



**Eyeing the AI Supply Chain Economy:
Unleashing America's AI Economic Potential**

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1. EXECUTIVE SUMMARY

Table 1. AI Bottlenecks with Aligned Strategies and Legislative Actions

Bottleneck/AI Constraints (Ranked based on BCI)	LACA Frequency	BCI Score	DMDU Strategy (Avg Resilience)	Recommendation
1. Fragmented AI governance across jurisdictions	176	.1672	Balanced Adaptive (0.584)	7.6 National Regulatory Framework
2. Absence of upskilling Programs for workers &	144	.15	Upskill Now (0.422)	7.2 Workforce Recruitment and Upskilling
5. Shortage of Skilled Talent	41	.0466		
3. Sparse Tools for Explainability &	118	.1195	Balanced Adaptive (0.584)	7.1 Modernized Federal Tax Code & 7.3 Computational Resources
4. Cybersecurity Risks	48	.0554		
6. Lack of widespread standards demonstrating AI Competency	22	.0410	Governance First (0.355)	7.6 National Regulatory Framework
7. Underfunded AI Public Infrastructure Investment &	39	.0409	Balanced Adaptive (0.584)	7.1 Modernized Federal Tax Code and 7.5 Small AI Business Development
8. Unequal Public-Private Collaboration	47	.0401		
9. Data Center Capacity &	34	.032	Balanced Adaptive (0.584)	7.3 Computational Resources & 7.4 Power Production
10. Data Silos	29	.028		

Artificial intelligence (AI) is poised to deliver unprecedented economic gains internationally, with estimates indicating a \$3.7 trillion increase to the United States' GDP by 2030 (Bughin et al., 2018). However, the nation is not structurally equipped to capitalize on this opportunity on multiple fronts. Four central bottlenecks—workforce preparedness, computing capabilities, power and energy infrastructure, and capital investment—threaten to stall progress, deepen regional inequality, and allow global competitors to outpace American innovation (NSCAI, 2021; Flexential, 2025). Recognizing this urgency, this report analyzes the policy landscape to identify scalable congressional actions that can unleash AI's full economic potential. If not addressed promptly, the U.S. could lose hundreds of billions in potential GDP growth, increase

regional economic gaps, and fall behind other countries in AI leadership.

A mixed-methods research design is employed to integrate qualitative and quantitative approaches. A review of over 1,000 industry reports, government studies, and think tank publications informed the development of the core framework. Comparative case analyses were employed to assess disparities in AI readiness across states, while a consensus model for content analysis helped identify the constraints that posed the most significant economic risks (de Reuver et al., 2024). Additionally, constitutional authority and economic viability were used to evaluate which interventions Congress can enact directly through spending, oversight, and statutory authority.

A systemic shortage in AI-skilled labor plagues American AI development and implementation, with over 80% of firms reporting difficulties filling roles in machine learning, data science, and cloud computing (West, 2023; Manyika et al., 2017). Projections show that without intervention, the U.S. may face a deficit of over 12 million skilled workers in AI-relevant fields by 2030 (Tenakwah & Watson, 2025). Concurrently, advanced computing infrastructure is highly geographically concentrated, with over four of five data centers in California, New York, and Massachusetts, leaving rural and underserved areas without access to competitive tools (Jin et al., 2025; NSCAI, 2021). By 2030, projections indicate a 20% increase in electricity needs in certain regions of the nation's already strained energy infrastructure. Grid congestion and permitting delays are leading to cancellations of data center projects and hindering AI scalability (Srivathsan et al., 2024; McKinsey & Company, 2023). Ultimately, the capital pipeline for AI investment has become skewed, with more than 60% of private funding directed towards consumer-facing applications rather than long-term infrastructure or foundational AI models. Funding jeopardizes the development of public-interest and industrial AI systems that Congress can support through economic policy (Polen Capital, 2024; BCG, 2024).

A DMDU analysis was conducted by simulating 10,000 futures by generating randomized bottleneck severity scores within defined scenario ranges to address the primary constraints to American AI. The most statistically significant approaches were determined, informing which strategies would be most effective for Congress to implement. First, Congress should consider modernizing workforce policy by expanding Department of Labor programs to fund AI-specific training initiatives and authorizing federal grants that incentivize regional upskilling partnerships (Porat et al., 2025; NSCAI, 2021). Second, equitable access to computing resources should be prioritized by establishing a national AI compute trust that enables researchers and small firms to access high-performance computing resources, modeled after the CHIPS and Science Act (Jin et al., 2025; Flexential, 2025). Third, Congress should consider accelerating grid modernization and expanding renewable energy tax credits tied to AI-ready data center development, ensuring that power constraints do not impede innovation (Srivathsan et al., 2024; Wadhwa et al., 2024). Lastly, targeted fiscal incentives should be created to redirect private investment into frontier AI development and infrastructure, including creating a public-private AI investment vehicle modeled after successful energy-sector mechanisms (Polen Capital, 2024; BCG, 2024).

Congressional leadership is crucial in creating the economic conditions necessary for AI's widespread and inclusive adoption. With appropriate oversight, investment, and legislative action,

Congress can ensure that AI not only advances innovation but also broadens economic opportunity, secures national competitiveness, and prepares the United States for the demands of the Fourth Industrial Revolution (Georgieva, 2024; Collier & Horvath, 2025). The alignment of bipartisan interest, public demand, and industry readiness creates a narrow but powerful legislative window to enact durable reforms that will shape America's AI trajectory for decades.

2. ISSUE STATEMENT

Humanity finds itself at a pivotal juncture in history. Rapidly evolving AI technologies pose the potential for societal impacts of unprecedented magnitude (Velarde, 2020). The seemingly limitless future implications of AI use have propelled the world to the precipice of the Fourth Industrial Revolution (4IR), as people, businesses, and governments attempt to utilize the powerful technology in daily tasks while mitigating its uncertain integration risks to workers, businesses, and society altogether (Velarde, 2020). Exponentially accelerating growth and competing national interests breed deep uncertainty for global decision-makers navigating the application of AI (Bassis, 2025). Countries that fail to develop robust AI strategies risk losing an estimated 25% of long-term GDP growth opportunities and jeopardizing national security through cyber and economic vulnerabilities (Chivvis & Kavanagh, 2024; NSCAI, 2021). As AI currently resides in a relatively early developmental stage, decisive action is paramount to harnessing the technological power and empowering its capabilities to secure economic viability and global competitiveness for generations (Margetts, 2022).

2.1 Fragmented American AI

Although the United States currently leads the global AI race, accounting for 40% of global private investment in AI in 2023, its domestic AI governance framework remains fragmented and volatile (Fattorini et al., 2024). The pace of AI innovation has significantly outpaced federal regulatory structures, resulting in widespread inconsistencies across sectors and jurisdictions, with over 700 state and local AI-related laws enacted nationwide (Johnson, 2025; Hendrix & Lima-Strong, 2025). The decentralized law structure ranges from narrow disclosure mandates in algorithmic hiring to broader frameworks governing AI in mental health and financial services, creating significant compliance challenges for developers, businesses, and public institutions (Oratz et al., 2025; Metnick et al., 2025). While such diverse frameworks reflect the strength of American federalism, they also breed legal uncertainty that undermines AI deployment and deters investment, especially for smaller firms that cannot navigate a patchwork of compliance obligations (Kohler, 2025; Collier & Horvath, 2025).

Inconsistent standards between states have led to regulatory bottlenecks that delay implementation timelines and reduce competitiveness, with surveys indicating that over 60% of AI executives cite policy fragmentation as a top barrier to scaling (Castro, 2025). Without a coherent federal approach, the U.S. risks losing market share to international competitors, such as China, which has invested over \$150 billion in national AI integration strategies, including unified platforms and content regulations (RAND, 2023; White & Case, 2025). Moreover, the absence of enforceable national ethical standards raises concerns among allies and global consumers, with OECD reports warning that trust in AI technologies is declining in jurisdictions lacking centralized governance (OECD, 2023; Heim, 2025). Congressional intervention is crucial in developing a

regulatory framework that aligns with international norms while fostering innovation. This is a vital step with 140 organizations already advocating for federal clarity to support safe and equitable AI deployment (Perrigo & Chow, 2025; Usman et al., 2023).

2.1.1 The One Big Beautiful Bill Act

The initial draft of the One Big Beautiful Bill Act (OBBBA) proposed sweeping federal preemption by instituting a 10-year moratorium on state and local AI regulation, aiming to override over 700 disparate AI laws to create a unified national standard (Hendrix & Lima-Strong, 2025). Proponents argued that this would streamline business compliance, as surveys show that 68% of AI firms experience delays due to conflicting local regulations (Castro, 2025; Oremus, 2025). Advocates of the moratorium claimed that centralized governance would reduce compliance costs by an estimated 15% to 25% annually, particularly for mid-sized AI developers (Hendrix & Lima-Strong, 2025). Conversely, opponents contended that the moratorium infringed on state sovereignty and obstructed locally responsive policies, citing that over 30 states had already implemented regulations addressing region-specific concerns such as environmental impacts, workforce disruption, and digital equity (Markey, 2025; Palmer, 2025). A coalition of 140 organizations, including civil rights groups, state attorneys general, and tech accountability advocates, urged the Senate to reject the moratorium provision, arguing that it would threaten state rights and silence the voices of local communities (Perrigo & Chow, 2025). Public opinion mirrored these concerns, with polls showing that 62% of Americans prefer a shared governance model over exclusive federal control of AI policy (Collier & Horvath, 2025). Critics further warned that a top-down framework might overlook critical risks to vulnerable populations and exacerbate digital divides, especially in areas with limited digital infrastructure (Thomas & Urwin, 2025; Heim, 2025).

The Senate removed the preemption clause in response to growing bipartisan resistance, citing the federal government's lack of readiness to enforce robust protections for groups such as children and creative workers affected by AI (Perrigo & Chow, 2025). The legislative reversal exposed a broader debate over AI governance: pursuing national uniformity to maximize economic efficiency or preserving state flexibility to manage localized risks (Hendrix & Lima-Strong, 2025). Centralized regulations may accelerate technological deployment by reducing fragmentation, but decentralized authority enables innovation tailored to community needs, including ethical AI usage, labor protections, and data transparency (Collier & Horvath, 2025; Thomas & Urwin, 2025). Without resolving this tension, the United States risks falling behind international competitors that have already harmonized their regulatory ecosystems for strategic AI advancement (OECD, 2023; RAND, 2023).

2.1.2 Executive Branch Actions

During President Biden's term, the federal government sought to centralize AI governance through initiatives like the U.S. AI Safety Institute, which emphasized ethical safeguards, algorithmic transparency, and public trust frameworks to address the projected 60% AI exposure rate among advanced economies (Lutnick, 2025; Georgieva, 2024). This effort marked a shift toward federal leadership on AI oversight, as prior governance had been decentralized and reactive, contributing to the regulatory patchwork of over 700 divergent state and local AI-related

policies (Johnson, 2025). However, under the Trump administration, many Biden-era directives were reversed or restructured to emphasize deregulation and accelerate the private sector, particularly through the creation of the Center for AI Standards and Innovation (CAISI), which prioritizes deployment in defense, commerce, and infrastructure applications (Lutnick, 2025). This realignment reflects President Trump's ideological pivot from safeguarding civil liberties to removing barriers to AI development, in line with Executive Order 14179, which aims to “sustain and enhance America’s global AI dominance” (Removing Barriers to American Leadership in Artificial Intelligence, 2025).

The Trump Administration’s AI policy direction was formalized through the July 2025 release of America’s AI Action Plan, a three-pillar strategy focused on accelerating innovation, building infrastructure, and asserting global diplomatic leadership in AI (The White House, 2025). The plan proposes removing what it describes as “onerous regulation” by rescinding prior executive orders, particularly those that advance equity audits or emphasize ethical guardrails, which the administration argues hinder competitiveness (The White House, 2025). The new policy framework conditions federal AI funding on a state’s regulatory climate, instructing agencies to restrict support to jurisdictions perceived as “innovation-friendly” (The White House, 2025). Under Executive Order 14179, the administration dismantled the Biden-era AI Safety Institute. It launched the Center for AI Standards and Innovation (CAISI), shifting federal oversight toward a deregulatory model emphasizing open-source systems, frontier model development, and national security applications (The White House, 2025). The plan promotes a laissez-faire vision of technological advancement, opposing “social engineering agendas” in AI outputs and instructing federal procurement to favor systems aligned with “objective truth” rather than misinformation and diversity-focused standards (The White House, 2025). The Trump administration’s ideological posture, paired with incentives for high-performance compute buildouts, workforce retraining for skilled trades, and prioritization of Department of Defense (DoD) adoption, represents a sharp pivot toward global AI dominance framed as a “national security imperative” (The White House, 2025).

Although deregulation may accelerate economic gains and potentially contribute up to \$4.4 trillion globally through productivity boosts in key sectors, it also risks compounding inequality and eroding democratic norms if not balanced with oversight (Chui et al., 2023; Jin et al., 2025). As states like California and New York enforce stricter AI rules, conflicting federal signals complicate compliance efforts for multistate firms and public institutions (Kohler & Klaus, 2024; Lutnick, 2025). Ultimately, executive branch leadership will shape the contours of federal AI governance, but its durability will depend on bipartisan support and institutional checks that can bridge the gap between innovation and accountability (Evans & Nellenbach, 2025; Collier & Horvath, 2025).

