2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #50501

AI Technician Workforce Demand and Community College Curriculum Development: A Systematic Mixed-Methods Analysis of Maryland's Eastern Shore

Mr. Daniel I. Adeniranye, Florida International University

Daniel Adeniranye [ah-deh-nee-RAHN-yeh] is a Ph.D. candidate in Engineering and Computing Education at Florida International University, where he serves as Instructor of Record for EGS 2053: Foundations of Interdisciplinary Engineering. He holds a B.Tech in Mechanical Engineering, a joint M.S. in Petroleum Engineering and Project Development, and an M.S. in Project Management. His research examines engineering transfer student pathways to four-year institutions, AI in education and workforce development, and culturally responsive pedagogy across U.S. and international contexts. He is Immediate Past Chair of the ASEE Student Division.

Dr. Bruk T Berhane, Florida International University

Dr. Bruk T. Berhane received his bachelorâ€™s degree in electrical engineering from the University of Maryland in 2003. He then completed a masterâ€™s degree in engineering management at George Washington University in 2007. In 2016, he earned a Ph

AI Technician Workforce Demand and Community College Curriculum Development: A Systematic Mixed-Methods Analysis of Maryland's Eastern Shore

Abstract

Background. Manufacturing and engineering sectors rapidly integrating artificial intelligence technologies face critical shortages of qualified technicians, with forty percent of manufacturing competency requirements projected to change within five years. Systematic analysis of regional workforce needs and educational responses remains limited, particularly for rural and semi-rural regions positioned to benefit from AI-driven economic development.

Purpose. Grounded in Human Capital Theory, Regional Innovation Systems Theory, and Skills-Based Technological Change Theory, this study examines workforce demand and associated competency requirements for AI-skilled technicians across national, state, and regional levels, with primary focus on Maryland's Eastern Shore, to identify implications for community college curriculum development.

Method. We employ a convergent mixed-methods secondary analysis synthesizing 32 high-quality sources through systematic content analysis and quantitative comparison. Sources underwent quality assessment using a six-dimension framework (18-point scale, 66.7 percent inclusion threshold), achieving a 91.4 percent inclusion rate and 94 percent inter-rater agreement. Analysis applied structured coding across eight a priori themes, multi-source triangulation across four source types, and geographic-level comparisons.

Results. Findings indicate substantial and growing demand for AI-skilled technicians nationally, with 87.5 percent source convergence documenting 1.9 to 3.8 million unfilled manufacturing positions by 2033. The Baltimore-Washington capital region is the nation's second-largest AI jobs hub, trailing only California. Eastern Shore documentation shows active Industry 4.0 investments and growing employer-education coordination. Three-quarters of sources identify community colleges as primary pathways, with technical competency convergence around machine learning (23 sources), data analysis (21 sources), and AI programming (19 sources).

Conclusions. Evidence supports investment in AI technician education on Maryland's Eastern Shore through modular credential pathways, deep industry partnerships, and sustained faculty development. The systematic multi-source analysis approach offers a replicable model for regional workforce assessment in emerging technology fields.

Keywords: *AI technician education; community college curriculum; workforce demand analysis; mixed-methods secondary analysis; regional workforce development; Maryland's Eastern Shore.*

1. Introduction

Artificial intelligence is reshaping manufacturing and engineering work at a pace that outstrips educational response. Industry projections indicate up to 3.8 million unfilled manufacturing positions by 2033, and roughly forty percent of manufacturing competency requirements are expected to change within the next five years [1-2]. The transformation extends beyond mechanical skill into analytics, programming, simulation, and design [3], with specific talent gaps emerging in data science, natural language processing, and automation technologies [4]. For community college leaders, who educate 52 percent of the STEM workforce without bachelor's degrees [5], two questions now compete for attention: how large is the demand, and what should graduates actually know how to do?

Both questions are especially difficult to answer at the regional level. Rural and semi-rural regions stand to benefit meaningfully from AI-driven growth, yet face well-documented constraints in developing responsive educational programs: limited employer density, dispersed commuting sheds, competition with metropolitan areas for talent and faculty, and thin institutional capacity for equipment-intensive curricula [6-10]. These constraints matter for AI technician education specifically because AI-enabled production systems require capital investment that clusters geographically, and because skill requirements emerge faster than curriculum cycles can absorb. Without systematic regional evidence, community college leaders must commit scarce resources to programs whose shape and scale are uncertain.

Existing guidance is thin. National projections describe demand at an aggregate level that obscures regional variation. Industry white papers describe competency needs in ways tailored to single employers or sectors. Peer-reviewed engineering education scholarship examines curriculum design without systematic integration of labor market evidence, despite the observation that engineering education has remained largely unchanged since 1955 [3]. The practical result is that institutional leaders navigate rapid technological change with limited evidence about what to build, where, and why.

This study addresses that gap through systematic analysis of AI technician workforce demand and associated competency requirements, with primary focus on Maryland's Eastern Shore. The Eastern Shore offers a useful analytical case because it shares characteristics with many rural regions positioned to benefit from advanced manufacturing investment: established manufacturing heritage, proximity to a metropolitan AI jobs hub, rural geography, and active state policy engagement. Three research questions guide the investigation:

- RQ1: What evidence exists across multiple data sources regarding AI technician workforce demand and associated competency requirements, from national to regional levels?
- RQ2: How do Maryland's Eastern Shore workforce needs compare to broader national and state patterns?

- RQ3: What specific curriculum development implications emerge for community college leadership?

Rather than relying on single data sources that may miss crucial patterns, the study synthesizes federal employment projections, industry research, peer-reviewed academic studies, and regional economic development documentation. Multi-source triangulation provides enhanced reliability compared with single-source analyses while keeping focus on actionable implications for educational practice [11-12]. The study contributes a replicable method for regional workforce assessment in emerging technology fields alongside immediate practical guidance for community college curriculum development and regional workforce planning.

2. Literature Review

2.1 AI Workforce Development Context

The integration of artificial intelligence into manufacturing represents what scholars describe as a fundamental restructuring of work rather than simple automation of existing tasks [13-14]. Unlike earlier technological transitions where machines replaced human labor on routine tasks, AI systems increasingly complement human workers in complex decision-making [15-16]. The resulting demand is for workers who combine domain-specific technical skills with the ability to collaborate effectively with intelligent systems [14]. Recent empirical analyses of AI-related job postings identify Python programming, machine learning, and data analysis as the most frequent competency requirements across sectors [4], [17], a pattern we revisit in the Findings.

Federal agencies have recognized this transformation through targeted policy investment. The National Science Foundation's Advanced Technological Education program prioritizes community college development of emerging technology curricula [18], and recent federal investment of $2.8 million targets AI education at two-year institutions [19]. These investments reflect a growing recognition that community colleges serve as critical infrastructure for workforce development, educating more than half of all STEM technicians nationally [5].

