Fostering AI-Ready Cultivating Resources CTE Pipelines

Implications for Policy, Practice & Research

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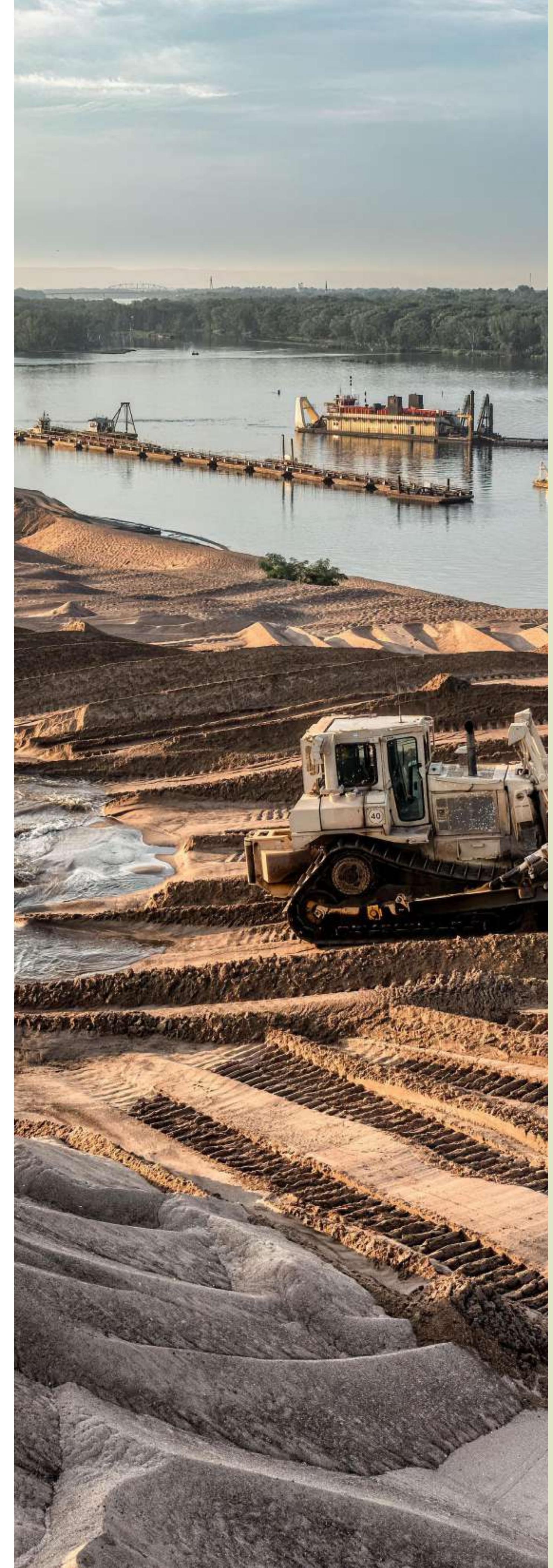


Introduction

Like the cotton gin and the Internet, AI is predicted to fundamentally reshape how, where, when, and what Americans do for work (Cazzaniga et al., 2024; Ellingrud et al., 2023; Makridakis, 2017).

There is widespread speculation that AI will generate new fields of work, more jobs, and overall economic growth (Shine, 2023; Stewart et al., 2015), but this is far from certain (Frey & Osborne, 2017). Indeed, there is little consensus on the degree to which AI might change the number of available jobs (Hatzius et al., 2023; Kessler, 2023).

Less contentious, however, is the belief that AI will likely change the composition of jobs. Existing research is clear: advances in technology have, over time, increased demand for jobs and workers able to perform non- routine, cognitive, and social tasks (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019). It is not entirely clear if, and to what degree, the accelerating usage of contemporary AI will reinforce this trend (Bick et al., 2024). Furthermore, not all education providers have the information or resources they need to act today and prepare students for the workplace of tomorrow.

The Education Research & Opportunity Center at the University of Tennessee Knoxville, Advance CTE, and ACTE are partnering on a series of briefs focused on the intersection of AI, workforce development, and community college career and technical education (CTE). This brief focuses on how current and projected developments in AI are revolutionizing occupations within the Cultivating Resources CTE Career Cluster, the potential exposure of Cultivating Resources occupations to AI-driven workforce automation, and how Cultivating Resources CTE providers can prepare their learners for a workplace increasingly shaped by AI technologies.

What Occupations Are Within the Cultivating Resources Cluster Grouping?