2.2 AI Development Constraints & Bottlenecks

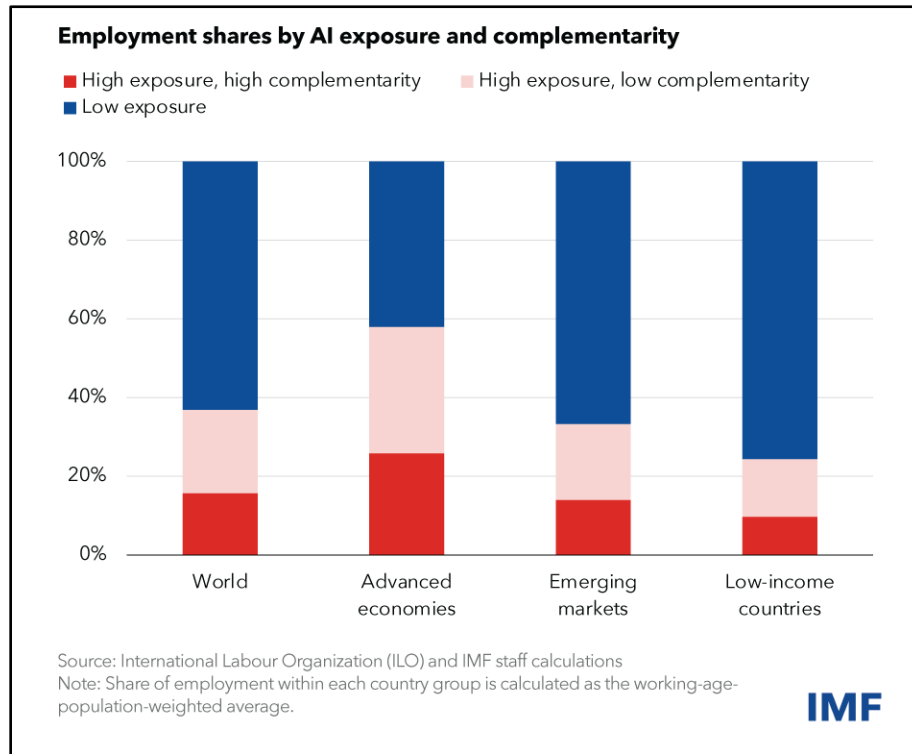
AI is expected to generate an estimated \$15.7 trillion in global economic output by 2030, making it this century's most transformative general-purpose technology (NSCAI, 2021). The technology’s development depends on a tightly interdependent ecosystem of talent, data, compute infrastructure, software, and governance frameworks (NSCAI, 2021; Margetts, 2022). Large language models (LLMs) are particularly resource-intensive, with the energy consumption of

training one trillion-parameter model requiring as much electricity as 100 U.S. households use annually, underscoring the urgency of modernizing national energy systems (Maslej et al., 2025; McKinsey & Company, 2023). Moreover, while private capital investment into AI reached \$67.22 billion in the U.S. in 2023, up from \$60.97 billion the prior year, critical bottlenecks in labor, computational prowess, power, and access to capital continue to slow deployment (Fattorini et al., 2024).

The four categories of labor, computation, energy production, and capital investment comprise the backbone of a globally competitive AI ecosystem, yet remain under-coordinated in the U.S., where regulatory fragmentation and infrastructure gaps persist (Gil et al., 2024; Flexential, 2025). Without swift congressional intervention to align workforce training, industrial strategy, energy infrastructure, and investment incentives, the U.S. risks falling behind countries like China, which has executed a \$150 billion AI strategy tied directly to public-sector computing and research and development (R&D) funding (RAND, 2023; OECD, 2023). Congress holds constitutionally grounded levers in tax policy, R&D funding, energy regulation, interstate commerce, education, and procurement, uniquely positioned to overcome these constraints and unlock AI's full economic and strategic potential (NSCAI, 2021).

2.2.1 Workforce Preparedness

A global shortage of AI-skilled labor is one of the most pressing constraints to U.S. AI development, with 51% of global technology leaders reporting talent scarcity as the top barrier to innovation in 2025 (Nash Squared, 2025). Moreover, 68% of American private sector executives acknowledge a “moderate-to-extreme” skills gap in AI-related fields, with many opting to replace workers rather than retrain them, resulting in labor displacement (Deloitte, 2020). AI technologies can already complete approximately 15% of current U.S. job tasks faster and at equal or higher quality, reflecting both productivity potential and employment risk (Eloundou et al., 2023). The demand for AI-skilled labor is expected to double the growth rate of the broader U.S. workforce over the next decade, further widening the skills mismatch (CompTIA, 2024). Job postings referencing generative AI skills increased by 170% between January 2024 and January 2025, signaling an accelerating demand for expertise in prompt engineering, machine learning, and algorithm development (Stahle, 2025).

Table 2. AI's Impact on Jobs (Georgieva, 2024)

As shown in Table 1, AI-driven automation is projected to affect 40% of global employment, with advanced economies facing even greater exposure at 60% due to their reliance on high-skill cognitive labor (Georgieva, 2024). The displacement potential of AI is especially pronounced in middle-skill jobs, where as many as 30% of workers may experience at least half of their tasks automated (Muro et al., 2025; Webb, 2020; Manning, 2024). While AI can augment workers and enable higher-value activities, without a structured workforce policy, automation risks eroding wages, shrinking labor force participation, and widening income inequality (Acemoglu & Restrepo, 2018; Frank et al., 2019). Competitive advantages from AI are best realized when humans are trained to work alongside automation in areas like logistics optimization, predictive maintenance, and sustainable innovation (Dash et al., 2019; Al-Sartawi & Ghura, 2025). However, only 1 in 10 workers today have developed skills in AI, and 40% of surveyed employees rank digital skills, particularly in AI and automation, as their most urgent training need (Salesforce, 2023).

Despite rising demand, the American education system is underprepared to meet the requirements of the AI workforce. Universities are facing a surge in student demand for AI and computer science. Still, many lack the capacity or instructors to expand their offerings due to faculty departures into the private sector (D'Agostino, 2022). Technology conglomerates such as Google and Meta actively recruit AI educators from elite universities, contributing to a "brain drain" that weakens the talent pipeline and reduces academic innovation capacity (Rasser et al., 2019). Major employers have dropped college degree requirements for entry-level positions and implemented internal AI training programs as a short-term solution, highlighting a private-sector

response to public-sector training gaps (D’Agostino, 2022). However, a decentralized model does not address the needs of rural workers and displaced laborers, which federal policy could reach through public investment in community college AI curricula, apprenticeship models, and workforce transition programs (West, 2023; NSCAI, 2021).

2.2.2 Computing Capabilities

The trajectory of American AI development hinges on access to advanced computing infrastructure, as training a single LLM can cost over \$100 million and require tens of thousands of graphics processing units (GPUs) running in parallel (Cottier & Rahman, 2024; Maslej et al., 2025). In 2023, nearly 1 trillion semiconductors were sold globally, generating more than \$527 billion in revenue. The U.S. semiconductor industry contributed over 25% of this value through its leadership in design and intellectual property (SIA, 2024). Despite substantial contributions, domestic production remains critically insufficient for cutting-edge chips under five nanometers, leaving the U.S. reliant on East Asia, particularly Taiwan, which produces over 90% of the world’s most advanced chips (Semiconductor Industry News, 2025; Nearly Invisible, 2025). The CHIPS and Science Act authorized \$52.7 billion in incentives to bring semiconductor production back to the United States. Still, demand has far outpaced funding, with over 600 project applications submitted and less than 20% of applicants selected for initial awards as of 2024 (Chipmakers Seek More, 2024).

Meeting future AI demand, projected to grow by more than 30% annually, will require Congress to fund not only chip fabrication plants but also packaging facilities, extreme ultraviolet (EUV) lithography equipment, and a specialized workforce, areas in which the U.S. currently lags behind competitors like South Korea and China (Congressional Research Service, 2023; Grand View Research, 2023). Semiconductor costs now account for up to 50% of the total expense in training generative AI models, making compute access the most expensive and constrained input in the AI economy (Cottier & Rahman, 2024). Tariffs on chip imports have yielded complex effects, with studies suggesting that a 25% tariff could initially reduce GDP by 0.18% but increase long-term domestic output by 0.76% through strategic reshoring and investment (Ezell et al., 2025). However, reshoring requires large-scale investment in land, construction, equipment, and talent (Shrivastava, 2025). Smaller firms, local governments, and universities often cannot absorb significant economic burdens without federal assistance (Cottier et al., 2025).

Data center infrastructure is approaching physical and environmental limits. AI workloads generate up to 10 times conventional applications’ power and cooling demands, straining regional grids and contributing to growing latency and performance issues (McKinsey & Company, 2023; Srivathsan et al., 2024). Meanwhile, U.S. developers lack access to a national virtual AI cloud or public-sector compute capacity—resources now standard in leading AI economies, such as China and the EU (OECD, 2023; RAND, 2023). As trillion-parameter models become the norm, data centers must accommodate exponential increases in compute density; however, 70% of U.S. counties lack the necessary electrical and cooling infrastructure to support AI training clusters at scale (SCSP, 2023).

Tax policy compounds the challenge. Although the Section 41 R&D tax credit allows up to \$500,000 in offsets for payroll taxes under the Inflation Reduction Act, AI firms face high

documentation burdens and narrow eligibility rules that exclude expenses like cloud compute, software licensing, and GPU use, which are key cost centers in AI development (IRS, 2023; KBKG, 2023; The Tax Adviser, 2014). As a result, only 4% of early-stage tech companies successfully claim the credit, leaving billions in potential reinvestment untapped (IRS, 2023).

Compute access is further constrained by market concentration. Hyperscalers, such as Amazon, Microsoft, and Google, dominate the AI compute market, controlling access to over 70% of high-end GPU clusters used for model training, which effectively blocks small firms and public institutions from participating in frontier research (Gao & Lakhani, 2024). Startups and universities often encounter inflated pricing, lengthy lead times, and restricted cloud access, which limit their ability to compete or experiment with cutting-edge AI models (SCSP, 2023). If the U.S. fails to modernize compute access and infrastructure, it will forfeit AI's estimated \$4.4 trillion in productivity gains and risk permanent technological disadvantage (Chui et al., 2023; NSCAI, 2021).

2.2.3 Power & Energy Infrastructure

The rise of AI has intensified American electricity demand, with data centers projected to consume over 35 gigawatts (GW) of power by 2030, which is more than double the 17 GW usage in 2022, primarily driven by generative AI and cloud computing growth (Davenport et al., 2024; Deloitte, 2025). Such rapid expansion exacerbates strain on an aging national grid, which already suffers from limited transmission capacity that impedes the delivery of clean energy to high-demand AI hubs, particularly across state lines (Green et al., 2024; Rouch et al., 2024). As of 2024, more than 2.6 terawatts (TW) of solar, wind, and energy storage projects sit in interconnection queues, waiting an average of five years for grid access due to fragmented regulatory processes and utility bottlenecks (Silverman et al., 2024; Wilson et al., 2024). The inadequacy of long-distance transmission infrastructure leads to curtailments and congestion, resulting in delays in new power supplies when AI demand is rapidly outpacing energy availability (Stauffer, 2025; Choi et al., 2024).

AI workloads require high reliability and low latency, yet grid resiliency remains a key vulnerability, especially during extreme weather events, which in 2023 alone caused \$92 billion in infrastructure damage nationwide (Choi et al., 2024; Stauffer, 2025). To manage renewable intermittency, energy storage must scale significantly; however, the current deployment rate is insufficient, constrained by capital costs, siting barriers, and the absence of national mandates or utility requirements (Ramachandran et al., 2024; Stansbury et al., 2025). Long-duration storage, a necessity for balancing AI demand with fluctuations in renewable energy, remains experimental mainly, with only 1 GW of such storage operating nationwide as of 2024 (Shehabi et al., 2024; Stansbury et al., 2025). Without strategic federal incentives, private developers struggle to justify investment in regions lacking favorable cost-recovery mechanisms or performance-based regulatory frameworks (Green et al., 2024).

Nuclear energy, a zero-emission baseload source critical for AI-scale compute continuity, faces persistent hurdles. Despite broad scientific consensus on its reliability, new U.S. atomic construction has stalled, with most projects taking 7 to 10 years due to regulatory complexity, permitting delays, and lack of public-private investment (Hardin et al., 2025; Sandback, 2024).

Small modular reactors (SMRs), which offer scalable deployment for data center clusters, remain in the early stages of commercialization, with only a handful of demonstration projects approved as of 2025 (Hardin et al., 2025). Without federal reforms to streamline permitting and guarantee power purchase agreements, SMRs are unlikely to reach scale to support the next generation of AI infrastructure (Sandback, 2024).

Challenges in air-based cooling compound energy infrastructure stress, consuming substantial electricity, while more efficient liquid cooling requires significant infrastructure retrofits and site-specific planning (Uptime Institute, 2024). Many new data centers are being built in remote, arid, or energy-constrained regions, such as the U.S. Southwest, where water access and grid capacity compete with agricultural and residential needs, leading to local pushback and planning delays (Green et al., 2024). If not addressed, poor planning for sustainable cooling could result in capacity shortfalls or costly retrofits in over 60% of projected AI-ready sites (Uptime Institute, 2024).

Moreover, the unequal distribution of energy infrastructure availability limits where AI systems can expand. Regions like the Southeast and Midwest benefit from surplus, lower-cost electricity, while states like California and Massachusetts face grid congestion and elevated prices that reduce their competitiveness for data center siting (Ramachandran et al., 2024; Rouch et al., 2024). Without a federal policy to facilitate the sharing of interstate power resources, these disparities risk widening the digital divide and limiting the disparate deployment of AI (Green et al., 2024).

Despite the need for regional expansion, energy project permitting timelines remain one of the most significant systemic bottlenecks in the industry. New renewable generation and long-distance transmission projects typically take 7 to 10 years to complete, slowed by environmental reviews, legal disputes, and jurisdictional fragmentation (Deloitte, 2025; Stansbury et al., 2025). In contrast, AI infrastructure is deployed in 12- to 24-month cycles, resulting in manufacturing misalignment between technological and energy system timelines (Hardin et al., 2025). Without reforms that expand the Federal Energy Regulatory Commission's (FERC) siting authority and allocate funding for multi-state infrastructure, the expansion of AI will remain constrained by outdated grid infrastructure (Wilson et al., 2024; Rouch et al., 2024).