2.2 Community Colleges, Regional Coordination, and the AI Technician Challenge

Community colleges occupy a distinctive position in workforce development, offering accessible pathways to technical careers while maintaining close relationships with regional employers [20-21]. Their historical strength lies in responsive curriculum development, with average program revision cycles of eighteen to twenty-four months compared with four to seven years at four-year institutions [22]. That agility is particularly valuable for AI-enabled manufacturing, where competency requirements evolve on short timescales.

Developing AI-related programs is difficult, however. Faculty expertise often lags technological advancement [23]. Industry partnerships require careful cultivation [24]. Equipment costs for advanced manufacturing exceed traditional program budgets [25]. These constraints are acute in rural regions where employer density limits partnership opportunities and resource pooling [9].

Regional planning challenges are not peripheral to AI technician demand; they shape the conditions under which demand can be met. Effective workforce development requires coordination across educational institutions, employers, economic development agencies, and government entities [26]. In rural regions, geographic dispersion, limited institutional capacity, and metropolitan pull on talent complicate collaborative effort [7], [10]. For AI technician education specifically, coordination problems compound: capital-intensive equipment is most efficiently shared across institutions, faculty with industry experience are scarce, and stackable credentials need regional articulation agreements to function. In other words, the same coordination challenges that constrain rural workforce development generally constrain AI technician education in particular, and doing so more sharply because of AI-specific infrastructure and expertise requirements.

Maryland's Eastern Shore exemplifies this dynamic. Its manufacturing base includes electronics assembly, precision machining, aerospace and defense subcontracting, and food processing operations, all increasingly adopting automation technologies [27-28]. Regional community colleges must serve employers across a broad geographic area while competing with Baltimore and Washington metropolitan regions for both students and faculty talent. These characteristics make the region an informative case for examining how evidence can inform educational practice.

3. Conceptual Framework

Three complementary theoretical frameworks address the multi-level nature of AI technician workforce development. Together, they offer analytical purchase at individual, regional, and task levels while maintaining coherence across levels.

Human Capital Theory [29] provides foundation for understanding individual-level investment in technical skills. The theory holds that education and training investments yield returns through enhanced productivity and earnings. For AI technician education, the framework helps identify specific competencies likely to generate returns for both workers and employers, while acknowledging that rapidly changing skill requirements complicate traditional human capital calculations [30].

Regional Innovation Systems Theory [31] addresses the institutional and geographic context of workforce development. Innovation and economic development emerge from interactions among firms, educational institutions, and supporting organizations within defined geographic areas. For community colleges, the framework highlights the importance of deep employer partnerships and regional coordination rather than isolated institutional effort.

Skills-Based Technological Change Theory [32] explains how technological advancement reshapes occupational skill requirements. Rather than simply automating existing tasks, AI technologies create new task configurations that require different combinations of human and machine capabilities. This framework guides the analysis of specific competency requirements and their evolution over time.

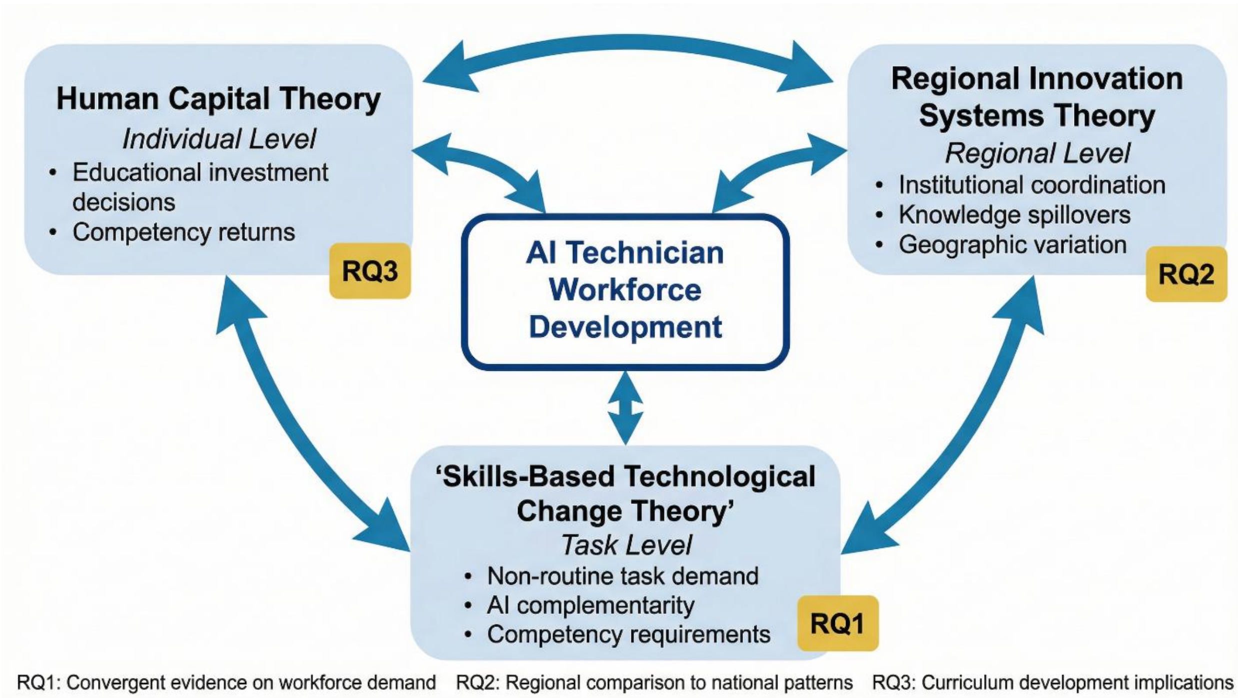

Figure 1. Integrated conceptual framework for AI technician workforce development.

Each research question aligns with one lens and one level of analysis, and each lens constrains what the corresponding findings can and cannot show. RQ1 examines convergent evidence on workforce demand and competency requirements, the central concerns of Skills-Based Technological Change Theory at the task level; findings are interpreted as signals about how AI is reconfiguring occupational tasks rather than as predictions of aggregate employment. RQ2 compares regional patterns to broader state and national patterns, the domain of Regional Innovation Systems Theory at the regional level; findings are interpreted as evidence about whether regional institutional conditions enable or impede AI workforce development. RQ3 addresses curriculum development implications, the domain of Human Capital Theory at the individual level; findings are interpreted as guidance for investments whose returns depend on credential design, delivery mode, and labor market demand. The three lenses do not substitute for one another. An answer at the task level does not automatically translate to a regional strategy, and an answer at the regional level does not automatically translate to an individual curriculum decision. Framing the analysis this way preserves the distinct logics of each level while enabling their integration.