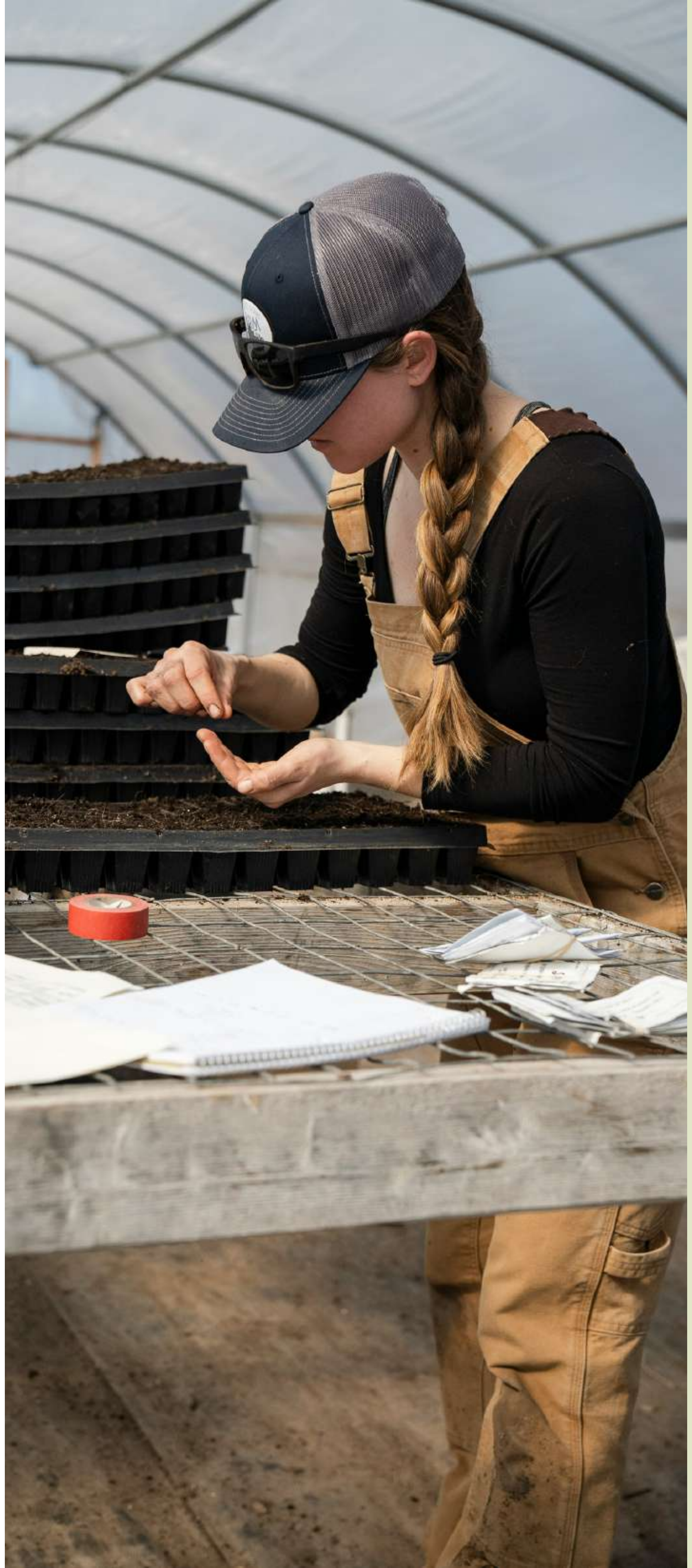
The National Career Clusters® Framework managed by Advance CTE provides a shared structure and language for CTE program design across the United States. In 2012, 94% of states had adopted the Career Cluster framework. In October 2024, Advance CTE released a modernized Career Clusters Framework designed to serve as a bridge between education and work and a central building block for consistently designed and high-quality CTE programs. This framework includes 6 Career Cluster Groupings that act as purpose-driven meta-sectors to help guide young people toward Clusters that are aligned with their interests and the impact they want to make on their communities.

The Cultivating Resources CTE Career Cluster Grouping consists of the Agriculture and Energy & Natural Resources Career Clusters[1]. The Agriculture Career Cluster attracts students with an interest in scientific advancement of agriscience, cultivation, processing, and distribution of agricultural products. Sub-Clusters within Agriculture include Agribusiness, Agricultural Technology & Automation, Animal Systems, Food & Science Processing, Plant Systems, and Water Systems.

Specific occupations tied to Agriculture include Animal Scientist, Forester, Animal Breeder, Farmer/Farmworker, and Food Science Technician.

The Energy & Natural Resources Career Cluster also falls within the Cultivating Resources Cluster Grouping and appeals to students dedicated to creating a sustainable future, innovating cleaner energy solutions, and preserving our planet's natural resources for generations to come. Sub-Clusters within Energy & Natural Resources include Clean & Alternative Energy, Conservation & Land Management, Ecological Research & Development, Environmental Protection, Resource Extraction, and Utilities. Occupations within the Energy & Natural Resources Career Cluster include, but are not limited to, Plant and Soil Scientists, Conservation Scientists, Power Plant Operators, and Wind Turbine Service Technicians. It is also worth noting that the Agriculture and Energy & Natural Resources Clusters have a lot of overlap and intersection, particularly around land management and conversation. Given this, a number of the AI examples used below could arguably be used in either Cluster.

1 https://careertech.org/career-clusters/



Cultivating Resources Clusters and Sub-Clusters

Agriculture

Agribusiness
Agricultural Technology & Automation
Animal Systems
Food & Science Processing
Plant Systems
Water Systems

Energy & Natural Resources

Clean & Alternative Energy
Conservation & Land Management
Ecological Research & Development
Environmental Protection
Resource Extraction
Utilities

How is AI Revolutionizing Cultivating Resources Occupations?

Agriculture

AI is having massive impacts on Agricultural occupations. The United State Department of Agriculture indicates that while some manual farming jobs are being displaced, new roles are emerging in areas like agricultural data science, robotics maintenance, and precision agriculture consulting (U.S. Government Accountability Office, 2024). For example, the formerly simple task of irrigation has transformed into a data-driven operation where workers must understand soil moisture sensors, weather prediction algorithms, and automated irrigation systems (US GAO, 2024). Additional AI-powered tools and technologies already impacting work within Agriculture include precision agriculture tools such as John Deere's See & Spray Select technology which "uses a color-detecting technology to identify and target spray green and brown soil" (John Deere, 2025).

Traditional farm labor roles are evolving into more technically sophisticated positions, with an estimated 40% of agricultural workers now requiring skills in operating AI-powered equipment and interpreting data from smart farming systems (Yang et al, 2023).

