identify areas where employees need to improve and provide targeted training and resources to help develop the required skills.

Furthermore, human resource professionals may establish partnership relationships with industry, government and educational institutions as well as workforce development organizations at all levels. With the aim of developing and offering training programs that are aligned with the needs of the robotics industry and providing apprenticeships, internships and OJT to help augment the portion of the middle-skilled workforce and the higher-skilled portion.

It is also critical for human resource professionals to develop a sufficient degree of technological competency to demonstrate their unique contributions to implementing skilling processes, initiatives and activities. For example, in skill gap assessment processes and subsequent design, development and delivery of training programs, sufficient technology competency will allow human resource professionals to work and communicate with subject-matter experts, managers and employees effectively to achieve the goals of reskilling and upskilling. Such competency is also necessary for assessing and evaluating the subsequent learning outcomes.

Implications for HRD policies

The technology-induced skill gaps in the middle-skilled workforce have created important policy implications in at least three areas: federal, state and local HRD policy formation to address the reskilling and upskilling challenges in different industries and sectors; implementing existing HRD national policies to address the reskilling challenges and analysis and assessment of policy implementation outcomes.

First, initial policy formation has been observed and documented at the federal level. The Creating Helpful Incentives to Produce Semiconductors for America Act as a federal statute was enacted in August 2022 to support and boost domestic research and manufacturing of semiconductors with $280bn federal investment, of which $13.2bn was allocated to research and workforce training for reskilling and upskilling (The White House, 2022a). More recently, the Biden administration established a Roadmap to Support Good Jobs initiative in May 2023 (The White House, 2023). The purpose of this initiative, according to The White House (2023), was to "build our workforce by ensuring every American – whether they go to college or not – will have equitable access to high-quality training, education and services that provide a path to a good career without leaving their community." Additionally, the government launched an Advanced Manufacturing Workforce Sprint initiative to expand and diversify pathways into good jobs and careers in advanced manufacturing that do not require a four-year college degree.

With increased attention, focus and investment from government agencies, policy implementation may become advantageous for human resource professionals. This is because programs and initiatives focusing on addressing skill gaps always come with a learning component, from the classroom or online learning to OTJ and mentoring. Human resource professionals may consider actively engaging in these policy implementation programs at the organizational or community level to demonstrate their contributions.

Finally, HRD national policy analysis, assessment and evaluation have long been a controversial area in the human resource literature concerning theory-building research (e.g. McLean *et al.*, 2008; Wang and Swanson, 2008). The current HRD national policy formation, implementation and assessment in addressing workforce skill gaps in the USA offer an excellent opportunity for human resource scholars interested in policy analysis to explore and examine the entire cycle and processes of policy change, formation, implementation and outcome assessment in the mainstream arena. The resulting findings may be used to compare similar HRD policy processes in a non-mainstream country. Such policy analysis and comparative research may contribute to additional HRD theory development research.

Conclusion

In today's rapidly changing environment, the interactions between humans and technology are increasingly complex. Assessing the success of the integration of AI and ML into the middle-skilled workforce requires a multi-faceted approach that considers performance metrics, cost-effectiveness, job satisfaction, environmental impact and innovation. AI and ML empower faster data collection and processing, accurate information, quick learning from mistakes, decisions to solve task-specific problems, managing workflows and strengthening business competitiveness. Middle-skilled workers may enhance their career sustainability and be prepared for future higher-skilled work at the human-technology frontier via a proactive strategic career development plan with AI integration. Employees with AI skills can be more competitive in the workforce and advance to high-skilled positions. Unleashing middle-skilled workforce potentials for future work created by AI and robotics and sustaining economic competitiveness may address the economic downturn caused by technology-induced unemployment and benefit not only the organization but also the entire society.

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