4. Positionality Statement

This research is shaped by our specific analytical perspectives. The research team brings direct experience in community college education, engineering technology program development, and regional workforce planning. Engagement with the Advanced Technological Education community has informed our understanding of the opportunities and constraints facing two-year institutions in emerging technology fields.

Our focus on Maryland's Eastern Shore reflects analytical opportunity and practical interest. The region's rural nature, manufacturing heritage, and proximity to major metropolitan areas align with the research questions while enabling collaboration with regional stakeholders. We approach the region not as detached observers but as researchers invested in how evidence can inform educational practice in regions often overlooked by national workforce analyses.

Our theoretical orientation toward multi-source analysis reflects epistemological commitments to triangulation and methodological rigor. Single-source analyses, while valuable, can miss patterns that become evident only through systematic comparison. This orientation shapes the methods and influences the interpretation of findings.

5. Methodology

5.1 Research Design

The study uses a convergent mixed-methods secondary analysis design [33], synthesizing existing data sources to address the research questions. Secondary analysis offers particular advantages for workforce research, enabling systematic comparison across sources while maintaining feasibility within resource constraints [34]. The design integrates qualitative content analysis of textual sources with quantitative comparison of employment projections and economic indicators.

5.2 Data Collection

Data collection proceeded in four phases: (1) systematic identification of potential sources through database searches and reference chaining; (2) preliminary screening against inclusion criteria; (3) quality assessment using the six-dimension framework described below; and (4) full-text analysis of sources meeting quality thresholds.

Searches covered academic databases (ERIC, ProQuest, Google Scholar), government repositories (BLS, NSF, Census), and industry sources (Deloitte, McKinsey, trade associations) using terms combining AI/artificial intelligence, workforce/employment, technician/technical, manufacturing/engineering, and community college/two-year. Initial searches yielded 47 potentially relevant sources. After applying inclusion criteria requiring substantive workforce data, methodological transparency, and publication within five years, 35 sources proceeded to quality assessment. Of those, 32 met the quality threshold (91.4 percent inclusion rate). The final corpus comprises federal government reports (n=8), state government and economic development documents (n=6), industry research reports (n=9), and peer-reviewed academic studies (n=9).

5.3 Quality Assessment Framework and Rationale

We developed a six-dimension quality assessment framework to accommodate the heterogeneity of our corpus, which spans peer-reviewed studies, federal reports, state and regional economic development documents, and industry white papers. Each dimension is scored from 0 (not addressed) to 3 (comprehensively addressed), yielding a maximum of 18 points. We set a 66.7 percent threshold (12 points) for inclusion, balancing analytical rigor with practical inclusion of valuable sources that excel on some dimensions while showing limitations on others. Two researchers independently assessed each source, achieving 94 percent initial agreement; disagreements were resolved through discussion, with a third researcher consulted for persistent discrepancies.

We considered established instruments including the Mixed Methods Appraisal Tool (MMAT) and the Critical Appraisal Skills Programme (CASP) checklists but chose not to adopt them. Both are designed to evaluate primary empirical studies, relying on criteria such as sampling strategy, measurement validity, and analytic rigor within a single study design. Applied to a heterogeneous corpus that includes government projections, industry white papers, and regional economic development documents, they produce large proportions of unscorable items because those sources do not report the required methodological detail. Our framework draws instead on two traditions better suited to heterogeneous secondary analysis: Gough's Weight-of-Evidence approach [35], which evaluates sources on their fitness for the specific review question rather than on a uniform methodological template, and AACODS criteria for grey literature [36], which weigh authority, accuracy, coverage, objectivity, date, and significance. Our six dimensions operationalize those principles for the specific context of regional AI workforce evidence. We do not claim the framework supersedes MMAT or CASP for primary-study reviews; we claim it is better aligned with the structure of this review's corpus.

Table 1 presents the framework dimensions and scoring criteria.

Table 1. Quality assessment framework with six dimensions and 0–3 scoring scale.

Dimension	0 (Poor)	1 (Fair)	2 (Good)	3 (Excellent)
Methodological Rigor	No method described	Basic description	Clear methodology	Detailed, replicable
Data Recency	Pre-2020	2020–2021	2022–2023	2024–2025
Geographic Relevance	No regional data	National only	State-level	Eastern Shore specific

Dimension	0 (Poor)	1 (Fair)	2 (Good)	3 (Excellent)
Sample Size / Scope	Limited or unclear	Moderate scope	Comprehensive	Large-scale, representative
Author Credibility	Unknown source	Industry source	Academic or government	Peer-reviewed or federal
Data Transparency	No data access	Summary only	Partial data	Full data available

Note. Each dimension scored 0–3 points; maximum total = 18 points; inclusion threshold = 12 points (66.7 percent).

5.4 Analytical Approach

Qualitative analysis applied a two-cycle coding approach [37]. In Cycle 1, descriptive coding applied eight a priori themes to each source. These themes were derived from the research questions and conceptual framework before data analysis began, not from the sources themselves. The themes were: national workforce demand (WD-NAT), regional workforce demand (WD-REG), technical competencies (SK-TECH), soft or common employability skills (SK-SOFT), community college education (ED-CC), curriculum development (ED-CURR), industry partnerships (IND-PART), and economic impact (ECON-IMP). Each theme has an operational definition and example indicators in a codebook. Cycle 1 therefore answers a descriptive question: to what extent does each source address each theme. In Cycle 2, pattern coding [37] moved to an inductive logic. Sub-themes emerged from within-theme patterns observed across sources, with particular attention to convergence and divergence across source types and geographic levels. Two to four sub-themes typically emerged within each primary theme. Figure 2 shows the process and its outputs.

Quantitative analysis operationalized three types of variables at the source level. First, for each source, each of the eight primary themes was coded as addressed (1) or not addressed (0), yielding a 32 by 8 source-theme matrix used to compute theme frequency (percentage of sources addressing each theme). Second, for each technical competency mentioned in at least one source, we counted the number of sources mentioning it, producing the competency frequency distribution visualized in Figure 3. Third, where sources reported numerical projections (shortfall magnitudes, growth rates, AI intensity figures), we extracted the reported values and their source types, and compared them using descriptive statistics (range, median, modal interval) and convergence metrics. Convergence defined a priori as agreement across 75 percent or more of the sources addressing a given indicator, following common thresholds in systematic reviews [33-34, 37]. The analysis did not attempt inferential statistics, which would require assumptions about representative sampling that are not appropriate for a purposive corpus. Quantitative and qualitative results were compared at the interpretation stage under a convergent mixed-methods logic [33], with points of agreement and disagreement between the two strands reported rather than averaged.