2.2.4 Capital Investment

The total private investment in U.S.-based AI reached \$67.22 billion in 2023, representing a \$7 billion increase from 2022, and solidifying the country's leadership with approximately 40% of global AI funding (Fattorini et al., 2024; Gil et al., 2024). However, the invested capital was highly concentrated among a few major firms, leaving small and medium-sized AI businesses without the funding and infrastructure necessary for growth (Aggarwal, 2021). Startups often face high upfront costs, including licensing fees, legal compliance, and access to computing infrastructure, which can exceed \$10 million for training a single frontier model (Cottier & Rahman, 2024). Such financial and regulatory barriers create structural disadvantages for smaller firms, with 70% of venture capital in AI concentrated in just three states: California, New York, and Massachusetts (Gil et al., 2024; Flexential, 2025).

As previously noted, public infrastructure investment lags have limited opportunities for capital. The U.S. has underinvested in clean energy development required to support AI-scale data centers, which can consume up to 50 megawatts (MW) of electricity (MIT News, 2025). As a result, capacity constraints are emerging across regional grids, particularly where renewable generation is insufficient to meet the surging demand for computing (Davenport et al., 2024; Green et al., 2024). Developers seeking to site new data centers in rural or underserved areas face lengthy permitting delays, high transmission interconnection costs, and limited federal incentives, stalling expansion into regions that could otherwise benefit from AI-driven job growth (Shark, 2025).

High operational costs for cloud compute access and GPU rentals disproportionately affect small businesses and public institutions, necessitating elevated expenses that compromise competitiveness and limit experimentation (Cottier & Rahman, 2024; Gao & Lakhani, 2024). R&D funding is also disproportionately concentrated. A few elite universities and private firms receive the majority of AI R&D dollars, while areas such as civic technology, rural applications, and health equity remain critically underfunded (Chui et al., 2023; Jin et al., 2025). At the same time, regulatory uncertainty has increased compliance costs by up to 30% for firms operating across jurisdictions, deterring investment and slowing product deployment (Johnson, 2025; Collier & Horvath, 2025). Public agencies often lack the digital procurement tools, technical expertise, and budget flexibility necessary to adopt AI systems for service delivery, resulting in critical sectors such as healthcare, transportation, and public safety being left without scalable AI integration (Jacobs, 2025; Flexential, 2025).

Finally, national AI hardware supply chains remain heavily dependent on foreign manufacturing, particularly semiconductors, GPUs, and data storage equipment. Over 90% of the most advanced chips are produced in Taiwan, and efforts to reshore production have faced cost overruns and delayed timelines, with some estimates placing the price of U.S. fab construction at three to five times that of Asian counterparts (Shrivastava, 2025; Ezell et al., 2025). Supply chain dependence on foreign nations introduces serious national security and economic vulnerabilities, with potential disruptions in the Taiwan Strait posing risks to over \$50 billion in U.S. tech sector output annually (RAND, 2023; Congressional Research Service, 2023). Without targeted congressional investment in domestic manufacturing, equitable access to capital, and incentives to diversify infrastructure, the U.S. risks falling short of its AI development and deployment goals.

2.3 Political Environment

The federal government faces mounting pressure to address AI development challenges across workforce training, computing infrastructure, energy availability, and capital access, yet remains hindered by regulatory fragmentation and uneven investment (NSCAI, 2021; Flexential, 2025). Although the U.S. accounted for nearly 40% of global AI private investment in 2023, institutional and legal inconsistencies continue to limit its capacity to scale innovation equitably and securely across all regions (Fattorini et al., 2024; Gil et al., 2024). Governmental constraints demand coordinated responses from federal, state, and international leaders to ensure that AI development benefits the broader American public rather than reinforcing existing disparities in economic opportunity and technological access (OECD, 2023; Collier & Horvath, 2025).

2.3.1 International Landscape

Globally, AI governance is characterized by divergent regulatory approaches, as nations weigh the balance between innovation and public protection. The European Union (EU) has enacted the AI Act, a comprehensive policy categorizing AI systems by risk and imposing stringent requirements on high-risk uses, including mandatory data governance and human oversight, which may hinder innovation and slow commercial deployment (European Parliament, 2025). Although the EU model promotes transparency and civil rights protections, it risks placing EU firms at a competitive disadvantage compared to the U.S. and China, where such restrictions are lighter or differently structured (White & Case, 2025).

In contrast, China has integrated AI into a \$150 billion national economic strategy, combining public compute platforms, government-subsidized chip manufacturing, and strict content controls to strengthen its global AI leadership while enhancing internal social control (RAND, 2023; OECD, 2023). Russia has also adopted sector-specific AI regulations prioritizing accountability in healthcare, education, and the arts, particularly in response to growing public concern over bias and algorithmic manipulation (BRICS Competition Law Centre, 2025). The evolving global policy environment reveals that while authoritarian regimes prioritize central control, democratic nations face more complex debates over equity, innovation, and the protection of civil liberties in the deployment of AI (Chivvis & Kavanagh, 2024; Heim, 2025).

2.3.2 National Context

AI policy remains in flux at the federal level, shaped by divergent administrative priorities and objectives. Under President Biden, the U.S. established the AI Safety Institute to lead ethical oversight, promote transparency, and align federal agency adoption of AI with public accountability principles (Lutnick, 2025). However, the Trump administration dismantled or restructured many of these efforts, replacing them with the Center for AI Standards and Innovation (CAISI), which emphasizes deregulatory frameworks and prioritizes economic development in strategic sectors such as defense, energy, and commerce (Removing Barriers to American Leadership in Artificial Intelligence, 2025; Lutnick, 2025). This realignment reflects a broader federal strategy shift, wherein Executive Order 14179 explicitly declares the U.S. goal of achieving “global AI dominance” to drive economic growth and national security, even if it requires rolling back consumer protection and anti-discrimination regulations (National Artificial Intelligence Initiative, 2023; Removing Barriers to American Leadership in Artificial Intelligence, 2025).

Congressional discourse remains divided, but bipartisan support has emerged for targeted measures, such as algorithmic bias audits and workforce retraining programs, which are supported by 72% of the public (Evans & Nellenbach, 2025; Kinder et al., 2024). Labor unions have expressed concern about job displacement, particularly in sectors such as logistics, retail, and clerical work, where 30% to 50% of tasks are projected to be impacted by AI-led automation (Eloundou et al., 2023; Acemoglu & Restrepo, 2018). Environmental advocates have also raised concerns about AI’s water and energy demands, particularly in regions facing resource constraints, such as the Southwest and Central Valley (Taft, 2025; Green et al., 2024). Community resistance is increasingly visible in public policy, as demonstrated by the veto of California Senate Bill 1047 and local opposition to new hyperscale data centers in residential areas (Kohler & Klaus, 2024). These pressures highlight the importance of inclusive AI policy development that engages stakeholders across sectors and geography (Jacobs, 2025).

President Trump has framed his 2025 trade platform around onshoring U.S. manufacturing, declaring AI and semiconductor independence essential to economic resilience (Economy, 2025). The America First Trade Policy and Executive Order 14179 articulate a vision for reshoring production, using tariffs and procurement preferences to stimulate domestic capacity (America First Trade Policy, 2025; Removing Barriers to American Leadership in Artificial Intelligence, 2025). While these efforts protect U.S. economic sovereignty, experts caution that reshoring alone may not overcome structural limitations without substantial investments in infrastructure, education, and innovation ecosystems (Shrivastava, 2025; Congressional Research Service, 2023).

2.3.3 Utah's Opportunity

Utah has emerged as a leader in AI governance among U.S. states, adopting a proactive, collaborative model that balances innovation with transparency. Senate Bill (SB) 149, which took effect in May 2024, mandates disclosure when consumers interact with AI systems and establishes the Office of AI Policy to oversee compliance and ethical oversight (Utah State Legislature, 2024a). Utah also passed SB 226 in 2025, which imposes enhanced transparency in high-risk sectors such as finance and law, reflecting the state's intention to protect consumers while attracting responsible AI investment (Utah State Legislature, 2025). Such measures make Utah one of only five U.S. states with comprehensive AI legislation as of 2025, and its regulatory framework is regarded as a model for striking a balance between economic growth and accountability (Oratz et al., 2025).

Utah's AI strategy is built on public-private partnerships, with major firms like NVIDIA and education leaders collaborating to expand workforce training and research and development (R&D) capacity (Utah Governor's Office of Economic Opportunity, 2025; Clarke, 2025). Programs like the "Learning Lab" offer legal safe harbors for testing AI technologies in controlled environments, accelerating innovation while preserving public trust (Winget, 2025). Utah's model has already established new AI research facilities and data infrastructure projects, contributing to regional economic development and setting a precedent for other states (Metnick et al., 2025).

The rejection of the OBBBA's preemption clause preserved Utah's authority to maintain its AI governance framework, but ongoing federal realignment under CAISI may still constrain state flexibility in the future (Duffy, 2025; Lutnick, 2025). The tension between centralized standardization and local adaptation remains unresolved, and Utah will need to monitor evolving federal priorities to ensure that its innovation-friendly policies are not overridden by future congressional or executive actions (Removing Barriers to American Leadership in Artificial Intelligence, 2025).

2.4 Other Narrative Considerations

While this Report focuses on the economic bottlenecks of the AI supply chain, AI's societal risks must not be overlooked, especially as public concern over misinformation, surveillance, and algorithmic bias intensifies. The rise of generative AI (genAI) has significantly increased the risk of disinformation, with over 60% of global respondents in a 2024 OECD survey citing deepfake

content as a significant societal concern (OECD, 2023). Public data used to train AI systems often contains embedded biases, which can lead to inaccurate or unfair outcomes, particularly in hiring, healthcare, and criminal justice (Farahani & Ghasemi, 2024; Kim, 2022). These biased outputs are exacerbated by the “black box” nature of large AI models, which prevents users from understanding how outputs are generated (WIPO, 2024).

Privacy is another growing concern. AI-powered hiring tools, for example, often collect and analyze large volumes of personal data, including speech patterns, facial expressions, and keystroke behavior, often without the informed consent of applicants (Milne, 2024; Werner, 2024). Surveys indicate that 58% of job seekers are concerned that AI systems will make decisions based on sensitive traits, such as race or gender, undermining trust in automated decision-making (Salesforce, 2023). These risks extend beyond employment: algorithmic tools are increasingly used in housing, education, and public safety, thereby raising the stakes for the fair, transparent, and accountable use of AI (Acemoglu & Restrepo, 2018; Frank et al., 2019).

To protect civil liberties and promote democratic values, AI systems must be designed with ethical safeguards prioritizing accountability, equity, and user agency (Floridi et al., 2018). This includes mechanisms for contesting unfair decisions, clear AI involvement disclosures, and legal auditing and oversight standards (WIPO, 2024). Without these protections, public trust in AI will erode, and the technology’s estimated economic potential of \$15.7 trillion by 2030 may be undermined by backlash, litigation, and regulatory retrenchment (NSCAI, 2021; Chui et al., 2023).

3. PURPOSE

With input from RAND Corporation analysts on the project’s needs and expectations, three objectives were determined to most effectively address the ever-evolving nature of AI and meet the dynamic needs of various stakeholders. The research team employed a pragmatic methodology to identify AI’s expansive societal rhetoric, interweaving industry studies and data trend reports to clear unnecessary barriers, bottlenecks, and challenges that inhibit America’s economic potential for AI development. The following research questions directed the research team’s data collection and analysis processes and catalyzed the findings and conclusions in this Report:

- 1) What consensus challenges impede AI development from maximizing its growth potential in the United States?
- 2) What are the degrees of impact that AI inefficiencies place on the American economy?
- 3) What policies, funding, and oversight can Congress establish to maximize the economic potential of American AI development?

4. RESEARCH METHODOLOGY

The research team developed a comprehensive framework to guide the inquiry into the vast and rapidly evolving field of American AI development. This study employs a multi-method research design that integrates a modified Qualitative Content Analysis to elicit consensus amongst industry, think tanks, academia, and mixed media (i.e., newspapers, magazines, blogs) on the bottlenecks affecting American AI development. These bottlenecks will be evaluated to determine the most impactful ones using four variables: frequency, impact, resolution, and urgency. Once

consensus on bottlenecks is determined through a rigorous Content Analysis, candidate congressional policy scenarios will be explored using Decision Making under Deep Uncertainty (DMDU) modeling to evaluate robust federal policy options that can alleviate structural bottlenecks in US AI development. Drawing on diverse disciplinary approaches and real-world data, the methodology supports a comprehensive and forward-looking framework for decision-making across four interdependent constraint areas: labor, computing, energy, and capital.

4.1 Data

Qualitative data from over 1,000 unique secondary sources, including industry, government, think tanks, academia, and mixed media (i.e., newspapers, magazines, blogs), established the quantification of frequencies across diverse publications. Data collection can be referenced in Appendix A. These publications were sourced from online public sources, downloaded as PDF files, and converted to TXT files for LACA. LACA was observed at the paragraph level as our unit of analysis; however, the LLM was instructed to group multi-paragraph sections when they cover the same theme. The data was used to elucidate answers to the following question: “What AI bottlenecks emerge from the literature and how can congressional policy mechanisms address them?” Appendix B describes potential congressional policy mechanisms that may address potential bottlenecks. The following table describes the data:

Table 3. Description of Data Sources

<u>Data Source</u>	<u>N (# of sources)</u>
Industry	160
Think Tank	334
Government	118
Academia	248
Mixed Media (newspaper, blog, magazine)	146

4.2. Qualitative Content Analysis

This study builds on the methodologies employed by Liu and Sun (2023), Lupo et al. (2024), Chew et al. (2023), and Dominguez-Díaz et al. (2025), which involved multiple studies using LLM-assisted content analysis (LACA). Both Lupo et al. (2024) and Dominguez-Díaz et al. (2025) determine that the best strategy involves providing the LLM with a detailed codebook, with Chew et al. (2023) recommending co-development with the LLM. The LLM used the codebook

as its coding instructions, along with developing a detailed prompt for how to code the documents. The researchers argue that the best strategy involves providing the LLM with a detailed codebook, development of a protocol (i.e., prompt) for OpenAI's ChatGPT to analyze and interpret text, tests of validity to determine the LLM's reasoning in coding decisions, and a need for human versus machine annotation comparison (Lupo et al., 2024; Dominguez-Diaz et al., 2025; Chew et al., 2025; Liu & Sun, 2023). Researchers found that ChatGPT-4 coding aligned with human coding at 77.89%, increasing to 96.02% when expanded to broader themes. In some instances, the GPT-4 model performs on par or outperforms human coders even “in complex annotation tasks involving a minority language, linguistic specificity, and complex labels” (Liu & Sun, 2023; Lupo et al., 2024). The following sections describe the protocol used to perform content analysis using a pre-tested codebook co-developed with the LLM to guide GPT-4o in content analysis with human oversight.