In his discussion with our team, Dr. Kevin Wade, associate professor and director of Dairy Information Systems at the McGill University, further discussed the importance of AI livestock monitoring. Dr. Wade introduced our team to the Irish startup Cainthus which produces AI-driven visual recognition and herd management technologies that allow dairy farmers to monitor herd activities, such as eating and sleeping patterns (Plug & Play Tech Center, 2019). Javid et al. (2023) found that successful modern farmers are increasingly taking on roles more akin to technology managers, spending up to 60% of their time analyzing AI-generated insights about crop and herd health, yield predictions, and resource optimization rather than performing traditional farming tasks.

Specifically in livestock management, AI tools like computer vision and wearable sensors track individual animals' behavior, movement, and health metrics, allowing for early detection of issues such as lameness, disease, or poor nutrition. AI algorithms are able analyze this data to detect subtle changes in a cow's gait or activity, which are often early indicators of critical health issues. These machine learning algorithms can analyze behavioral patterns in cattle to detect early signs of illness before clinical symptoms appear (Bushby et al., 2024; Silva et al., 202). By flagging these changes early, the system enables farmers to intervene promptly, providing timely veterinary care or adjusting the animal's environment to prevent further complications. The technology extends

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U.S. Government Accountability Office, 2024

beyond health monitoring—AI can optimize grazing patterns by analyzing satellite imagery and local weather data, leading to improved pasture utilization and increase in sustainable carrying capacity (Chelotti et al., 2024).

While AI is changing livestock farming, it is not eradicating it, but is merely enhancing its processes. Precision Livestock Farming is where automated real-team monitoring that can be guided by AI algorithms to monitor and even guide herds, reducing labor costs while improving animal welfare through constant, non-intrusive observation (Berckmans, 2017).

As discussed in the previous paragraph, AI is not only being used for farmers who specifically work the livestock, but also by farmers who work within the broader crop sector. Agriculture and water management systems using AI-powered sensors and machine learning algorithms are being deployed to optimize irrigation schedules and reduce water usage by up to 30% while maintaining crop yields (Arogundada & Njoku, 2024). Programs such as Taranis and AeroFarms are platforms that optimize irrigation and reduce water usage. To help with the 30% reduction in water usage, crop farmers are integrating precision irrigation methods to monitor and manage water supply to plants (Lakhiar et al. 2024). AI-powered sensors and precision irrigation systems have optimized the overall crop production within greenhouses and even outperform manual (traditional) crop growing (Hemming et al., 2019).

Nonetheless, manual crop growing is still a part of agriculture within the United States and across the globe. Traditional crop farmers who have opted to use smartphone-based AI applications have enabled them to identify crop diseases with 99.53% accuracy through simple photo analysis (Ahsan et al., 2022). These AI applications also support farmers in making precise decisions about planting and harvesting times, resulting in yield improvements of 15-20% across various regions (Patil, 2024). Lastly, these applications, with enough data entered into the machine learning algorithms, can analyze historical crop data and local climate patterns to recommend optimal crop varieties (Van Klompenburg et al., 2020).

In the field of food and science processing, AI is playing a transformative role by enhancing efficiency, quality control, and innovation across the entire food production chain. AI tools are being used to analyze vast datasets from sensory testing, chemical compositions, and consumer preferences to develop new flavors, textures, and formulations. Machine learning algorithms predict the properties of food products, such as shelf life, nutritional content, and taste profiles, helping researchers design safer, more sustainable, and tailored food options. Kurniawan et al. (2024) found that these machine learning algorithms can achieve a 98% accuracy rate in detecting foreign objects in processed foods using hyperspectral imaging. AI is also used in real-time monitoring systems to control critical factors during processing, such as temperature, humidity, and pressure, ensuring food safety and quality while reducing the likelihood of defects or contamination. For example, computer vision and machine learning algorithms can inspect food products on assembly lines, detecting issues like deformities, contamination, improper packaging, and automatically rejecting faulty items.

INTERVIEW SPOTLIGHT

Dr. Kevin Wade is an Associate Professor of Information Systems and the Director of the Dairy Information Systems Group in the Department of Animal Science at McGill University. As the Faculty's Dairy Academic Lead, Dr. Wade spearheads large-scale initiatives in dairy-production research focused on applications of AI, big data, and on-farm management systems related to milk production. Artificial Intelligence has a growing number of use cases in dairy production according to Dr. Wade. “When we're looking at animal wellbeing, specifically looking at instances where the cows may get lame or may have problems with walking because of the environment they're in. The machine learning algorithms are able pick out those points in the video we're looking for. Then the student or the researcher can come along, open up the video and it will go directly to the time sequence where there was something specific.” Dr. Kevin Wade, Associate Professor, Director of Dairy Information Systems, McGill University

Energy & Natural Resources

AI is playing an increasingly critical role in occupations connected to the Energy & Natural Resources CTE cluster area, with applications that drive efficiency, reduce environmental impact, and enhance safety. In the oil and gas industry, AI-powered predictive maintenance systems help detect potential equipment failures before they occur (Rashid et al., 2024). By analyzing sensor data from drilling equipment and pipelines, AI can identify patterns that indicate wear or stress, allowing maintenance teams to act before a failure happens, thus reducing downtime and avoiding costly repairs.

In clean and alternative energy, AI is used for optimizing energy production from solar and wind farms. Machine learning algorithms can predict weather patterns and adjust operations, allowing operators to maximize energy capture and improve grid integration, a key factor in sustainable energy management.