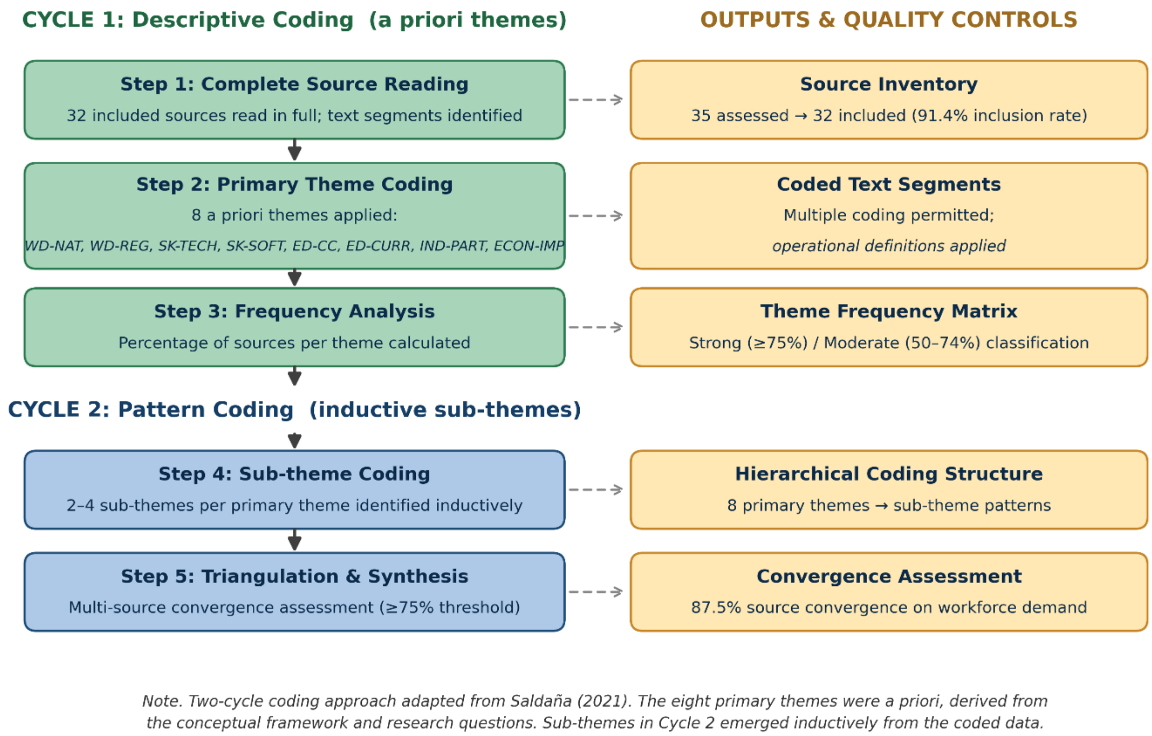

Figure 2. Qualitative content analysis process showing two-cycle coding approach.

6. Findings

6.1 National Workforce Demand (RQ1)

National-level analysis reveals substantial and growing demand for AI-skilled technicians, with notable convergence across diverse source types. Among the 24 sources addressing national workforce patterns, 87.5 percent (21 sources) document significant current shortages and projected growth in AI-related technical occupations.

Quantitative projections converge around several key findings. Manufacturing sectors face projected shortfalls of 1.9 to 3.8 million positions requiring AI competencies by 2033 [1-2]. Engineering technician occupations show projected growth rates 11 to 25 percent faster than average employment, with the Bureau of Labor Statistics specifically noting AI-driven demand expansion [38]. Industry surveys indicate that 89 percent of manufacturing executives report difficulty filling technical positions requiring AI-adjacent skills [2].

The nature of demand aligns with the theoretical framework's emphasis on task reconfiguration rather than simple job creation. Sources consistently describe emerging roles that combine traditional technical functions with AI system oversight, data interpretation, and human-machine collaboration [3-4], [16]. This pattern matches the Skills-Based Technological Change prediction that technological advancement reshapes occupational boundaries rather than simply adding new occupations [32].

6.2 Maryland State-Level Patterns

Maryland sits within a favorable context for AI technician workforce development, though care is needed in interpreting state-level positioning. The University of Maryland and LinkUp AI Maps project, using natural language inference over 100 percent of U.S. career-page job postings, identifies the Baltimore-Washington capital region as the second-largest hub for AI-skilled job creation nationally, trailing only California [39]. By AI intensity (AI jobs as a share of all postings), the District of Columbia ranks first, Virginia second, and Maryland seventh [39]. This positioning reflects the concentration of federal agencies with significant AI investment, defense and aerospace contractors, and major research universities that generate both workforce supply and industry partnerships.

State policy initiatives, including the Manufacturing 4.0 program, provide infrastructure support for Industry 4.0 adoption at manufacturers across the state [40]. State-level aggregates, however, mask significant regional variation. The concentration of AI employment in the Baltimore-Washington corridor creates both opportunity and challenge for outlying regions. Community colleges outside metropolitan areas must navigate the tension between serving local employer needs and preparing students for employment that may require relocation.

6.3 Eastern Shore Regional Analysis (RQ2)

Maryland's Eastern Shore presents a distinctive context for AI technician workforce development, shaped by manufacturing heritage, rural geography, and strategic positioning within the Delmarva Peninsula economic region. Analysis of regional economic development documentation [27-28], [40] reveals active Industry 4.0 adoption among Eastern Shore manufacturers. Regional manufacturing clusters include electronics and component assembly, precision machining and metal fabrication, aerospace and defense subcontracting, and food processing with increasing automation. Recent Manufacturing 4.0 grants have supported automation investments at Eastern Shore facilities [40], indicating growing employer demand for workers capable of operating and maintaining AI-enabled systems.

Employer demand documentation from regional economic development sources indicates specific needs for CNC programming, industrial automation, quality control with statistical process capability, and basic data analysis competencies [27-28]. These requirements align closely with national patterns while reflecting the region's specific manufacturing specializations. Geographic positioning offers both advantages and constraints. Location within the broader Delmarva Peninsula manufacturing corridor creates opportunities for regional workforce coordination extending beyond Maryland state boundaries; distance from major metropolitan areas limits student access to employers concentrated in urban centers and makes it difficult to attract faculty with current industry experience.

6.4 Competency Requirements

Technical competency requirements show substantial convergence across the source corpus, providing clear guidance for curriculum development. Figure 3 presents the frequency of competency mentions across sources, disaggregated by geographic focus of the source.