4.2.1 Codebook Development & Deductive Coding Process

According to Chew et al. (2020), the first step in LACA is the development of measures (categories) that operationalize the concepts under study, along with the accompanying codebook or document containing the study's coding scheme. Appendix C identifies the codebook used for the LACA, which includes 13 categories and 112 separate codes, each accompanied by definitions, examples from the text, and justification for its inclusion. The initial deductive coding was developed by human coding analysts and expanded using ChatGPT LLM through iterative steps for introducing data from our dataset until a final codebook was established. The human coding analysts refined the definitions and examples from text in the dataset to ensure minimal overlap between codes while capturing as many possible bottlenecks, types, and potential causes as possible. The codebook's development provides codes for bottlenecks, or the pitfalls that may impede AI's development. It served as a way to reach consensus on the most impactful ones by quantifying the frequency of these codes.

4.2.2 Tests of Validity & Prompt Engineering

The codebook was tested against a random sample of five (5) uncoded data sources from the dataset. This process utilized the codebook and prompt instructions to train the LLM to code documents (Chew et al., 2023). The goal of the testing is to assess whether the LLM “understands” the coding task and “can produce valid results that capture the underlying construct of interest,” or to determine whether the LLM can code AI bottlenecks from the data using the codebook as its instruction (Chew et al. 2023). This is an iterative process of testing, manually reviewing the results by human coding analysts, and improving the codebook definitions to assess the LLMs' generated coding decisions. Codebook revisions are necessary after reviewing the test results because some codes may be underperforming, leading to an incorrect coding schema (Chew et al., 2023). The codebook was revised to provide more context, narrower definitions, additional examples, or more justification (Chew et al., 2023). This iterative process was repeated 17 times, and testing was concluded once the sample data set provided consistent results over a minimum of five trials. Appendix D provides examples of codebook revisions used in this study.

Chew et al. (2023) suggest engineering prompts that provide a coding decision and the LLM's reasoning behind the coding decision (p. 3). To further assess the validity of the LACA

process, the prompt included instructions for the LLM to justify its coding decision. Forcing LLMs to work through their reasoning for complex content analysis has improved performance and increased their trust (Wei et al., 2022). Appendix E provides examples of model coding, including the model's reasoning for selecting the bottleneck. To further assist the human analyst in understanding the model's reasoning, the prompt instructed the LLM to provide highlights of the text that justified its coding decisions. This process created a separate .TXT file containing a direct citation from the data used by the LLM to provide additional context on coding reasoning. This reliability assessment was added as an extra measure of validity and a tool to aid the human coding analyst in evaluating the LLM's ability to code the data accurately. Appendix F provides an example of the model's highlight output for reference 1234.

The prompt engineering was similarly an iterative process, with each iteration adding context, instruction, and deliverables as the prompt engineering was continuously improved. The final prompt resulted in a 4-step process that starts with context, a review of policy mechanisms, a step to ensure understanding of the process, and the final instructional prompt that attaches 10 .TXT files at a time. Appendix G provides the final prompt that was engineered and used throughout the LACA.

4.2.3 Tests of Reliability Between Human Coders & LLM

As standard practice, once the prompts and the codebooks are developed and testing has been completed, a small sample of uncoded data is coded by human coders and compared against LLM (Chew et al., 2023). Human coding analysts coded a sample of five (5) uncoded data. After conducting these assessments, the research team determined whether the model generated codes comparable to those created by humans. If found to be inferior, prompt engineering may be utilized to modify the prompts or the codebook for underperforming categories (Chew et al., 2023). The process of human coding comparison did not yield any changes to the codebook or the final prompt, as the human coding analysts found the coding model reliably agreed with how the documents should be coded.

4.2.4 Use of LLM to Perform LACA

Chew et al. (2023) suggest that once the model generates codes that are deemed “non-inferior” to human-coded responses, the final step is to use the LLM for final coding (p. 5). The codebook, prompt, and 10 .TXT files were run each time with results reviewed by human coding analysts. The results were aggregated and further inspected for accuracy and consistency.

4.2.5 Limitations of LACA

The LACA process had several limitations that should be considered. The limitations on the number of .TXT files were low, and the run time varied from 4 minutes to up to 20 minutes. After running the same prompt approximately six or more times, the coding schema would begin to overlap with other categories, and the model would need to be reminded about the codebook. As a best practice, the codebook was typically introduced at each prompting; however, this approach would both reduce the number of files reviewed and increase processing time. While the

model needed constant human oversight, it demonstrated an impressive ability to capture textual nuances and maintain consistency in its coding (Liu & Sun, 2023).

Further, the LACA process synthesizes secondary sources and captures published convergence of expert views. This structure captures written expert opinion across several publications types and sources, and does not elicit expert consensus through an iterative, anonymous, structured, group-based communication process such as the gold-standard Delphi method (Khodyakov et al, 2023). The unit of analysis in LACA is the published document at the paragraph level rather than an anonymous expert. However, the LACA process here followed researched best practices that scans large records of published data to map and prioritize issues and produce inputs for the methodologies described in the following subsections.

4.3 Calculating & Standardizing the AI Bottleneck Variables

Results from the LACA process informed the existence of bottlenecks impeding AI's development in the U.S. To rank the impact of the bottlenecks, each bottleneck was standardized based on the variables listed in Table 3.

Table 4. Variable and Scoring Criteria

Variable	Scoring Criteria	Justification
Frequency	Scaled from 0 to 1 by dividing by the max count (most frequent bottleneck)	How often was the bottleneck coded across our dataset
Impact	High = 1.0, Moderate = 0.6, Low = 0.3	How severely does the bottleneck constrain AI development
Resolution Potential	Remediable = 1.0, Structural = 0.5, Intractable = .1	Likelihood of being fixed through public policy
Urgency	Current = 1.0, Emerging = 0.7, Historic = .1	Indicates whether the bottleneck is currently, has been, or will affect progress

A Bottleneck Composite Index (BCI) is calculated to evaluate and prioritize the bottlenecks impeding AI Development in the U.S. The BCI offers a structured, quantitative approach for identifying and prioritizing the most pressing bottlenecks. Rather than relying solely on frequency, the BCI combines qualitative coding data with a systematic scoring methodology to transform the qualitative coding in the LACA matrix into a ranked decision-making framework. A composite score indicated those bottlenecks that are frequently mentioned, urgent, fixable, and highly consequential to AI's development. Because a bottleneck may appear multiple times with varying codings across Impact, Resolution, and Urgency, the average score of these variables was

considered. Typically, qualitative coding across documents yields variation, making averaging the scores appropriate. Frequency was scaled to values between 0 and 1 using the calculation:

$$Frequency Scaled_i = \frac{Frequency_i}{Max Frequency}$$

Average Impact Score was calculated as follows to provide the mean of all coded impact levels for the bottleneck (with the same calculations done for Average Resolution and Average Urgency):

$$Avg Impact_i = \frac{1}{n_i} \sum_{j=1}^{n_i} Impact Score_{ij}$$

Our method utilized a multiplicative normalization formula to calculate a raw weight for each unique bottleneck, i . The multiplicative normalization is used to avoid overweighing a variable, ensuring a bottleneck's score represents its impact, resolution, and urgency. The raw weighted score is calculated as:

$$Raw Weight_i = \left(\frac{Frequency_i}{Max Frequency} \right) \times Avg Impact_i \times Avg Resolution_i \times Avg Urgency_i$$

With the Normalized BCI then computed as

$$Normalized BCI_i = \frac{Raw Weight_i}{\sum_{j=1}^n Raw Weight_j}$$

Where:

i is the individual bottleneck (out of 47)

j is the coded mention of the bottleneck

$Frequency_i$ is the number of times the bottleneck i appears in the dataset. (same as n_i)

$Max Frequency$ is the largest frequency across all bottlenecks (176)

n_i is the number of times bottleneck i was coded across all sources (short form of $Frequency_i$)

$Impact Score_{ij}$ is the numeric impact for the j -th mention of the bottleneck i (high = 1, moderate = .6, low = .3). The same was done for Resolution and Urgency.

$Avg Impact_i$ Score (ranges .3 - 1.0)

$Avg Resolution_i$ Score (ranges .1 - 1.0)

$Avg Urgency_i$ Score (ranges .1 - 1.0)

$Raw Weight_i$ is the unnormalized composite for bottleneck i

Normalized BCI_i is the final normalized index for bottleneck *i*

The final BCI is normalized across all bottlenecks, yielding a score between 0 and 1 for each. By building a composite index based on the rigorous LACA process, the index can transform qualitative data into a ranked list of bottlenecks that is comparable and interpretable. The BCI provided a ranked list of bottlenecks that can be analyzed to potentially identify candidate congressional policy mechanisms that address and alleviate these bottlenecks. The candidate policies were used in the DMDU modeling described in the next section.

4.4 Decision Making Under Deep Uncertainty (DMDU)

The DMDU framework was implemented in three layers: Robust Decision Making (RDM), Dynamic Adaptive Policy Pathways (DAPP), and Exploratory Modeling. The RDM component simulated 10,000 futures by generating randomized bottleneck severity scores within defined scenario ranges. Each risk range was drawn from expert-coded expectations: for instance, the severity of the upskilling gap was simulated between 0.4 and 0.8 based on the large number of sources citing it as a high and current concern, while explainability tool limitations were simulated between 0.2 and 0.7, reflecting a less severe but still credible level of system exposure. These range choices were derived from the Research Matrix’s assigned urgency and impact levels, where a higher average score widened the upper bound of plausible risk.

To operationalize our analysis, we developed a set of candidate policies tailored to address the most critical bottlenecks identified through our structured evidence review. The top-ranked bottlenecks formed the basis for policy design. Each candidate policy was then defined as a bundle of targeted interventions, with mitigation intensities assigned to each bottleneck it sought to address. These policies were input into a simulation environment that models 10,000 plausible futures, each characterized by different combinations of bottleneck severity. Within the DMDU model, candidate policies are evaluated for their ability to reduce aggregate risk, with each policy’s performance influenced by both its mitigation effectiveness and a feasibility score that represents institutional and political constraints. In static simulations (Robust Decision Making), each policy is held constant across all futures; in dynamic runs (Dynamic Adaptive Policy Pathways), the model selects among policies based on real-time threshold triggers embedded in the scenario conditions. This integrated structure enables the model to test not only whether a policy works, but also under what specific conditions it is most effective.

To reflect the potential for systemic tipping points, we introduced scenario-based thresholds into the simulation model. These thresholds serve as inflection points beyond which the risk associated with a given bottleneck either incurs a penalty or shifts the policy pathway. For example, in scenarios where the simulated severity of the *Upskilling Gap* exceeds 0.70, the model applies an additional 0.05 penalty to simulate increased labor market disruption and social unrest. Similarly, if *Fragmented Governance* exceeds a severity level of 0.80, an added penalty of 0.03 reflects heightened risks of administrative gridlock and coordination failure. These numeric thresholds were derived from empirical coding in the Research Matrix. Specifically, the *Upskilling Gap* appeared in 90 unique entries, 94% of which (85 out of 90) were coded as having “High” impact, 91% as “Remediable,” and 87% as “Current” in temporal urgency—placing it among the most tractable and pressing issues in the dataset. Likewise, *Fragmented AI Governance* was cited

in 107 instances and had similarly high rates of “High” impact and “Remediable” categorization. These distributions suggest a policy window in which these bottlenecks are likely to intensify in future scenarios and receive congressional or agency attention. As such, thresholds of 0.70 and 0.80 were chosen not arbitrarily, but to represent the upper bound of plausible risk levels for high-weight, high-urgency bottlenecks as quantified by the source evidence.

The DAPP layer formed policy adaptiveness by selecting the most appropriate strategy for each future scenario based on these same bottleneck thresholds. If *Upskilling Gap* was above 0.75, the model dynamically switched to the *Upskill Now* policy; if *Fragmented Governance* was above 0.8, it deployed *Governance First*. In all other cases, *Balanced Adaptive* served as the default. This logic reflects real-world policymaking under uncertainty, where interventions often shift in response to early indicators or evolving conditions.

Finally, all scenario-level results were exported as structured data for exploratory modeling. This enabled the identification of conditions under which strategies failed or succeeded, the comparison of performance across risk clusters, and the detection of scenario types that consistently outperformed others. For instance, scenarios with high explainability risk but moderate governance fragmentation favored the Balanced Adaptive approach, while governance-dominant scenarios triggered *Governance First* with marginal success. This layer of exploratory modeling serves as both a validation tool and a planning instrument for future federal policy, as it supports scenario discovery, tipping point detection, and the design of real-time monitoring.