Energy grid management increasingly relies on AI for balancing supply and demand. Real-time data analysis allows grid operators to respond dynamically to fluctuations in power usage, reducing the need for fossil fuel-based energy backup and supporting cleaner, more efficient energy systems. For example, AI systems are enabling energy grid technicians to predicate maintenance needs, energy forecasting, system monitoring, and control strategies (Ukoba et al., 2024).

In natural resource management, AI-driven remote sensing technology is transforming the monitoring of forests, mining sites, and water resources. For example, by analyzing satellite and drone imagery, AI systems can track changes in land use, deforestation, water levels, and wildlife populations, all while detecting environmental threats in real-time with remarkable accuracy (Coulson, et al., 1987; Dam, 2024; Schmoldt & Rauscher, 1996). AI-powered systems analyze multispectral satellite data to identify early signs of deforestation or disease outbreaks in vegetation, allowing conservation teams to respond more quickly and effectively (Ibrahim, 2024). More importantly, integration of AI into natural resource management represents a significant shift from reactive to proactive conservation strategies, enabling industry to anticipate and prevent environmental challenges rather than simply responding to them after they occur.

Artificial Intelligence is also revolutionizing conservation and land management by enhancing monitoring, analysis, and decision-making processes to support biodiversity protection, sustainable land use, and habitat restoration.

INTERVIEW SPOTLIGHT

In a recent interview with our team, Daniel Goldsmith described how Julius Education is utilizing AI-driven Large Language Models and Natural Language Processing algorithms to identify green jobs within local economies. Historically, researchers have relied on the Standard Occupational Classification (SOC) system managed by the Bureau of Labor Statistics to designate and categorize occupations within the broader US economy. However, the SOC system poses challenges for identifying "green" occupations. First, individual SOC codes mask variation in occupational titles. Second, virtually any occupation can be classified as "green" if the employer is within a green industry. Third, jobs not characteristically associated with the green economy are increasingly tied to the growing green workforce (think electricians). Julius Education is supporting community college and employer partnerships in the energy and natural resources industries by using AI to help community colleges identify the full range of green labor market opportunities in their communities.

One significant application is the automated analysis of camera trap images and acoustic recordings for wildlife identification. According to Vélez et al. (2023), machine learning models trained to recognize different species have dramatically reduced the time and effort researchers spend on biodiversity monitoring. This technology has shown remarkable success, as demonstrated in the African Serengeti where AI-powered image recognition achieved 99.3% accuracy in identifying animals across 3.2 million images (Norouzzadeh et al., 2018).

AI is also proving invaluable in combating wildlife crime. Through the analysis of historical poaching data, weather conditions, animal movement patterns, and human activity, AI systems can predict potential poaching activities and identify high-risk areas (AAU, 2019).

The Protection for Wildlife Security (PAWS) system, now integrated with the Spatial Monitoring and Reporting Tool (SMART), exemplifies this approach. In Uganda in 2016, rangers using this technology successfully identified a poaching hotspot where an elephant had been killed for its tusks and subsequently discovered and removed multiple elephant and antelope snares (Zewe, 2019).

The integration of artificial intelligence into resource extraction operations has yielded significant improvements in safety, efficiency, and environmental protection. In mining operations, AI-powered autonomous vehicles and drilling systems now enable companies to remove personnel from hazardous environments while simultaneously increasing operational efficiency (Diasselliss, 2024). The application of machine learning algorithms to geological data analysis has transformed the site selection and drilling processes. These sophisticated systems analyze complex geological datasets to identify optimal extraction sites and establish efficient drilling patterns. As a result, companies have achieved substantial reductions in both exploration costs and environmental impact (Mkono et al., 2025).

Lastly, in the oil and gas sector, AI technology has revolutionized maintenance and safety protocols. Advanced AI systems now provide real-time monitoring of equipment health, enabling predictive maintenance that prevents costly failures. Additionally, the implementation of smart sensors and computer vision technology ensures immediate detection of leaks and environmental hazards (Jambol et al., 2024). This comprehensive monitoring approach significantly reduces operational risks while enhancing environmental protection measures.

INTERVIEW SPOTLIGHT

Dr. Ben Hertz-Shargel, Global Head of Grid Edge at Wood MacKenzie, has worked in the clean energy technology industry for over 10 years, where he has led research projects related to electrification, grid digitization and decentralization, distributed energy resources, and demand flexibility. In a recent discussion with our team, Dr. Hertz-Shargel said that “AI is a big opportunity to help train and be an assistant to younger grid operators in their very sort of complex job and I think to a lesser extent, that can also be true in other positions. Where you're dealing with a lot of data, a lot of information, it theoretically can save time in terms of gathering and organizing information.” Dr. Hertz-Shargel also believes that “training is a category where there is a lot of opportunity [for AI] to get people up to speed on these complex areas. In terms of aligning sort of people's jobs to this industry, I think if you can remove the manual side, (the sort of the data analyst role and a lot of the manual work required to deal with the amount of data that is otherwise required to make decisions),” and make them enabled by AI, “then you lose that position for a person, but you enable people to provide a kind of higher value, insights and roles in an organization.
I think in a way, [AI is] upskilling people.”

Will AI Automate Cultivating Resources Occupations?

As we discussed in a previous brief[2], tasks constitute jobs, jobs constitute occupations, and occupations constitute industries (U. S. Government Accountability Office, 2022).