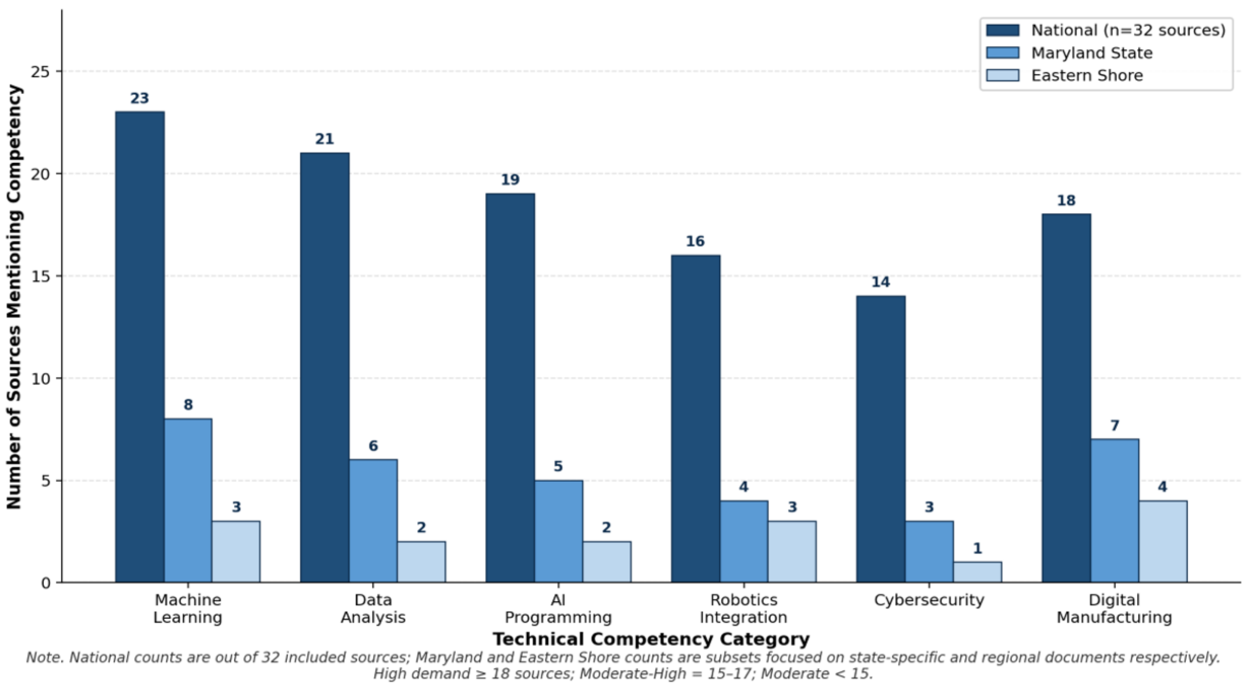

Figure 3. Technical competency demand frequency across geographic levels.

The most frequently cited technical competencies include machine learning fundamentals (23 sources, 71.9 percent), data analysis and interpretation (21 sources, 65.6 percent), AI programming basics including Python (19 sources, 59.4 percent), industrial automation systems (18 sources, 56.3 percent), and quality control with statistical methods (16 sources, 50.0 percent). Convergence across federal, industry, academic, and regional sources provides strong evidentiary support for curriculum priorities.

Beyond technical skill, sources consistently emphasize workplace competencies: critical thinking and problem-solving (19 sources), collaboration and communication (17 sources), adaptability and continuous learning orientation (15 sources), and ethical awareness regarding AI systems (12 sources). Employers particularly stress that technical competence alone proves insufficient without accompanying workplace skills [24].

6.5 Educational Pathway Findings (RQ3)

Sources show strong consensus regarding community colleges' central role in AI technician education. Three-quarters of sources (24 of 32) identify community colleges as primary pathways for technician workforce development, with this pattern consistent across federal, industry, and academic sources [5], [18-20]. Industry partnerships emerge as essential to effective programming: 65.6 percent of sources (21 of 32) emphasize partnerships extending beyond traditional advisory relationships to include work-integrated learning, equipment sharing, curriculum co-development, and faculty exchanges [24], [22], [25]. This finding aligns with Regional Innovation Systems Theory's emphasis on institutional relationships rather than isolated organizational effort.

Credential structure shows notable patterns, with sources indicating a roughly 4:1 ratio of certificate-to-degree growth in AI-related technical fields [5]. This pattern suggests employer demand focuses on specific competency demonstration rather than comprehensive degree completion, with implications for curriculum modularity and stackable credential design.

7. Discussion

7.1 Addressing the Research Questions

RQ1 synthesis. Multi-source analysis demonstrates substantial and growing demand for AI-skilled technicians across national and state levels. Convergence across 87.5 percent of sources regarding workforce shortages, combined with consistent competency requirements, provides a strong evidentiary foundation for educational investment. The convergence pattern aligns with Skills-Based Technological Change Theory predictions that technological transformation creates consistent, identifiable competency demands across affected sectors [32]. The finding that machine learning fundamentals, data analysis, and AI programming appear most frequently across sources suggests these represent core curriculum components rather than specialized electives, mirroring empirical analyses of AI and machine learning job postings that identified the same three competencies as dominant requirements [4], [17]. The documented 1.9 to 3.8 million unfilled manufacturing positions by 2033 represents a workforce challenge of substantial scale. Our findings extend industry analyses [2] by showing that similar demand patterns appear across federal, academic, and regional sources, not merely industry projections. Convergence across methodologically diverse sources strengthens confidence that observed demand reflects genuine labor market conditions rather than advocacy-driven projections. The finding that forty percent of manufacturing competency requirements will change within five years also aligns with Zarifhonarvar's analysis suggesting AI could fully impact 32.8 percent of occupations while partially affecting another 36.5 percent [16].

RQ2 synthesis. Maryland's Eastern Shore patterns are consistent with broader trends while presenting region-specific opportunities. The Baltimore-Washington capital region's position as the nation's second-largest AI jobs hub [39] indicates strong state-level demand that creates spillover opportunities for regional workforce development. Eastern Shore manufacturing clusters in electronics, precision machining, and aerospace provide immediate employment pathways for AI-skilled technicians, while Manufacturing 4.0 investments signal sustained demand [40]. These patterns align with Regional Innovation Systems Theory predictions that regions with established industrial infrastructure and coordination mechanisms can leverage technology adoption for competitive advantage [31]. Our approach also addresses concerns raised by Frank and colleagues [15] regarding barriers that inhibit measurement of AI effects on work, including limited high-quality data on skill requirements and limited understanding of how AI interacts with regional dynamics. By synthesizing federal projections with regional economic development documentation, this study demonstrates a methodological route around data limitations that have constrained prior regional analyses. The Eastern Shore context further illustrates scholars observation that rural regions face particular challenges in workforce development, including limited employment numbers and constrained educational infrastructure, while showing that such regions can position themselves advantageously when industrial clustering and educational coordination are present [7, 9].