In sum, the model successfully integrates candidate policies into a three-method DMDU framework. Each strategy is tested across a broad spectrum of plausible futures, adjusted based on scenario-specific thresholds, and then stored for further analysis of patterns. The thresholds, risk ranges, and weights used throughout the model are grounded in empirical data from the Research Matrix, ensuring that both the model logic and policy implications are evidence-based, reproducible, and actionable.

5. FINDINGS

This section presents the key empirical results from the LACA and the BCI process, which together highlight the most pressing constraints on U.S. AI development. While LACA identified 47 unique bottlenecks from over 1,000 mixed sources, the BCI applied a weighting methodology to those results by normalizing scores based on frequency, impact, urgency, and resolution potential to determine which constraints are most severe and actionable for congressional policy intervention. The findings are organized below to first explore the breadth and thematic clustering of bottlenecks in Section 5.1 and then to narrow in on their weighted policy significance in Section 5.2.

5.1 LACA Findings

As a result of executing the LACA process, a total of 1,006 sources produced 47 coded bottlenecks. The top 22 bottlenecks are coded at least 10 times, and the top 10 show a cumulative coverage of 68.5%, or 690, of coding frequencies. Furthermore, the top 20 bottlenecks exhibit a cumulative coverage of 89.4%, or 899, of coding frequencies, indicating that the bottom 27

bottlenecks are only coded approximately 10.6% of the time across the entire dataset. Congressional action may only need to tackle 20 of these 47 bottlenecks to address nearly 90% of the problem space. This concentration signals that a relatively small number of structural and recurring obstacles dominate the national conversation across industry, think tank, government, academia, and media. These top bottlenecks, detailed in Table 4, serve as the empirical foundation for downstream prioritization in the BCI and DMDU modeling, with the complete list provided in Appendix H.

The most frequently cited constraint, coded as Fragmented AI Governance Across Jurisdictions, was referenced in 176 distinct sources, constituting over 17.5% of all coded mentions. This signals a perceived policy breakdown and misalignment of agencies across the U.S. According to the National Conference of State Legislatures (2025), all 50 U.S. states have introduced legislation on AI in 2025, with 38 states adopting or enacting 100 measures this year alone. The hundreds of disparate AI-related laws across state and local jurisdictions have created a compliance patchwork that disincentivizes innovation, confuses developers, and complicates investment decisions. This bottleneck highlights a systemic need for a coherent federal framework that strikes a balance between state autonomy and national competitiveness.

Following closely behind is the absence of upskilling programs for workers, which appears 144 times. This bottleneck reflects the growing mismatch between technological advancement and labor force readiness, particularly the underinvestment in scalable workforce transition programs capable of preparing displaced or emerging workers for AI-intensive environments. The third most cited bottleneck is the lack of explainability tools, appearing in 118 sources, which signals a cross-sector concern about the interpretability, transparency, and accountability of AI systems. These top three bottlenecks alone represent a significant share of all mentions (n=438 or ~43.5%) and potentially reflect core pillars of effective AI development, namely regulatory clarity, workforce capacity, and technological reliability.

Beyond these dominant constraints, the remainder of the top twenty bottlenecks includes concerns such as cybersecurity risks, unequal public-private collaboration, the absence of widespread competency standards, and data infrastructure limitations, including silos, compute shortages, and grid connectivity delays.

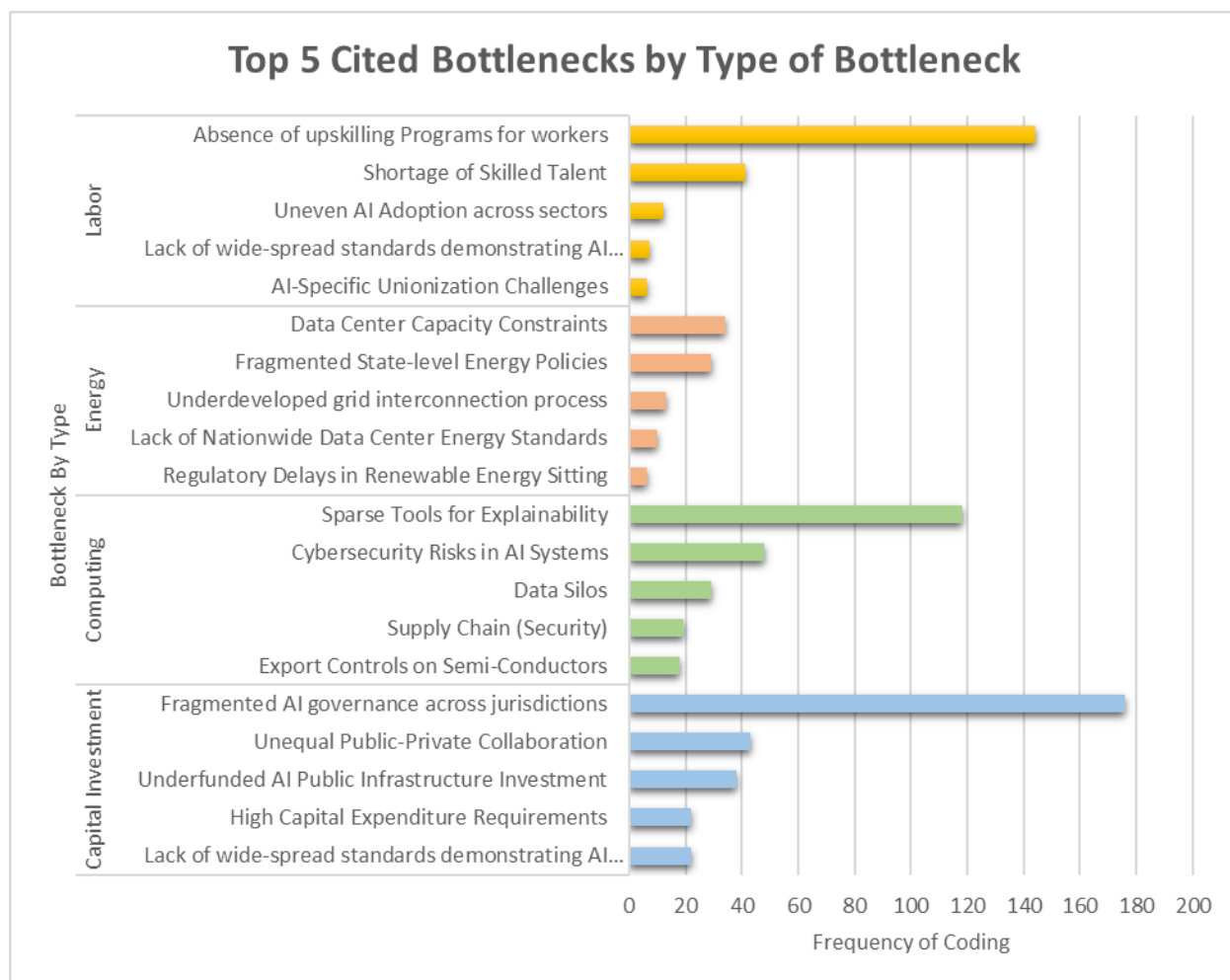
Table 5. Top 20 Cited Bottlenecks by Coding Frequency

No.	Bottleneck Code	Coding Frequency
1	Fragmented AI governance across jurisdictions	176
2	Absence of upskilling Programs for workers	144
3	Sparse Tools for Explainability	118

4	Cybersecurity Risks in AI Systems	48
5	Unequal Public-Private Collaboration	47
6	Lack of widespread standards demonstrating AI Competency	43
7	Shortage of Skilled Talent	41
8	Underfunded AI Public Infrastructure Investment	39
9	Data Center Capacity Constraints	34
10	Data Silos	29
11	Fragmented State-level Energy Policies	29
12	Uncertainty Around Intellectual Property (IP)	25
13	Uneven AI Adoption across Sectors	25
14	High Capital Expenditure Requirements	23
15	Supply Chain (Security)	21
16	Export Controls on Semiconductors	18
17	Labeling and Annotation (Scarcity of high-quality data in specialized domains)	14
18	Underdeveloped grid interconnection process	13
19	Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc.)	12
20	Regulatory Delays in Renewable Energy Siting	11

Further, the LACA identified bottlenecks that were coded based on their category types, and the complete list can be found in Appendix I. Table 5 provides the top 5 bottlenecks that were identified within each dominating dimension (Labor, Energy, Computing, and Capital Investment). The findings indicate that the most cited labor-related bottleneck is the absence of upskilling programs ($n = 144$), while the most critical energy-related bottleneck is data center capacity ($n = 34$). In the computing domain, the scarcity of explainability tools ($n = 118$) and cybersecurity concerns ($n = 48$) were the most frequently cited, whereas in the capital domain, fragmented governance ($n = 176$) and unequal public-private collaboration ($n = 47$) are the most prominent issues. This cross-domain complexity demonstrates that AI development constraints are not siloed within a single policy arena but rather intersect across institutional, technical, and economic systems. By disaggregating bottlenecks in this way, congressional strategies can be designed to address multiple domains and bottlenecks simultaneously.

Table 6. Top 5 Cited Bottlenecks by Type



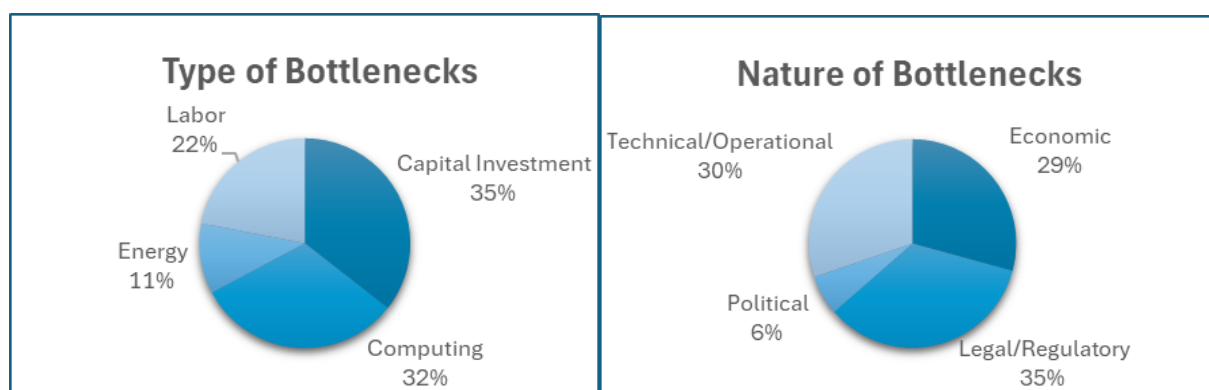
Figures 1 through 7 present the results of the LACA, which included 10 additional coding categories. The data shows that bottlenecks related to capital investment are the most prevalent at 35%, followed by computing at 32%, which collectively account for 67% of all bottlenecks. Labor-related bottlenecks make up 22%, while energy issues account for 11%. This highlights a capital and compute-heavy distribution of bottlenecks. The nature of the AI bottlenecks were generally legal/regulatory (34%) indicating a need for consistent and clear laws for this emerging technology, technical/operational (30%) which points to infrastructure gaps, model explainability challenges or general compute shortages, and economic (29%) which highlights the high cost and upfront capital investment to AI development. Using congressional policy mechanisms, legal and operational changes are feasible. This is further supported by the distribution of bottleneck sources, which are almost evenly attributed amongst the federal government (31%) and private firms (30%), with 26% coding as involving both. This shared distribution of responsibility highlights that no single actor can resolve these challenges, underscoring the need for increased public-private coordination to overcome these bottlenecks. At the national level, immigration policy, R&D funding, and procurement barriers are the primary causes of bottlenecks. However, bottlenecks such as underinvestment in labor upskilling and compute monopolization can be traced back to the private sector. While the state (12%) is coded lower, bottlenecks in local permits or State AI laws can be challenging. Federal policy may be designed to incentivize private sector

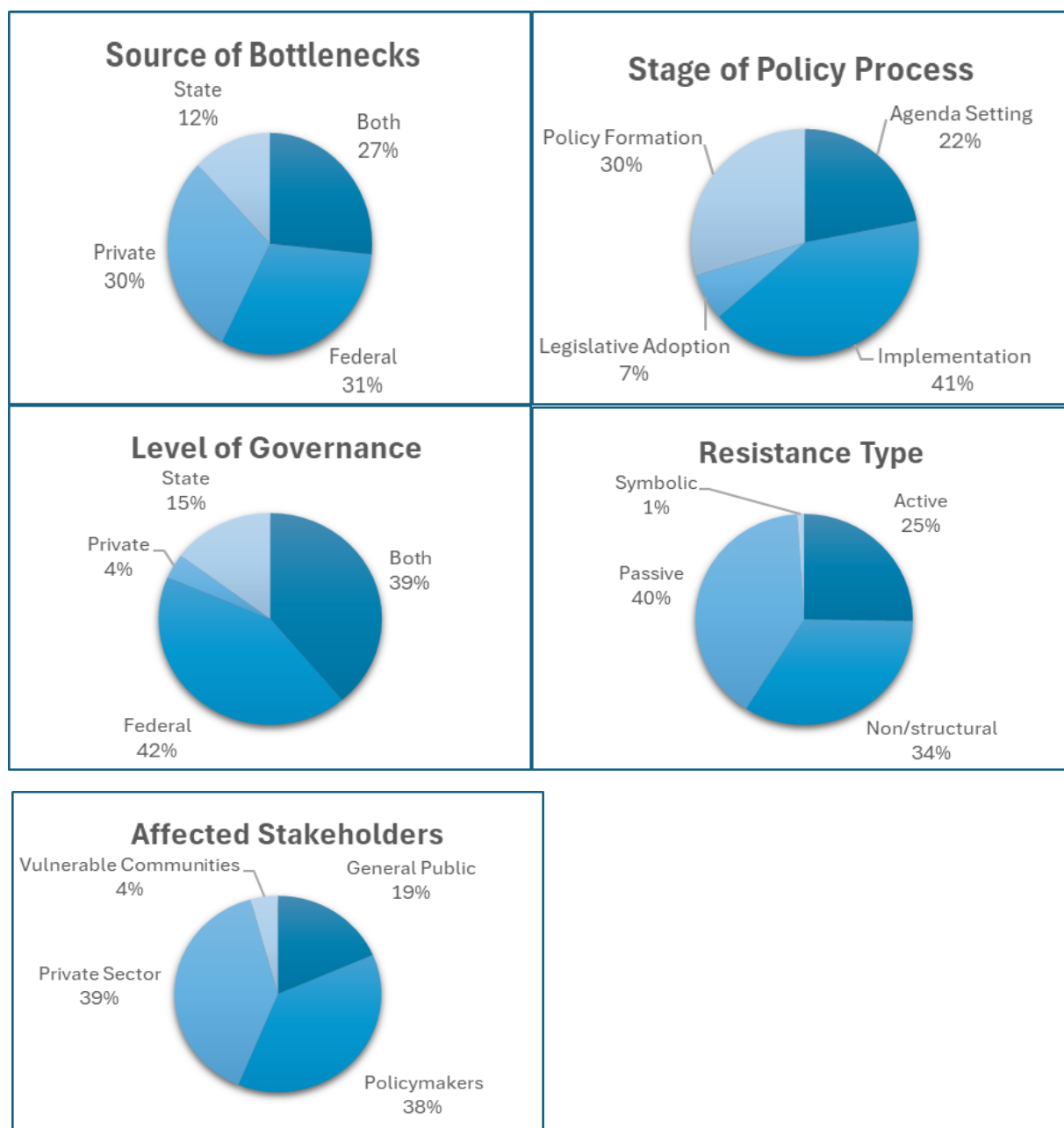
alignment, but private institutions must be ready to meet coordinated national standards and compliance mandates.