Technological development can either substitute or complement the human skill required to complete job-related tasks. Substitution occurs when technology replaces human skill to perform a task. If enough tasks are substituted, the probability of occupation-level automation increases (U. S. Government Accountability Office, 2022). But substitution is not the only outcome; by contrast, technologies can complement and enhance the human skills needed to complete tasks, increase task efficiency, and actually bolster demand for those technologies and skills. Put simply, there is a long-standing recognition that technologies act on tasks directly, and occupations only indirectly (Acemoglu & Autor, 2011; U. S. Government Accountability Office, 2022).

There is no doubting whether existing and projected AI technologies will change the tasks and skills required to perform jobs in Cultivating Resources occupations.

The question centers around what this change might look like and whether we can expect AI to drive task substitution, complementarity, and/or creation. According to our analysis of O*NET occupational skills and job activities (i.e., tasks) data[3], the most prominent skills and activities required to perform jobs in the Cultivating Resource occupations are both technical (e.g., inspecting equipment, structures and materials) and transferable (e.g., negotiation, active listening, speaking, critical thinking). Technical skills are specific to Cultivating Resources job related tasks. For example, technical skills include computer coding, operating equipment, and recording information. On the other hand, transferable skills transcend specific occupations and can be applied in different settings and tasks. Active listening, critical thinking and deductive reasoning are transferable skills. The distinction matters because existing research suggests transferable skills are less prone to AI driven automation.

Appendix Tables 1-2 list the 10 largest occupations in the Cultivating Resources Career Clusters (by 2023 employment, according to the Bureau of Labor Statistics) and the five most important job-related skills and activities required of those occupations. Appendix Tables 1-2 also include two measures for understanding the degree to which AI may impact these Cultivating Resources occupations by focusing on the task/ skill composition within them. The first measure is the Artificial Intelligence Occupational Exposure (AIOE) index (Felten et al, 2021) which quantifies the degree to which capabilities (i.e., skills) of AI overlap with the task and skills for specific occupations (e.g., Plumbers). The AIOE index is standardized with a mean of 0 and standard deviation of 1. Higher AIOE scores can be interpreted as greater occupational exposure to AI; lower scores are interpreted as less occupational exposure to AI. Our findings show that increases in technology over time correspond to an increasing premium on jobs with a high share of nonroutine tasks, otherwise understood as tasks that require skills that cannot be easily automated by available technologies. The second measure is the Task Routinization Index (Acemoglu & Autor, 2011). Unlike the AIOE which assigns a single score to an occupation, the Task Routinization Index decomposes occupations into tasks that are either routine/non-routine and/or cognitive/manual and determines how relevant each category of task is within an occupation. Scores on the Task Routinization Index range from 1 (not important) to 5 (very important).[4]

One can see from Appendix Tables 1-2 that there is wide variation in AIOE and Task Routinization Index scores across the most prominent occupations within the Cultivating Resources Cluster Grouping. Overall, AIOE scores tend to be lower for many of the most heavily employed Cultivating Resources occupations relative to the average for all US occupations (as evidenced by the negative AIOE scores). This is a good thing for those concerned about loss of jobs in this area, as it suggests that Cultivating Resources occupations are less exposed to contemporary AI capabilities relative to other Career Clusters.

2 https://cehhs.utk.edu/ero/building-automation-resilient-community-and-technical-college-cte-pipelines-evidence-and-best-practices-from-tennessee/

3 https://www.onetonline.org/

4 The Task Routinization Index (Acemoglu & Autor, 2011) decomposes occupations into task categories, according to the influence of AI and automation technologies (using O*NET measures for the importance of tasks to an occupation). We aggregate scores back to the SOC level by averaging the task importance within each category for each occupation.

There are exceptions, however, such as the "high skill" Cultivating Resources occupations that have higher education entry level requirements, including Biological Scientists, Natural Sciences Managers, and Environmental Scientists. This is likely explained by the high share of both routine and non-routine cognitive tasks required to perform these occupations and the fact that AI is believed to have limited influence on the role of physical abilities in occupations and industries and is "likely to have the biggest impact on abilities related to information processing" (Felten et al, 2021, p. 2203) and other cognitive tasks. This is why physicists, for example, have greater exposure to AI than surgeons. Both occupations require cognitive abilities, but surgeons rely much more heavily on a broad range of abilities including dynamic physical, psychomotor, and sensory abilities (Felten et al, 2021).

Figure 1 of the Appendix provides visual confirmation that Cultivating Resources occupations have slightly above average or less than average AI occupational exposure relative to all occupations. As one can see, Agriculture occupations have an average AIOE score that is just slightly lower than the overall average, while occupations linked to Energy & Natural Resources occupations have average AIOE scores that are just slightly higher than the national average for all occupations. Importantly, Figure 1 of the Appendix also illustrates that there is a high degree of variation across occupations requiring different entry education levels. Across the board, occupations requiring a bachelor's degree or higher are at greatest AI exposure. By contrast, occupations requiring just a high school degree or less are the least exposed to AI. This is likely for two reasons. First, cognitive tasks predominate within occupations requiring more formal education. (Appendix Tables 1-2; Acemoglu & Autor, 2011). There is a strong overlap between the capabilities of contemporary AI and human cognitive abilities, such as information processing (Brynjolfsson & Mitchell, 2017; Felten et al, 2021). Importantly, AIOE scores alone cannot tell us how AI will impact demand for occupations. The AIOE index simply correlates human and AI abilities in specific occupational settings. It is natural, therefore, to conclude that occupations with higher AIOE scores would be at greater risk of AI-driven automation. Yet, while automation is certainly a possibility and existing research illustrates that smart machines have, over time, eliminated occupations heavily reliant on routine manual and cognitive tasks, it is equally possible that occupations with AIOE scores would require more human workers to develop, utilize, monitor, and refine AI technologies in those occupations.