RQ3 synthesis. Curriculum development implications center on modular credential design, deep industry partnerships, and faculty development that addresses rapid technological change. The 75 percent convergence on community colleges' central role, combined with 65.6 percent emphasis on partnerships extending beyond traditional advisory relationships, suggests that successful programs require deeper integration with regional employers. This finding extends Gauthier's [24], [41] research on employer perspectives in community college career and technical education, which documented that graduates need both specialized technical competencies and common employability competencies. The four-to-one growth ratio of certificate programs over associate degrees indicates demand for modular, stackable credentials that accommodate both traditional students and incumbent workers seeking to add AI competencies [5], consistent with research finding that community college students strategically select shorter credential pathways under uncertain labor market conditions [42]. Faculty development emerged as a critical implementation requirement, with sources emphasizing the need for ongoing professional development addressing the rapid pace of technological change [23], [25]. Haviland and Robbins [20] note that career and technical education roles are evolving more rapidly than research can track, with practices changing ahead of scholarly understanding, a challenge that is particularly acute for AI technician education where the documented forty-percent competency evolution rate within five years exceeds the typical curriculum revision cycle at most community colleges.

7.2 Interpreting Findings Through Human Capital Theory

Human Capital Theory (HCT) is named in the conceptual framework but warrants explicit interpretation of what the findings say about individual-level educational investment. Three themes in the results map onto core HCT constructs in ways that carry concrete curricular implications.

First, the 4:1 certificate-to-degree growth ratio [5] reflects an HCT logic of investment under uncertainty. When the expected lifetime of a given competency is short, the rational learner invests in shorter-duration, lower-sunk-cost credentials that can be supplemented as requirements evolve. The pattern observed in the corpus suggests that learners and employers alike are selecting into a shared-cost arrangement where general human capital is built cumulatively rather than in large, one-time investments, a logic consistent with Becker's distinction between general and specific human capital [29] adapted to a high-velocity skill domain [30]. Curricular implication: stackable credential designs with clear articulation into associate and bachelor's pathways maximize flexibility of returns.

Second, the 65.6 percent convergence on deep industry partnerships reflects the classic HCT problem of who invests in firm-specific human capital. When employers co-invest in training through work-integrated learning, equipment contribution, and faculty exchange, the specific human capital component becomes more attractive because the employer shares the risk and captures part of the return through reduced turnover and lower hiring costs. Becker's original framing [29] anticipated exactly this structure. Curricular implication: partnership models that formalize employer contribution (paid internships, preceptor-supervised projects, employer-provided equipment) align private returns for the learner with productivity returns for the firm.

Third, the emphasis on workplace competencies alongside technical skill reflects the HCT observation that returns to education are highest when skills are complementary rather than substitutable across settings. Critical thinking, communication, and collaboration are portable forms of human capital that amplify returns to domain-specific technical skill [11], [29]. Curricular implication: programs that integrate workplace competency development with technical content maintain the complementarity that produces the highest individual-level returns, rather than relegating workplace skills to separate, optional modules.

7.3 Theoretical and Methodological Implications

The integrated application of three frameworks demonstrates value for multi-level workforce analysis that no single theory achieves independently. Human Capital Theory explains why learners and employers select modular credentials under uncertainty. Regional Innovation Systems Theory explains why Eastern Shore manufacturing clusters create competitive advantage for AI technician development [31]. Skills-Based Technological Change Theory clarifies which specific competencies warrant curriculum priority, extending research on employment growth concentrating in non-routine occupations [32] to the specific context of technician education.

The findings also suggest that AI integration in manufacturing creates complementary rather than substitutive competency demands at the technician level. Rather than replacing traditional technical competencies, AI technologies require workers who combine domain expertise with AI tool proficiency. This pattern confirms arguments that AI creates complementary demand for human capabilities [14], while extending the analysis specifically to technician-level education. The emphasis on applied integration competencies, combining AI tools with manufacturing, quality control, and automation expertise, suggests that curriculum development should embed AI within existing technical domains rather than treating AI as a standalone subject. Finally, the consistent emphasis on industry partnerships across source types suggests that traditional community college advisory relationships may be insufficient for AI technician education: partnership models need work-integrated learning, industry-validated competency frameworks, and continuous curriculum updating that responds to technological advancement in near-real-time, consistent with the task-level dynamic described by Acemoglu and Restrepo [43].

8. Study Limitations

Several limitations bound the findings. First, secondary analysis depends on the quality and scope of available sources; gaps in existing documentation may mask important patterns, particularly for emerging competencies not yet reflected in published research [34]. Second, geographic focus on Maryland's Eastern Shore, while enabling depth of regional analysis, limits direct generalizability to regions with different economic and institutional characteristics. Third, the rapid pace of AI technological advancement means that competency requirements identified in the analysis may shift substantially within the typical two- to three-year curriculum development cycle [16]. Fourth, the quality assessment framework, while systematically applied, involves judgment that may have influenced source inclusion; we addressed this through dual independent coding and documented disagreement resolution, but subjectivity cannot be fully eliminated. Fifth, the 32-source corpus, while meeting quality standards, represents a purposive rather than exhaustive sample of available evidence.

Finally, the study's scope is bounded to hiring demand and does not evaluate net employment effects, including any displacement of incumbent workers associated with AI adoption. Recent large-scale analysis of U.S. job postings reports no empirical evidence that AI is reducing overall labor market demand [39], though the net regional employment effects of AI adoption in manufacturing remain an open empirical question. Rigorous evaluation requires firm-level longitudinal data beyond the scope of this review and represents an important direction for future work.

9. Implications and Future Research

9.1 Implications for Practice

Based on the findings, we offer the following recommendations for community college practitioners and regional workforce development stakeholders:

1. Develop modular credential pathways. The 4:1 certificate-to-degree growth ratio and the emphasis on specific competency demonstration support curriculum structures enabling stackable credentials [5]. Programs should enable students to build credentials incrementally while demonstrating employable skill at each stage [22].

2. Cultivate deep industry partnerships. Consistent emphasis on partnerships extending beyond advisory relationships requires intentional relationship development [24]. Effective partnerships should encompass work-integrated learning, equipment sharing, curriculum co-development, and faculty industry engagement [25].
3. Prioritize faculty development. Rapid technological change requires ongoing faculty development addressing both technical competencies and pedagogical approaches for emerging technologies [23]. Industry partnerships can support faculty development through exchanges and joint projects.
4. Leverage regional coordination. For regions like Maryland's Eastern Shore, coordination across institutional and jurisdictional boundaries can address resource constraints while serving broader employer needs [26]. The Delmarva Peninsula's cross-state manufacturing corridor presents opportunities for educational collaboration [31].
5. Balance technical and workplace competencies. Findings consistently indicate that technical skill alone is insufficient [24]. Programs should intentionally integrate critical thinking, communication, and collaboration with technical content [16].