Federal-level issues dominate AI bottlenecks, accounting for 42% of coded bottlenecks within the federal jurisdiction, followed by multilevel governance at 39%, with the State and private sector rounding out at 19%. This means over 80% of AI constraints either originate from or are affected by federal jurisdiction, signaling the critical role that Congress has in enabling cross-sector coordination. Further analysis of the policy process stage reveals that most bottlenecks occur during the implementation stage, suggesting that they may arise after laws are passed. Specifically, 41% of bottlenecks are associated with the implementation phase, while 30% occur during the policy formation stage and 22% during agenda setting. Only 7% of bottlenecks were attributed to legislative adoption, suggesting that while political debate and consensus on AI policy may be debated, the real frictions emerge once policies are enacted.

Finally, the LACA indicates that bottlenecks are not politically or ideologically polarizing. Passive and non-structural resistance types together account for approximately 74% of the coded resistance types, indicating barriers such as procedural delays or infrastructure gaps that congressional policy mechanisms may address. Active resistance, which accounts for 25% of the coding, indicates strategic pushback from opposing coalitions or legal challenges, while symbolic resistance represents only 1% of the coding and is rare, likely having no significant impact. This coding dynamic indicates that most bottlenecks are technically solvable through policy tools such as funding, permitting reform, tax incentives, and procurement strategy. This is further reinforced by the stakeholders most affected. Stakeholders most affected by AI are nearly evenly split between the private sector (39%) and policymakers (38%), highlighting that coordination between government and industry will be necessary to remove barriers and scale innovation.

Figures 1-7. Coding Category Findings

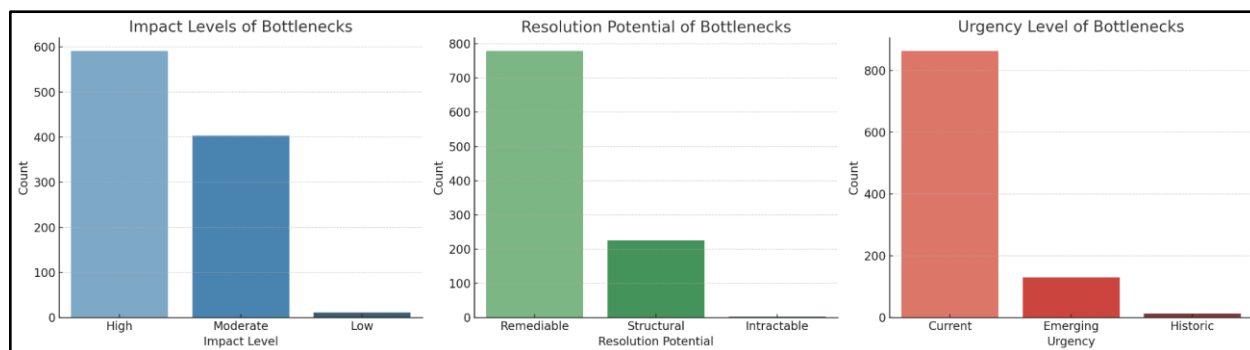




The impact, resolution, and urgency coding categories can be found side-by-side in Figure 8 and are presented in the BCI to offer critical insight into how damaging, fixable, and urgent the bottleneck is to inform intervention. The coding analysis reveals that approximately 59% of bottlenecks are considered high-impact, confirming that the majority of constraints pose significant threats to AI development, scaling, or adoption. Furthermore, the data indicates that 77% of the bottlenecks are considered remediable. This suggests that most constraints are not systemic inevitabilities but rather obstacles that can be overcome through congressional policy mechanisms, such as conditional grants, workforce development programs, permitting reform, or tax incentives. This high remediability score strengthens the case for federal intervention, especially since many of the identified bottlenecks fall under congressional authority or are shaped

by federal administrative frameworks. Lastly, the urgency category provides added clarity. Approximately 86% of all bottlenecks are currently coded, indicating that they are actively hindering AI development at this moment. This underscores the urgency for policy action, as continued inaction could allow these constraints to accumulate and deepen structural disparities, stalling innovation and enabling global competitors to gain ground on American AI dominance.

Figure 8. Impact, Resolution, and Urgency of Bottlenecks



When combined, these three dimensions reveal an urgent risk landscape that congressional action can effectively address. Rather than portraying a bottleneck landscape with insurmountable challenges, the LACA results suggest an environment that is geared towards a strategic policy response. The timing is appropriate to address current concerns, the policy tools are within Congress's authority, and the potential payoff for targeted federal action is significant to AI's development. These findings directly inform the weighted prioritization presented in the following section, where the BCI evaluates each constraint not only by its frequency of occurrence but also by its impact, fixability, and time sensitivity in practice.

5.2 BCI Findings

Building on the LACA results, the BCI provides an additional layer of insight by applying a weighted ranking to each bottleneck. This scoring system was constructed using the categories of frequency, average impact, resolution potential, and urgency as described in the codebook. These inputs are normalized to produce a composite index that reflects the practical severity of each bottleneck in the context of AI development tied to LACA. While LACA identifies how often bottlenecks appear in the literature, the BCI helps describe how significant and addressable each constraint is.

The BCI results confirm the prominence of several high-frequency bottlenecks while also introducing others that were cited less often but carry considerable weight due to their high impact, urgency, or potential for resolution. The bottleneck with the highest BCI score is Fragmented AI Governance Across Jurisdictions, with a normalized score of 0.1672. It is followed by Absence of Upskilling Programs for Workers, with a score of 0.1500, and Sparse Tools for Explainability, which scored 0.1195. These three bottlenecks together account for over 43% of the total composite score across the top twenty, suggesting that they are highly cited, impactful, timely, and potentially fixable bottlenecks.

The weighted BCI was calculated, and the top 20 ranked bottlenecks, based on their coding frequency and average impact, resolution, and urgency, are provided in Table 6. The complete list of 47 bottlenecks can be found in Appendix J. The bottleneck type (labor, computing, energy, or capital) was assigned based on its most frequently coded type, as listed in Appendix I. Mapping the ranked bottlenecks in Table 6 reveals 6 Capital Investment, 3 Labor, 7 Computing, and 4 Energy types of bottlenecks. Capital Investment accounts for 34.24% of the top 20's composite score, followed by Computing at 26.24%, and Energy at 8.7%. While Labor has the lowest number of bottlenecks in terms of count, this bottleneck type accounts for 22.2% of the composite score, highlighting the importance of this bottleneck domain. These domain assignments provide continuity with earlier findings and enable continued analysis of how resource constraints intersect with structural barriers to AI development.

Table 7. Top 20 BCI-Ranked Bottlenecks

Rank	Bottleneck Type (Freq.)	Bottleneck	Normalized BCI
1	Capital Investment (n=176)	Fragmented AI governance across jurisdictions	0.1672
2	Labor (n=144)	Absence of upskilling Programs for workers	0.1500
3	Computing (n=118)	Sparse Tools for Explainability	0.1195
4	Computing (n=48)	Cybersecurity Risks in AI Systems	0.0554
5	Labor (n=41)	Shortage of Skilled Talent	0.0466
6	Capital Investment (n=22)	Lack of widespread standards demonstrating AI Competency	0.0410
7	Capital Investment (n=38)	Underfunded AI Public Infrastructure Investment	0.0409
8	Capital Investment (n=43)	Unequal Public-Private Collaboration	0.0401
9	Energy (n=34)	Data Center Capacity Constraints	0.0325
10	Computing (n=29)	Data Silos	0.0283
11	Capital Investment (n=17)	Uncertainty Around Intellectual Property (IP)	0.0280
12	Energy (n=29)	Fragmented State-level Energy Policies	0.0277
13	Labor (n=12)	Uneven AI Adoption across sectors	0.0254
14	Capital Investment (n=22)	High Capital Expenditure Requirements	0.0252
15	Computing (n=19)	Supply Chain (Security)	0.0187
16	Computing (n=18)	Export Controls on Semiconductors	0.0154

17	Energy (n=13)	Underdeveloped grid interconnection process	0.0142
18	Computing (n=14)	Labeling and Annotation (Scarcity of high-quality data in specialized domains)	0.0139
19	Energy (n=10)	Lack of Nationwide Data Center Energy Standards	0.0126
20	Computing (n=7)	Supply Chain (Component Shortages in the US) (transformers, chips, circuit breakers, etc.)	0.0112

Figure 9 presents a visual distribution of the top BCI scores. A noticeable drop in composite scores occurs after the third-ranked bottleneck. This decline begins with Cybersecurity Risks in AI Systems, which has a BCI score of 0.0554, and continues downward through the rest of the ranked bottlenecks. Although these lower-scoring bottlenecks appear less frequently in the literature, they remain elevated in the index due to their high scores in other categories. Examples include Data Silos, Uncertainty Around Intellectual Property, and Grid Interconnection Delays. These bottlenecks are not among the most cited, but their structural role in AI development makes them noteworthy within the composite ranking.

The BCI differs from a simple frequency count by revealing bottlenecks that are both significant and potentially responsive to intervention. 77% of bottlenecks were coded as remediable, and 86% were coded as current. This suggests that most challenges are neither speculative nor irreversible. Instead, a majority of bottlenecks reflect real and present constraints that may be addressed through existing policy mechanisms and institutional coordination.