Simply put, where there are higher AIOE scores, there is a higher likelihood that AI will be integrated into those fields of work.

Therefore, Figure 1 of the Appendix suggests that many Cultivating Resources occupations - especially those requiring a bachelor's degree - may be increasingly dependent on AI not for replacing human labor, but for enhancing it.

How Can Cultivating Resources Students Thrive in an AI Driven Workforce?

Career and technical education providers, industry partners, and policymakers can act now to ensure that students gain the skills and literacies needed to thrive in an increasingly AI-driven work environment. While our analysis shows that Cultivating Resources occupations are not likely to be entirely automated by AI, there is no doubt that AI will change the skill composition required for future workers. These jobs will become increasingly reliant on a variety of AI technologies. As we discussed, AI is already flowing into the work-related tasks in both Agriculture and Energy & Natural Resources occupations. It is critical, therefore, that the next generation of CTE programs are designed with these developments in mind.

Career and Technical Education Providers

SHIFT THE NARRATIVE

Career and technical education providers we spoke with repeatedly stressed the tensions on campuses that exist between essentially two "camps" of CTE educators: the early adopters and the cautiously suspicious. The early adopters have eagerly embraced AI for themselves and their students. These are faculty and administrators who actively follow AI developments, regularly use and experiment with AI tools, and encourage their students to do the same. The cautiously suspicious, by contrast, are far more reserved and reluctant to embrace AI for a host of reasons including, but not limited to, concerns around data privacy, student tracking, and ethics. This group of faculty and administrators is also concerned about plagiarism, instructional quality, and learning assessment.

The narrative needs to shift from "either/or" to "both/and." AI is fundamentally changing the world of work students are training for.

Exposing students to AI tools and technologies cannot be optional, it must be mandatory. Every course and every program within the Cultivating Resources Cluster grouping must train students on AI applications in the fields of work they are preparing for. At the same time, we must take student privacy seriously, and we must listen to and address the concerns expressed by faculty who are worried about the downstream impacts of AI on educational quality. We strongly recommend campus/school wide conversations and dialogue. An individuated, teacher-by-teacher, class-by-class AI policy approach is not only ineffective, but it places students at risk and fosters inequities. Yet, the individuated model prevails at the current moment. There is evidence that colleges serving more affluent students are more likely to offer training, courses and programs in AI compared to open access institutions like community colleges (Palmer, 2025). Highly-selective, elite institutions cannot be the only ones aggressively engaging AI; open-access, community and technical colleges providing Cultivating Resources courses and programs must do the same. Jensen Huang, CEO of NVIDIA, explains why: “If you are not engaging AI actively and aggressively, you are doing it wrong. You are not going to lose your job to AI, you’re going to lose your job to someone who uses AI.”

FOCUS ON SKILLS, NOT ONLY JOBS

It is exceedingly difficult to predict which individual occupations will be impacted - positively or negatively - by AI (Merisotis, 2020). Not only is it guesswork, but it is also flawed thinking, rooted in a misunderstanding of how technology impacts work (Acemoglu & Autor, 2011; Park & Kim, 2022).

Technology does not impact occupations directly, it acts on them through tasks and skills and the traditional approach to thinking of education in terms of majors, courses, and degrees does learners a disservice.

By contrast, our focus needs to be on the skills students enrolled in Cultivating Resources programs of study/pathways acquire. Technical skills are crucial for Cultivating Resources occupations, but the growing influence of AI in Cultivating Resources sectors means learners must also acquire skills to generate (e.g., prompt engineering) and critically audit and assess AI output. These skills, along with fundamental skills in critical thinking, group communication, creativity, problem-solving, and research, will be essential for carrying out job-related tasks in all occupations, including those in the Cultivating Resources Clusters. Appendix Tables 1-2 show that the most heavily employed Cultivating Resources occupations already require these skills. But how will AI change what they look like in practice, on the job? For example, what does quality control analysis, writing, critical thinking, judgment and decision making, and reading comprehension look like for Farmers or Natural Science Managers in the AI age? These are critical questions for community college leaders, faculty, and industry representatives to ask and answer.

Industry Partners

BRIDGE THE GAP(S)

Rapid advances and deployment of AI across Cultivating Resources occupations emphasizes the importance of industry partnerships. Education providers cannot prepare students for AI-driven Cultivating Resources occupations without knowing the AI technologies and applications employers are focused on. This is the purpose of local workforce advisory boards as well as numerous federal and state policies designed to close the gap between educators and employers.

Industry partners can support the work of community and technical college Cultivating Resources programs by identifying and sharing the AI applications and use cases in their industry. Industry partners can also aid providers by advocating for the AI skills they need and will be hiring for. Industry can further assist by equipping Cultivating Resources classrooms with next generation AI-driven software, machines, technologies, and robotics so students can access and train on them immediately. At the same time, numerous CTE educators and industry representatives have shared that industry itself is unsure of the AI landscape and how to respond. One community college dean told us that he was often the voice of authority and information on AI during meetings within industry partners. The challenges of keeping ahead of AI developments and knowing precisely how to deploy AI are particularly acute for small and medium sized businesses and especially those in rural areas.

Policymakers

BUILD ON WHAT WORKS

Recent changes to federal CTE and workforce education policies have given community and technical colleges, as well as employers, many helpful tools to work with. For example, the comprehensive local needs assessment within Perkins V is a fantastic framework on which to build and strengthen private/public partnerships to address the AI exigency. This particular policy requires community and technical college CTE providers to assess local labor market conditions and consult with stakeholders, including local businesses, to help make funding decisions. This policy mandate should be leveraged and improved to address any emergent AI skills mismatches in local economies.