9.2 Directions for Future Research

Our study opens several avenues for future investigation. Longitudinal competency tracking would identify patterns of emergence, stabilization, and obsolescence in AI-related skills and inform curriculum revision cycles [16], [32]. Comparative regional analysis extending the approach to additional rural and semi-rural regions would test the generalizability of Eastern Shore patterns while identifying region-specific factors influencing workforce development success [7], [10]. Partnership effectiveness evaluation would examine which partnership models produce superior outcomes, moving beyond the finding that partnerships matter toward evidence about which structures matter most [24], [41]. Student outcome tracking would track graduate employment outcomes, wage progression, and career advancement as AI technician programs develop [20], [42]. Faculty development impact studies would examine the relationship between professional development approaches and student learning outcomes in AI-related programs [23]. Finally, firm-level longitudinal research is needed to evaluate net regional employment effects of AI adoption, distinguishing new hires with AI skills from any reductions in incumbent employment.

10. Conclusions

Our systematic analysis of AI technician workforce demand provides evidence-based guidance for community college curriculum development, with particular implications for Maryland's Eastern Shore and similar rural regions. Convergence across 32 high-quality sources regarding workforce shortages, competency requirements, and educational pathways offers a foundation for institutional planning and investment decisions.

Community colleges are positioned to lead regional AI workforce development through their historical strengths in responsive curriculum development, employer relationships, and accessible education [5], [20-21]. Success requires moving beyond traditional models toward modular credentials, deep industry partnerships, and continuous faculty development [22-24]. For Maryland's Eastern Shore, the combination of manufacturing heritage, strategic geographic positioning within the second-largest AI jobs hub in the nation, and recent Industry 4.0 investment creates favorable conditions for educational innovation [27-28], [39-40].

Beyond the specific findings, this study contributes a replicable method for regional workforce assessment in emerging technology fields. The quality assessment framework, multi-level geographic analysis, and cross-source triangulation can be applied to other technologies (advanced manufacturing robotics, cybersecurity, clean energy systems) and other rural regions facing similar workforce challenges [33], [34]. Three priorities now warrant attention from community college leaders, regional workforce boards, and funding agencies: coordinated investment in modular credential infrastructure that can evolve as competencies do; formalized partnership models that shift industry engagement from advisory to co-investment; and sustained faculty development pipelines that keep pace with technological change. As AI continues reshaping manufacturing and engineering work [13], [14], [15], the window for establishing regional AI technician education is narrow. Community colleges working in deep partnership with regional employers [31] can convert that window into durable institutional capacity. The evidence assembled here points the way; the remaining work is institutional, political, and sustained.

11. Author Contributions

This research emerged during the development of a National Science Foundation proposal. While conducting preliminary work to support the proposal, one author identified a gap in the literature concerning systematic regional workforce assessment for AI technician education, recognizing the need for evidence-based guidance that could inform both the proposed project and broader community college practice. The other author provided initial project direction and the framework within which this research need was identified. Both authors contributed to the analysis and the manuscript.

12. Acknowledgements

This research emerged from proposal development activities supported by the authors' institution. The authors acknowledge the National Science Foundation's Advanced Technological Education program, whose call for proposals catalyzed this investigation into AI technician workforce development. The authors also thank the regional economic development organizations and workforce development professionals whose publicly available documentation made this systematic analysis possible.

13. References

[1] National Association of Manufacturers, "Study: Manufacturing in U.S. could need up to 3.8 million workers," Apr. 2024. [Online]. Available: https://nam.org/study-manufacturing-in-u-s-could-need-up-to-3-8-million-workers-30626/

[2] J. Coykendall, K. Keller, V. Leszinski, and C. Wellener, "Taking charge: Manufacturers support growth with active workforce strategies," Deloitte Insights and The Manufacturing Institute, 2024. [Online]. Available: https://www2.deloitte.com/us/en/insights/industry/manufacturing/supporting-us-manufacturing-growth-amid-workforce-challenges.html

[3] A. Huderson, E. Peiffer, S. Shamsi, F. Plaza, and E. Collins, "Future of mechanical engineering, manufacturing engineering, and machinist roles for Industry 4.0," in Proc. 2022 ASEE Annu. Conf. Expo., Minneapolis, MN, USA, 2022, paper 41625. [Online]. Available: https://doi.org/10.18260/1-2--41625

[4] N. Kumar, R. Satpute, E. Akpabio, A. Kumar, K. Gaurav, and M. I. Alam, "The growing need for AI and machine learning talent in a transforming world," in Proc. 2025 IEEE Int. Conf. Contemp. Comput. Commun. (InC4), 2025, pp. 1–7. [Online]. Available: https://doi.org/10.1109/InC465408.2025.11256356

[5] National Science Board, "The STEM labor force: Scientists, engineers, and skilled technical workers," Rep. NSB-2024-5, National Science Foundation, 2024. [Online]. Available: https://ncses.nsf.gov/pubs/nsb20245/u-s-stem-workforce-size-growth-and-employment

[6] T. J. Bartik, Making Sense of Incentives: Taming Business Incentives to Promote Prosperity. Kalamazoo, MI, USA: W. E. Upjohn Institute, 2019.

[7] M. Muro, R. Maxim, and J. Whiton, "Automation and artificial intelligence: How machines are affecting people and places," Brookings Institution, Washington, DC, USA, 2019.

[8] B. Hardy and J. P. Ziliak, "Decomposing trends in income volatility: The 'wild ride' at the top and bottom," Econ. Inquiry, vol. 52, no. 1, pp. 459–476, 2014.

[9] G. Timko, M. Harris, D. Hayde, and K. Peterman, "Sustainable development of community-supported STEM-learning ecosystems in rural areas of the United States," Community Dev. J., vol. 58, no. 3, pp. 492–511, 2023. [Online]. Available: https://doi.org/10.1093/cdj/bsac016

[10] G. A. Erickcek, "Key research and policy questions in economic development and workforce development," Econ. Dev. Q., vol. 37, no. 1, pp. 5–6, 2023. [Online]. Available: https://doi.org/10.1177/08912424221148563

[11] D. Acemoglu and D. Autor, "Skills, tasks and technologies: Implications for employment and earnings," in Handbook of Labor Economics, vol. 4B, O. Ashenfelter and D. Card, Eds. Amsterdam, The Netherlands: Elsevier, 2011, pp. 1043–1171.

[12] K. Hollenbeck, "Suggestions for future research in the area of workforce development systems and regional economic development in the United States," Econ. Dev. Q., vol. 37, no. 1, pp. 49–53, 2023. [Online]. Available: https://doi.org/10.1177/08912424221142840

[13] D. Autor, "Why are there still so many jobs? The history and future of workplace automation," J. Econ. Perspect., vol. 29, no. 3, pp. 3–30, 2015.

[14] E. Brynjolfsson and T. Mitchell, "What can machine learning do? Workforce implications," Science, vol. 358, no. 6370, pp. 1530–1534, 2017.