Figure 9. Line Chart of Normalized BCI Across Top 20 Bottlenecks

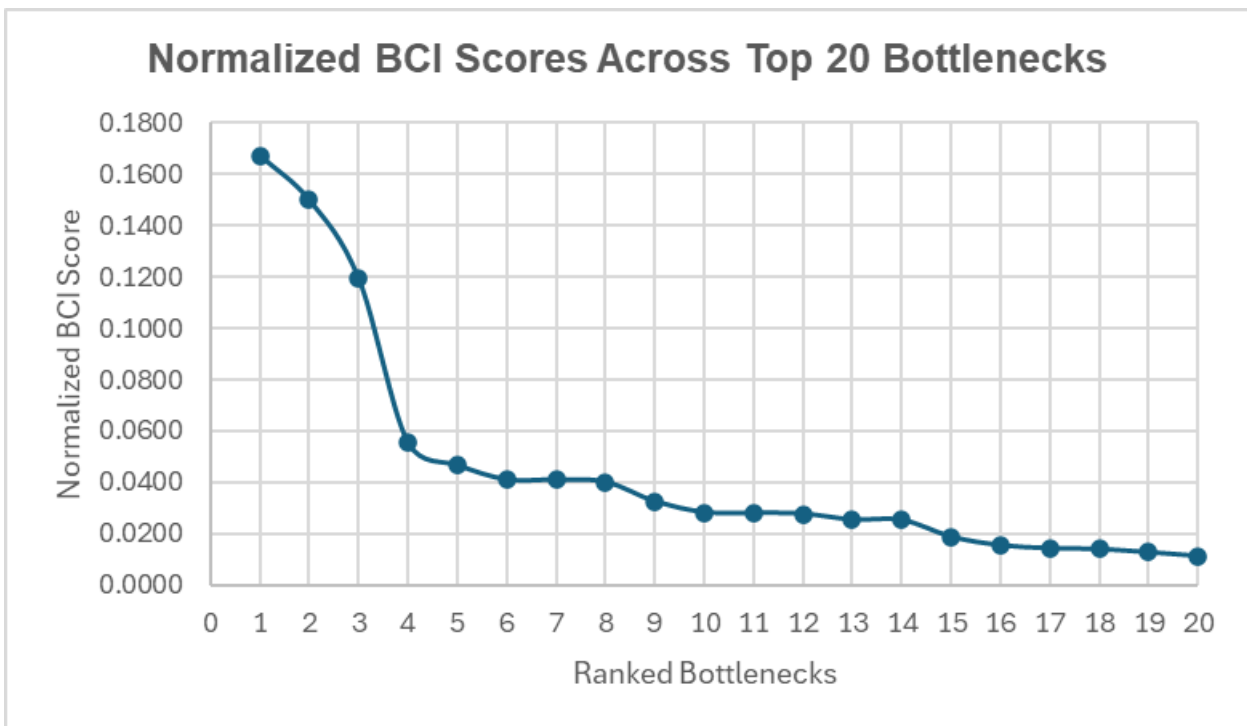
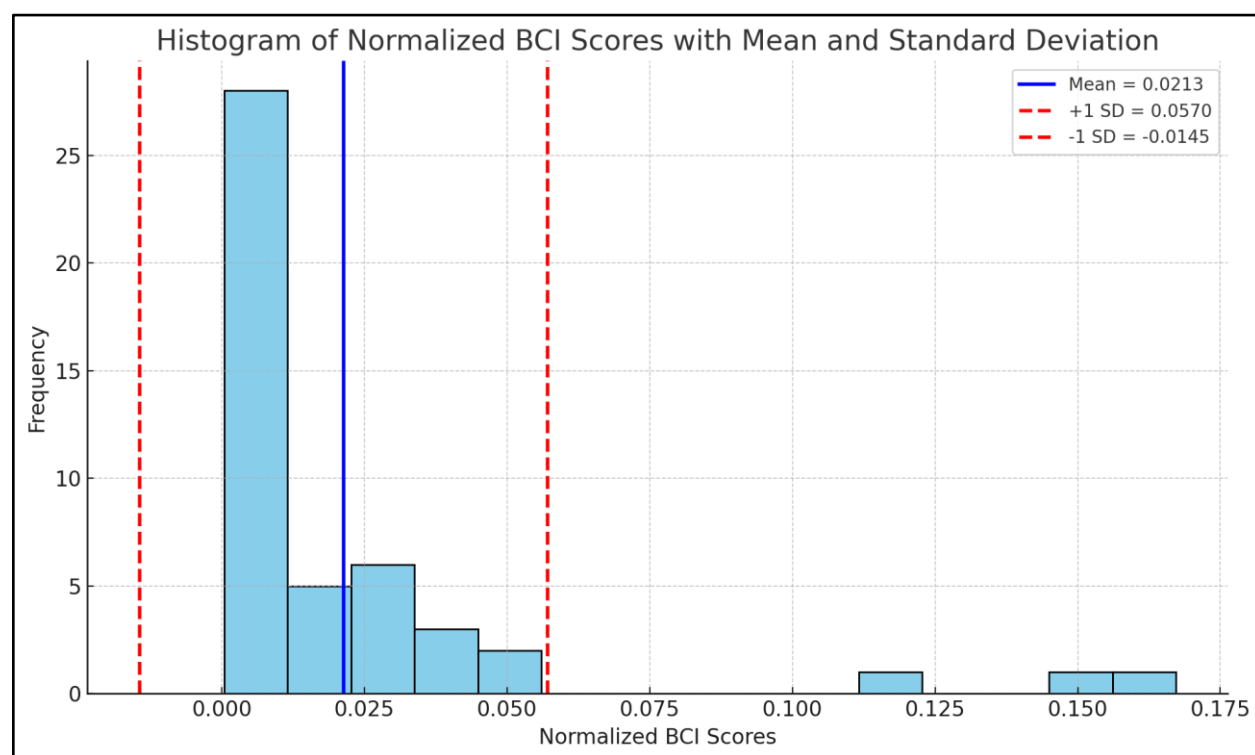


Figure 10 shows a histogram of all normalized BCI scores. To understand how individual scores relate to one another and the overall distribution, the mean and standard deviation were calculated. These measures help contextualize individual scores by providing a sense of how typical or unusual each bottleneck is within the broader set. Bottlenecks scoring above 0.0570 (one standard deviation above the mean) indicate a notably higher combined frequency, impact, urgency, and remediability compared to other bottlenecks. These bottlenecks are consistent with other findings, including fragmented AI Governance Across Jurisdictions, the Absence of Upskilling Programs for Workers, and Sparse Tools for Explainability. While this does not create a formal indicator for congressional action, it suggests that these bottlenecks stand out from the mean distribution and may warrant closer attention based on their combined levels of frequency, impact, urgency, and resolution. There were no bottlenecks one standard deviation below the mean.

Taken together, the BCI and LACA findings provide different perspectives on the AI development landscape. LACA provides insight into which bottlenecks dominate the conversation, while the BCI reveals which ones carry the most significant weight when factoring in impact, urgency, and potential for resolution. Both tools describe a policy environment shaped by overlapping infrastructure, governance, investment, and workforce challenges, many of which appear identifiable, measurable, and potentially fixable. The findings in this section offer a descriptive basis for the analytical framework that follows.

Figure 10. Distribution of Normalized BCI Scores



6. ANALYSIS

This section interprets and explains the significance of the findings and map potential congressional policy mechanisms that may alleviate the constraints of AI. The analysis will demonstrate how the bottlenecks are interdependent and can be categorized into four major bottleneck types: Labor, Computing, Energy, and Capital. To address these bottlenecks, policy mechanisms can be identified as congressional policy levers that can alleviate them. Furthermore, policy strategies are proposed and tested using DMDU modeling to determine the most robust policy options. Interpretation of the findings requires examining why these obstacles prevail, how they interact, and what Congress can do within its existing constitutional powers to alleviate pressure on the national AI supply chain.

6.1 Analysis of Labor, Computing, Energy, & Capital Bottlenecks

The weighted evidence indicates that the most critical bottlenecks are not confined to a single area but are spread across Labor, Computing, Energy, and Capital types. Notably, issues in the Computing and Capital domains dominate the bottleneck frequencies. For example, “fragmented AI governance across jurisdictions” (a capital-domain issue) appears in 176 separate pieces of evidence and suggests widespread concern about policy coordination and investment framework. Likewise, multiple high-ranking bottlenecks fall under computing, including technical constraints (data silos, cybersecurity vulnerabilities) and supply-chain issues (export controls on chips, GPU shortages), indicating that limitations in AI’s technical manufacturing capabilities and supply lines are broadly recognized as pivotal risks. By contrast, the Labor type contributes fewer distinct bottlenecks (i.e., the AI talent shortage and lack of upskilling programs). Still, those that it does contribute to are recorded as high-impact and urgent. In the Energy type, a moderate number of bottlenecks, such as data center power capacity and grid connectivity, are significant because they are crucial to enabling or supporting the infrastructure that powers computing systems. In sum, BCI results reveal a landscape in which computing and capital challenges lead in frequency and severity, with energy and labor constraints not far behind (Appendix H, Table 5). Successful AI development depends on the alignment of multiple systems, particularly in areas where bottlenecks exist, such as talent, computing infrastructure, energy supply, and financial policy. Addressing one constraint in isolation, such as workforce shortages, will have a limited effect if other barriers, like insufficient compute capacity or inadequate energy infrastructure, remain in place.

6.2 Concentration of Risk & Bottleneck Interdependence

The findings show a landscape in which a small cluster of obstacles carries disproportionate weight for the future of AI in the U.S. Twenty bottlenecks account for nearly 90% of coded evidence, and three of them (fragmented governance, inadequate worker upskilling, and limited explainability tools) stand out as the most impactful to AI’s development in the U.S. This concentration suggests that targeted federal action on a narrow front could unlock a significant portion of currently latent AI potential.

Beyond their impacts, many bottlenecks are interdependent, forming clustered risk nexuses that cut across the four domains. The qualitative coding analysis (Appendix I) identified bottlenecks that frequently appear together in the evidence, indicating a link between bottlenecks that any effective policy must address in tandem. An example of interconnectedness between Energy and Computing is the "underdeveloped grid interconnection process," which directly constrains both "data center capacity" and its expansion. To further illustrate the interconnectedness, Senator Curtis of Utah spoke about the need for grid improvements to support additional AI capabilities without hindering small business development (Office of John Curtis, 2025). In real-world applications, AI scaling would be constrained if data centers cannot connect to an adequate electric grid, even if chip shortages and computing power issues are resolved. Conversely, the energy sector experiences new strains due to the rapid growth in AI computing demand, as these power-intensive data center facilities necessitate a constant electric supply.

Additional bottleneck interconnectedness is seen in Labor and Capital: the "shortage of skilled AI talent" goes hand-in-hand with the "absence of upskilling programs," and these workforce gaps are exacerbated by uneven funding for training and education (a capital investment issue). This means policies to boost AI talent must coordinate education investments with incentives for industry to hire and retain new trainees. The interconnectedness of "fragmented AI governance across jurisdictions" often co-occurs with "unequal public-private collaboration" and "uneven AI adoption across sectors", a triad indicating that when government coordination is weak, it hampers both industry uptake of AI and the formation of unified standards. AI security bottlenecks, such as cybersecurity risks in AI systems alongside supply chain vulnerabilities, reinforce each other, since vulnerable supply chains can potentially increase cybersecurity threats. Appendix I's cluster mapping underscores that bottlenecks do not exist in isolation. They form a network of constraints where solving one in a cluster without the other may yield little net progress. The likely interconnectedness of electricity supply for data centers and computing capacity, or between workforce skills and AI adoption, confirms that a piecemeal policy approach would leave critical gaps. Effective intervention must therefore be coordinated, targeting the linked bottlenecks together so that the continued existence of another does not undercut relief of one constraint.

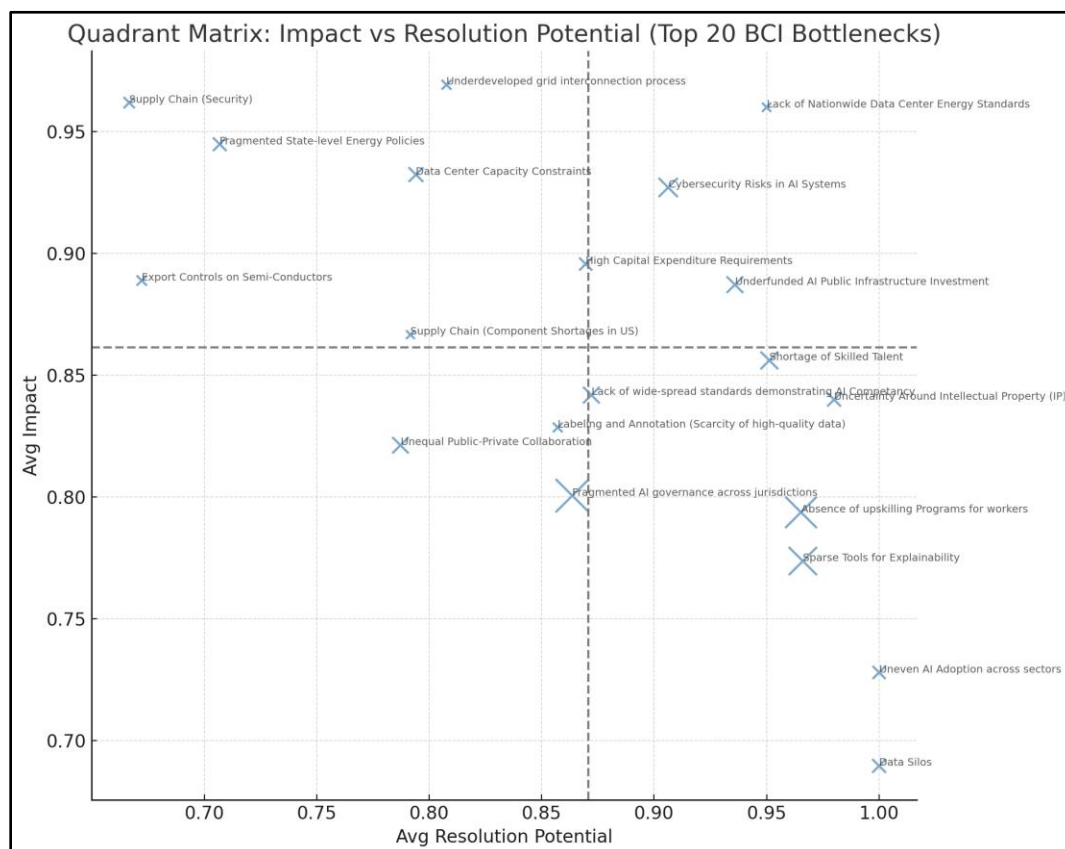
6.3 Illustration of Remediable Bottlenecks & Policy Mapping

The analysis identified a subset of potentially remediable bottlenecks that fall within quadrants characterized by constraints that are both high-impact and can be addressed through congressional action. These bottlenecks may warrant high attention due to their high potential to yield tangible returns if addressed early, as opposed to structural challenges that may require long-term transformation or cross-sectoral overhaul.

Figure 10 presents this subset visually through a 2x2 quadrant matrix. Each bottleneck is plotted by its average impact (vertical axis) and resolution potential (horizontal axis), with a plotted symbol size proportional to its composite BCI score. Bottlenecks in the upper-right quadrant are both highly consequential and tractable, making them ideal candidates for immediate-term policy attention. These include, for example, cybersecurity risks in AI systems, underfunded AI public infrastructure investments, and nationwide data center energy standards, each of which ranks high on impact and is considered resolvable given the current legislative toolkit. In contrast, bottlenecks in the upper-left quadrant, such as Fragmented State-Level Energy Policies or Supply Chain Security, remain high in impact but may require deeper structural reform. Bottlenecks in the lower

quadrants are either less severe or more difficult to remediate and thus present lower-priority targets in the short term.

Figure 11. 2x2 Quadrant Matrix of Impact vs Resolution vs BCI



To move from diagnosis to design, suggested policy levers were mapped to each of the top 20 BCI-ranked bottlenecks to a default set of congressional policy mechanisms. Each bottleneck was first assigned to one of four primary bottleneck types: Labor, Computing, Energy, or Capital, as indicated in Table 6 of Section 5.2. For each type, two congressional tools were predefined, based on their historical fit and relevance to the kind. If the combined bottleneck's nature category was primarily coded as "Legal/Regulatory," a third mechanism, regulation and standard-setting, was added to reflect the need for rulemaking or agency mandates that will ensure the constraint to AI development is more narrowly addressed.