Similar to Perkins, additional policy efforts are needed to increase funding for apprenticeship and work-based learning programs, which would enable students to gain tangible, occupation-specific AI applications and skills.

Policymakers need to act to ensure community and technical college students have access to meaningful learning opportunities at places of work where AI innovations will first appear.

INVEST IN THE FUTURE

It is crucial that Cultivating Resources classrooms give learners access to the most innovative, state-of-the-art AI tools and technologies. Industry partnerships are crucial for this reason: as close collaborators, industry partners and local employers can provide community and technical colleges with real-world equipment for students to train on. This may include advanced, AI-powered electric vehicles, AI-enabled diagnostic technologies, AR/VR wearables, or robotics for large-scale manufacturing. These technologies are expensive, however, and not every community and technical college can count on local employers for learner access. One community college dean estimated that building a modern automotive technologies program can cost over $1M to establish and additional thousands to maintain and update. Recruiting and retaining trained faculty is an additional challenge and cost. Policymakers can help by continuing to funnel investments that foster private public partnerships and help CTE providers gain classroom access to the technologies students will later use in the workplace.

NOT A TIME FOR FEDERAL RETREAT

Though CTE is largely driven by policymakers and system leaders at the state level, the federal government plays an essential role. First, the federal government directs states and local CTE providers to set accountability targets for CTE providers. Second, the federal government provides over one billion dollars in CTE funding in the form of state allocation grants through Perkins V legislation. These grants supplement state funding sources, balance out funding shortfalls, and reduce inequities. Third, funding for CTE connects with other statutes like the Workforce Innovation and Opportunity Act (WIOA), The Higher Education Act, the Individuals with Disabilities Education Act, and Every Student Succeeds Act.

Collectively, these statutes help CTE providers to braid funding streams, build workforce development pipelines, and increase access and success for disadvantaged learners.

The Trump Administration is rapidly working to decrease size and reach of crucial federal agencies. For example, President Trump and the Department of Government Efficiency are weighing drastic cuts to the Department of Labor, which is home to the WIOA. President Trump has also made eliminating the Department of Education a known objective. While we support efforts to improve efficiency, we also support policies that have been proven effective and the data are quite clear: contemporary CTE policy works. CTE students are more likely to graduate high school, enroll in college, and enjoy employment and wage premiums relative to their counterparts in the general education curriculum (Bozick, et al, 2014; Carruthers & Stanford, 2018; Dougherty, 2018; Ecton & Dougherty, 2023; Stevens et al, 2019). States have played an important role in bringing about these positive outcomes, but bipartisan action at the federal level has been the key driver. This report makes clear that AI presents a number of exciting opportunities as well as formidable challenges for CTE providers. This is not a time for federal retreat. By contrast, we believe strong, bipartisan support among federal policymakers for effective and efficient CTE has never been more critical.

Conclusion

Agriculture and Energy & Natural Resources occupations provide bright, innovative, and hands-on learners with exciting, rewarding, and remunerative career pathways.

Students pursuing these occupations will help the nation use and conserve its natural resources, to modernize utilities, care for natural spaces and wildlife, provide sustainable and abundant food and nutrition systems and lead us towards a safer and more sustainable future, This said, AI will have massive impacts on Cultivating Resources work. AI may substitute some routine and repetitive job-related tasks and even entirely automate some roles, but the vast majority of Cultivating Resources occupations will persist and workers with the right combination of technical and transferable skills and AI literacies will thrive. It is the job of the nation's community and technical colleges to prepare learners for this future.

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TABLE 1

Largest Occupations, top skills, and AI Occupational Exposure: *Agriculture*

Occupation	Top Skills	Top Activities	AIOE	Routine Manual	Non-Routine Manual	Routine Cognitive	Non-Routine Cognitive
Animal caretakers	• Monitoring • Judgment and Decision Making • Reading Comprehension • Active Listening • Service Orientation	• Getting Information • Communicating with Supervisors, Peers, or Subordinates • Performing General Physical Activities • Identifying Objects, Actions, and Events • Handling and Moving Objects	-0.89	2.11	2.53	2.96	2.90
Farmworkers and laborers, crop, nursery, and greenhouse	• Speaking • Operations Monitoring • Active Listening • Operation and Control • Writing	• Performing General Physical Activities • Handling and Moving Objects • Getting Information • Identifying Objects, Actions, and Events • Communicating with Supervisors, Peers, or Subordinates	-1.6	3.05	2.98	2.71	2.17
Meat, poultry, and fish cutters and trimmers	• Active Listening • Judgement and Decision Making • Monitoring • Critical Thinking • Speaking	• Getting Information • Identifying Objects, Actions, and Events • Handling and Moving Objects • Inspecting Equipment, Structures, or Materials • Communicating with Supervisors, Peers, or Subordinates	-1.11	4.23	3.02	3.72	3.20
Butchers and meat cutters	• Active Listening • Social Perceptiveness • Monitoring • Service Orientation • Critical Thinking	• Performing for or Working Directly with the Public • Getting Information • Inspecting Equipment, Structures, or Materials • Performing General Physical Activities • Selling or Influencing Others	-0.97	3.80	3.08	3.13	3.01
Veterinary technologists and technicians	• Critical Thinking • Active Listening • Speaking • Reading Comprehension • Monitoring	• Identifying Objects, Actions, and Events • Assisting and Caring for Others • Documenting/Recording Information • Getting Information • Inspecting Equipment, Structures, or Materials	-0.36	2.52	2.54	3.30	3.23
Veterinary assistants and laboratory animal caretakers	• Active Listening • Critical Thinking • Writing • Reading Comprehension • Monitoring	• Documenting/Recording Information • Performing General Physical Activities • Communicating with Supervisors, Peers, or Subordinates • Assisting and Caring for Others • Monitoring Processes, Materials, or Surroundings	-0.77	2.66	2.56	3.73	3.19
Pest control workers	• Active Listening • Critical Thinking • Speaking • Writing • Monitoring • Active Listening	• Getting Information • Identifying Objects, Actions, and Events • Operating Vehicles, Mechanized Devices, or Equipment • Inspecting Equipment, Structures, or Materials • Making Decisions and Solving Problems	-0.73	2.78	3.49	3.06	2.97
Veterinarians	• Reading Comprehension • Active Learning • Speaking • Critical Thinking	• Getting Information • Updating and Using Relevant Knowledge • Identifying Objects, Actions, and Events • Documenting/Recording Information	-0.07	2.36	2.44	3.14	3.38
Slaughterers and meat packers	• Speaking • Active Listening • Social Perceptiveness • Critical Thinking • Operations Monitoring	• Handling and Moving Objects • Inspecting Equipment, Structures, or Materials • Performing General Physical Activities • Monitoring Processes, Materials, or Surroundings	-1.83	3.83	2.65	3.14	2.34
Biological scientist, all other	• Science • Reading Comprehension • Writing	• Working with Computers • Getting Information • Analyzing Data or Information • Thinking Creatively • Working with Computers	1.01	2.11	1.90	3.00	3.94