[15] M. R. Frank et al., "Toward understanding the impact of artificial intelligence on labor," Proc. Natl. Acad. Sci., vol. 116, no. 14, pp. 6531–6539, 2019. [Online]. Available: https://doi.org/10.1073/pnas.1900949116

[16] A. Zarifhonarvar, "Economics of ChatGPT: A labor market view on the occupational impact of artificial intelligence," J. Electron. Bus. Digit. Econ., vol. 3, no. 2, pp. 100–116, 2024. [Online]. Available: https://doi.org/10.1108/JEBDE-10-2023-0021

[17] D. Ather, G. Singh, N. Chaudhary, P. Verma, R. Kler, and A. Gupta, "Analyzing trends, skills demand, and salary prediction in the AI and ML job market," in Proc. 2024 Int. Conf. Intell. Innov. Pract. Eng. Manage. (IIPEM), 2024, pp. 1–8. [Online]. Available: https://doi.org/10.1109/IIPEM62726.2024.10925738

[18] National Science Foundation, "NSF 24-584: Advanced Technological Education (ATE)," Program Solicitation, 2024. [Online]. Available: https://www.nsf.gov/funding/opportunities/ate-advanced-technological-education/nsf24-584/solicitation

[19] National Science Foundation, "NSF invests $2.8M to strengthen technical AI education at two-year institutions," 2024. [Online]. Available: https://www.nsf.gov/news/nsf-invests-28m-strengthen-technical-ai-education

[20] S. Haviland and S. Robbins, "Career and technical education as a conduit for skilled technical careers: A targeted research review and framework for future research," ETS Res. Rep. Ser., vol. 2021, no. 1, pp. 1–42, 2021. [Online]. Available: https://doi.org/10.1002/ets2.12318

[21] C. Servin, E. K. Hawthorne, L. Postner, C. Tang, and C. S. Tucker, "Curricular and pedagogical considerations in computer science education: The role of community colleges for the next decade," in Proc. 55th ACM Tech. Symp. Comput. Sci. Educ. V. 1, 2024, pp. 1196–1201. [Online]. Available: https://doi.org/10.1145/3626252.3630819

[22] New America, "A new network for community college partnerships in economic development and industrial policy implementation," 2024. [Online]. Available: https://www.newamerica.org/education-policy/edcentral/empowering-community-colleges-partnerships-for-economic-development-and-industrial-policy/

[23] S. Jyotishi, "Community colleges unite to scale AI education and workforce development," New America, 2024. [Online]. Available: https://www.newamerica.org/education-policy/edcentral/community-colleges-unite-to-scale-ai-workforce-education/

[24] T. Gauthier, "The role of community colleges in preparing students with special and common skills for the workforce: A longitudinal case study," Higher Educ., Skills Work-Based Learn., vol. 14, no. 5, pp. 1026–1041, 2024. [Online]. Available: https://doi.org/10.1108/HESWBL-02-2023-0054

[25] Intel Corporation, "AI workforce program in the US for students," Intel Digital Readiness, 2024. [Online]. Available: https://www.intel.com/content/www/us/en/corporate/artificial-intelligence/ai-for-workforce-us.html

[26] National Science Foundation, "Bridging the future: Defining and empowering the STEM workforce of tomorrow," 2024. [Online]. Available: https://www.nsf.gov/funding/initiatives/ige/updates/bridging-future-defining-empowering-stem-workforce-tomorrow

[27] Lower Eastern Shore Maryland, "Electronics and component manufacturing," 2021. [Online]. Available: https://lesmd.net/manufacturing/electronics-component-manufacturer

[28] Lower Eastern Shore Maryland, "Manufacturing," 2022. [Online]. Available: https://lesmd.net/manufacturing

[29] G. S. Becker, "Human capital revisited," in Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, 3rd ed. Chicago, IL, USA: Univ. Chicago Press, 1994, pp. 15–28.

[30] D. H. Autor, F. Levy, and R. J. Murnane, "The skill content of recent technological change: An empirical exploration," Q. J. Econ., vol. 118, no. 4, pp. 1279–1333, 2003.

[31] P. Cooke, "Regional innovation systems: Competitive regulation in the new Europe," Geoforum, vol. 23, no. 3, pp. 365–382, 1992. [Online]. Available: https://doi.org/10.1016/0016-7185(92)90048-9

[32] D. Acemoglu and P. Restrepo, "The race between man and machine: Implications of technology for growth, factor shares, and employment," Amer. Econ. Rev., vol. 108, no. 6, pp. 1488–1542, 2018.

[33] J. W. Creswell and V. L. Plano Clark, Designing and Conducting Mixed Methods Research, 3rd ed. Thousand Oaks, CA, USA: SAGE, 2018.

[34] J. Heaton, "Secondary analysis of qualitative data: An overview," Hist. Soc. Res., vol. 33, no. 3, pp. 33–45, 2008.

[35] D. Gough, "Weight of evidence: A framework for the appraisal of the quality and relevance of evidence," Res. Papers Educ., vol. 22, no. 2, pp. 213–228, 2007.

[36] J. Tyndall, "AACODS checklist," Flinders Univ., Adelaide, Australia, 2010. [Online]. Available: https://coilink.org/20.500.12592/kg54zf

[37] J. Saldaña, The Coding Manual for Qualitative Researchers, 4th ed. Thousand Oaks, CA, USA: SAGE, 2021.

[38] U.S. Bureau of Labor Statistics, "AI impacts in BLS employment projections," The Economics Daily, 2025. [Online]. Available: https://www.bls.gov/opub/ted/2025/ai-impacts-in-bls-employment-projections.htm

[39] A. K. Gupta, S. Viswanathan, K. Zhang, and H. Shi, "From West to the Rest: The changing geography of AI jobs in the United States," UMD-LinkUp AI Maps white paper, Robert H. Smith School of Business, Univ. Maryland, College Park, MD, USA, 2024. [Online]. Available: https://www.aimaps.ai/

[40] Maryland Economic Development Association, "Governor Moore announces Maryland Manufacturing 4.0 grant recipients," 2025. [Online]. Available: https://www.medamd.com/program-development/governor-moore-announces-maryland-manufacturing-4-0-grant-recipients/

[41] T. Gauthier, "Employer perspectives of community college career and technical programs: A manufacturing and engineering focus group exploration," Career Tech. Educ. Res., vol. 47, no. 1, pp. 55–74, 2022. [Online]. Available: https://doi.org/10.5328/cter47.1.55

[42] P. R. Bahr, "The labor market returns to a community college education for noncompleting students," J. Higher Educ., vol. 90, no. 2, pp. 210–243, 2019. [Online]. Available: https://doi.org/10.1080/00221546.2018.1486656

[43] D. Acemoglu and P. Restrepo, "Automation and new tasks: How technology displaces and reinstates labor," J. Econ. Perspect., vol. 33, no. 2, pp. 3–30, 2019. [Online]. Available: https://doi.org/10.1257/jep.33.2.3