TABLE 2

Largest Occupations, top skills, and AI Occupational Exposure: *Energy & Natural Resources*

Occupation	Top Skills	Top Activities	AIOE	Routine Manual	Non-Routine Manual	Routine Cognitive	Non-Routine Cognitive
Firefighters	• Critical Thinking • Judgment and Decision Making • Service Orientation • Coordination • Active Learning	• Inspecting Equipment, Structures, or Materials • Operating Vehicles, Mechanized Devices, or Equipment • Assisting and Caring for Others • Making Decisions and Solving Problems • Performing General Physical Activities	-1.32	3.02	3.79	3.13	3.40
Telecommunications equipment installers and repairers, except line installers	• Repairing • Troubleshooting • Operations Monitoring • Critical Thinking • Quality Control Analysis	• Working with Computers • Getting Information • Making Decisions and Solving Problems • Operating Vehicles, Mechanized Devices, or Equipment • Communicating with Supervisors, Peers, or Subordinates	-0.85	2.39	3.65	3.43	3.02
Refuse and recyclable material collectors	• Operation and Control • Operations Monitoring • Active Listening • Speaking • Equipment Maintenance	• Operating Vehicles, Mechanized Devices, or Equipment • Performing General Physical Activities • Handling and Moving Objects • Inspecting Equipment, Structures, or Materials • Communicating with Supervisors, Peers, or Subordinates	-1.28	3.81	3.80	3.30	2.51
Water and wastewater treatment plant and system operators	• Operations Monitoring • Operation and Control • Monitoring • Active Listening • Quality Control Analysis	• Evaluating Information to Determine Compliance with Standards • Controlling Machines and Processes • Monitoring Processes, Materials, or Surroundings • Making Decisions and Solving Problems • Processing Information	-0.45	3.14	2.76	3.20	3.47
Electrical power-line installers and repairers	• Troubleshooting • Active Listening • Monitoring • Operations Monitoring • Operation and Control	• Operating Vehicles, Mechanized Devices, or Equipment • Performing General Physical Activities • Handling and Moving Objects • Inspecting Equipment, Structures, or Materials • Controlling Machines and Processes	-1.08	3.28	3.74	3.07	3.73
Telecommunications line installers and repairers	• Operations Monitoring • Speaking • Critical Thinking • Complex Problem Solving • Active Listening	• Performing General Physical Activities • Operating Vehicles, Mechanized Devices, or Equipment • Making Decisions and Solving Problems • Handling and Moving Objects • Identifying Objects, Actions, and Events	-1.08	3.14	3.57	3.25	3.14
Natural sciences managers	• Science • Writing • Speaking • Reading Comprehension • Active Listening	• Monitoring Processes, Materials, or Surroundings • Making Decisions and Solving Problems • Organizing, Planning, and Prioritizing Work • Communicating with Supervisors, Peers, or Subordinates • Analyzing Data or Information	1.33	1.87	1.53	2.72	3.75
Electronics engineers, except computer	• Complex Problem Solving • Critical Thinking • Reading Comprehension • Speaking	• Working with Computers • Making Decisions and Solving Problems • Analyzing Data or Information • Thinking Creatively	0.67	2.21	2.03	3.07	3.30
Environmental scientists and specialists, including health	• Reading Comprehension • Science • Writing • Speaking	• Getting Information • Analyzing Data or Information • Evaluating Information to Determine Compliance with Standards	1.01	1.71	1.78	2.66	3.62
Civil engineering technologists and technicians	• Critical Thinking • Reading Comprehension • Active Listening • Mathematics • Speaking	• Getting Information • Working with Computers • Processing Information • Evaluating Information to Determine Compliance with Standards • Identifying Objects, Actions, and Events	0.93	2.28	2.35	3.14	3.20

FIGURE 1

Average Artificial Intelligence Occupational Exposure Scores for Building & Moving Career Clusters