This process identified two to three actionable levers per bottleneck, enabling a strategic match between problem types and policy interventions. For instance, the shortage of skilled AI talent is matched with immigration pathways and workforce funding, while compute infrastructure gaps are paired with fiscal appropriations and investment screening tools. These mappings offer a systematic foundation for coordinating congressional tools with manageable AI limitations.

Table 7 presents the mapping framework for illustrative policy mechanisms, showing how each domain aligns with two potential congressional tools that may aid in alleviating the constraint, with an optional third mechanism included for legal or regulatory issues. Having constructed a

tailored menu of policy levers for each bottleneck, the following section seeks to further develop congressional policy tools into full strategy bundles that direct congressional efforts toward AI development while eliminating constraints.

Table 8. Congressional Policy Mapping by Bottleneck Type

Type	Mechanism 1	Mechanism 2	Conditional Mechanism (if Legal/Regulatory)
Labor	Immigration & workforce levers	Conditional grants-in-aid	Regulation & standard-setting mandates
Computing	Power of the purse (appropriations)	Trade & investment screening tools	Regulation & standard-setting mandates
Energy	Tax expenditure & Permit Streamlining	Federal procurement & acquisitions	Regulation & standard-setting mandates
Capital	Grants & Tax innovation policy	Oversight & investigatory powers	Regulation & standard-setting mandates

6.4 Policy Strategy Candidates

Building upon the bottleneck-to-lever mapping developed from the 1,000+ source Research Matrix, the analysis constructed five composite federal strategies designed to alleviate the most severe AI-related constraints. Each strategy represents a distinct theory of change and prioritizes a different configuration of policy instruments. The design of these strategies reflects both the empirical weight of bottlenecks in the evidence base and the distribution of federal levers available to Congress, including appropriations, regulation, grants, tax expenditures, and oversight.

The five candidate strategies evaluated include a baseline *Do Nothing* scenario, *Upskill Now*, *Governance First*, *Balanced Adaptive*, and *DAPP*. These strategies were implemented in a DMDU model to simulate their performance across 10,000 possible futures, each characterized by varying severity levels for critical bottlenecks. The structure and operational focus of each strategy are summarized in Table 8.

Table 9. Policy Strategies

Strategy	Bottleneck Type Focus	Key Mechanisms
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Do Nothing	None (Baseline)	None
Upskill Now	Labor	Workforce grants, upskilling incentives, Immigration reform (H1-B1 Visa)
Governance First	Capital (Governance)	Regulation, Oversight, Coordination
Balanced Adaptive	All (Balanced)	Grants, Infrastructure investment, Regulation, Tax Incentives for Innovation support
DAPP	Adaptive (Conditional)	Pilot programs, Conditional triggers, Adaptive rollouts

Upskill Now is a labor-centric strategy that addresses talent shortages through expanded federal investment in workforce development, including job retraining grants and streamlined immigration pathways for AI-related roles. Based on the Research Matrix, “Upskilling Gap” was among the most frequently cited bottlenecks, with over 90% of its entries coded as “High” impact, “Remediable,” and of “Current” urgency. Accordingly, this strategy applies concentrated mitigation to this domain. While highly feasible due to bipartisan support for workforce investment, it underperforms in scenarios where computational, infrastructure, or governance bottlenecks are binding.

Governance First concentrates on legal, institutional, and coordination-related failures that delay AI deployment. Its primary levers include statutory clarification, federal oversight expansion, and cross-agency alignment efforts. The Research Matrix indicates that “Fragmented AI Governance” was the single most frequently cited bottleneck, comprising over one-third of the normalized weight in our DMDU model. As such, this strategy applies deep mitigation to regulatory and jurisdictional ambiguities. However, its narrow scope leaves compute, data, and talent challenges largely unaddressed. Feasibility is moderate due to institutional inertia and anticipated pushback from decentralized state and industry actors.

Balanced Adaptive adopts a portfolio approach, blending tools across labor, capital, governance, and infrastructure domains. It reflects the judgment that AI bottlenecks are interdependent and must be addressed in parallel to achieve resilience at scale. The strategy delivers moderate mitigation across all top bottlenecks, rather than overinvesting in a single policy area. It performs best in aggregate simulations, achieving the highest average resilience score under DMDU testing. Politically, it demands multi-stakeholder cooperation but avoids the pitfalls of overcommitting to contentious single-issue interventions.

DAPP applies adaptive logic. Instead of committing to a fixed policy upfront, it begins with a light-touch cross-domain baseline and dynamically activates targeted strategies when certain risk thresholds are triggered. For example, if the *Upskilling Gap* exceeds a modeled threshold of 0.75, the DAPP logic activates the *Upskill Now* pathway; if *Fragmented Governance* rises above 0.80, it triggers *Governance First*. These thresholds were empirically derived from the Research Matrix based on the proportion of sources coding these bottlenecks as both “High” impact and “Current” in urgency—representing likely inflection points for federal response. The DAPP strategy achieved a composite resilience score comparable to static strategies while offering greater flexibility under deep uncertainty. However, its effectiveness relies on policy continuity and institutional readiness to act on scenario-specific triggers.

Do Nothing serves as a counterfactual baseline. It assumes no additional legislative or executive intervention beyond the status quo. While it achieves maximal short-term feasibility (1.0), it does not mitigate any future risk and exposes the system to compounding vulnerabilities. Its inclusion provides a reference point for understanding the value added by even modest federal intervention.

Each of these strategies was formally evaluated through the DMDU framework, as detailed in the subsequent modeling section.

6.5 DMDU Modeling and Analysis

A DMDU framework was employed to assess the resilience and feasibility of various U.S. federal policy strategies addressing AI infrastructure and governance bottlenecks. Drawing on more than 1,000 expert-coded sources organized in a Research Matrix, the team categorized and weighted key bottlenecks in AI advancement. These values were numerically scored and multiplied to derive weighted priorities for each bottleneck, which were then normalized across the five most critical constraints: Upskilling Gap, Fragmented Governance, Sparse Explainability Tools, Public-Private Collaboration, and Lack of AI Standards.

These bottlenecks were encoded into a Python-based simulation model that operationalized three DMDU modalities: RDM, DAPP, and Exploratory Modeling. The model simulated how five policy strategies would perform under 10,000 plausible futures: Do Nothing, Upskill Now, Governance First, Balanced Adaptive, and DAPP. Each scenario randomly sampled a severity score for each bottleneck from a calibrated uncertainty range. These ranges (e.g., 0.4 to 0.8 for Upskilling Gap) were informed by the frequency of “High” ratings in the Research Matrix and adjusted to reflect both empirical bounds and expert consensus.

To reflect the risk of cascading failures, thresholds were introduced into the model. For example, if the simulated value for the Upskilling Gap exceeded 0.7, the model added a 0.05 penalty to simulate downstream labor market unrest. Similarly, a Fragmented Governance value over 0.8 incurred a 0.03 penalty, representing regulatory paralysis. These thresholds were calibrated by identifying the upper quartiles of impact severity in the source-coded matrix, where these two bottlenecks consistently appeared with “High” impact, “Remediable” resolution potential, and “Current” urgency across the majority of reviewed literature.

Each policy strategy applied a unique mitigation profile—quantified as a value between 0 (no mitigation) and 1 (full mitigation)—to each bottleneck. For example, the Upskill Now strategy mitigated the Upskilling Gap by 0.7 but applied only a 0.3 mitigation to Governance issues. After mitigation was applied, the model calculated a scenario-specific resilience score by subtracting the weighted harm from 1 and multiplying the result by the strategy’s feasibility score (e.g., 0.6 for Upskill Now). This produced a normalized resilience value between 0 and 1 for each strategy in the scenario.

To justify the comparability of the average resilience score across all policy strategies, it is important to clarify both the design of the simulation model and the mathematical consistency of the scoring framework.

Each strategy in the simulation was subjected to the same set of 10,000 randomly generated futures, where each future consisted of a unique combination of five bottleneck severity values drawn from calibrated distributions (e.g., upskilling gap ranging from 0.4 to 0.8). These futures were designed to reflect plausible variations in risk exposure, and they were held constant across all strategies, ensuring that every policy configuration was evaluated against identical uncertainty conditions.

Within each scenario, the strategy's mitigation profile was applied to reduce the harm associated with each bottleneck. The remaining risk—after mitigation—was multiplied by a corresponding weight derived from the Research Matrix BCI, then summed to calculate total scenario harm. The resilience score was defined as 1 minus the weighted harm, meaning higher values represent better systemic performance. Finally, this resilience value was multiplied by the strategy's feasibility score, simulating the likelihood that its benefits would be realized in practice.

Because each strategy was evaluated against the same scenario distribution, scored using the same harm-reduction and feasibility formula, and normalized to a bounded 0–1 scale, the resulting average resilience score is directly comparable across strategies. This score reflects a statistically meaningful central tendency that incorporates both technical effectiveness (in reducing harm) and political feasibility (in implementing the policy). As such, the average resilience can be interpreted as a composite indicator of expected performance under uncertainty, making it valid for cross-strategy comparison and strategic prioritization in federal policy design.

Table 9 below summarizes the average resilience and feasibility outcomes for each static strategy:

Table 10. Strategy Evaluation Summary (RDM)

Strategy	Avg Resilience	Feasibility	Scenarios
Do Nothing	0.515	1.0	10,000
Upskill Now	0.422	0.6	10,000
Governance First	0.355	0.5	10,000
Balanced Adaptive	0.584	0.8	10,000

Balanced Adaptive emerged as the most effective static strategy, achieving the highest average resilience score (0.584) while maintaining a moderate-to-high feasibility rating. This approach distributed resources evenly across all five bottlenecks, avoiding over-concentration on any single risk.

To simulate real-world policy flexibility, a dynamic logic layer was added using the Dynamic Adaptive Policy Pathways (DAPP) method. Under this logic, the model selects different strategies based on the severity of bottlenecks in each scenario. For instance, if the Upskilling Gap exceeds 0.75, the model assigns the Upskill Now strategy. If Fragmented Governance exceeds 0.8, Governance First is applied. Otherwise, the model defaults to Balanced Adaptive.

The DAPP framework outperformed the static Do Nothing, Upskill Now, and Governance First strategies by dynamically tailoring policy responses. Its breakdown is summarized below:

Table 11. DAPP Strategy Breakdown

Strategy Used in DAPP	Scenarios Selected	Share of Total
Balanced Adaptive	6,357	63.57%
Upskill Now	2,391	23.91%
Governance First	1,252	12.52%

This dynamic selection led to an overall average resilience score of 0.522, with an effective feasibility rating of 0.715 (calculated as the weighted average feasibility of the three strategies applied). The DAPP approach therefore demonstrated higher performance than any single static strategy except for Balanced Adaptive, which it selected in the majority of simulations.

To further evaluate the performance of each policy strategy under deep uncertainty, exploratory modeling was conducted as a component of the DMDU framework. In this phase, each of the 10,000 simulated futures included not only randomized bottleneck severity values but also a record of the strategy applied and the resulting resilience score. These resilience scores, ranging from 0 (total systemic failure) to 1 (complete mitigation), assessed not just average performance but also the variability and statistical behavior of each strategy across the full distribution of plausible futures.

The three primary strategies assessed, Balanced Adaptive, Upskill Now, and Governance First, demonstrated distinct statistical characteristics. Balanced Adaptive emerged as the most robust option, with a mean resilience score of 0.599 and the lowest standard deviation, at 0.0227, indicating high and consistent performance across futures. In contrast, Upskill Now produced a lower average score of 0.410, with a higher spread (standard deviation 0.0242), reflecting greater outcome variability. Governance First yielded the weakest performance, with a mean resilience of 0.351 and a standard deviation of 0.0140, suggesting relatively poor yet stable results.

To interpret these differences in relation to the broader simulation context, z-scores were calculated for each strategy. The z-score measures how many standard deviations each strategy's mean resilience score deviates from the global mean resilience score, which across all strategies

and scenarios was 0.522, with a standard deviation of 0.1044. Balanced Adaptive achieved a z-score of +0.73, meaning it outperformed the global average by nearly three-quarters of a standard deviation. In contrast, Upskill Now recorded a z-score of −1.08, while Governance First was even lower, at −1.64. These z-scores quantify the relative effectiveness of each strategy and indicate that Balanced Adaptive is not only high-performing on average but also statistically more resilient under deep uncertainty.

The underlying math for these metrics was directly derived from the simulation output. For each strategy, the mean (μ_{strategy}) was calculated by averaging all scenario-level resilience scores associated with that strategy. The standard deviation (σ_{strategy}) captured the spread of these values. The z-score was then computed using the following formula.

$$Z = \frac{\mu_{\text{strategy}} - \mu_{\text{global}}}{\sigma_{\text{global}}}$$

For Balanced Adaptive, this equated to:

$$Z = \frac{0.599 - 0.522}{0.1044} \approx +0.73$$

These other strategy values are summarized in the following table:

Table 12. DAPP Standard Deviation and Z-Score Summary

Strategy	Mean Resilience	Standard Deviation	Z-Score	N (Samples)
Balanced Adaptive	0.599	0.0227	+0.73	6,357
Upskill Now	0.410	0.0242	−1.08	2,391
Governance First	0.351	0.0140	−1.64	1,252

Together, the use of DMDU, via static robustness tests, dynamic strategy switching, and exploratory scenario discovery, confirms the reliability of the Balanced Adaptive strategy. Not only does a Balanced Adaptive strategy outperform others in average resilience, but its low variance and high z-score indicate a dependable and scalable option for long-term federal implementation.

7. RECOMMENDATIONS

To ensure the U.S. remains the international leader in AI competitive dominance, we propose that Congress consider pursuing a comprehensive legislative agenda focused on five strategic priorities: access to computing resources, workforce development, infrastructure modernization, support for small businesses, and regulatory alignment. Together, the following five recommendations outline a proactive path for Congress to unleash the full economic potential of AI while preserving public trust, equity, and national security. However, despite the

7.1 Modernize Federal Tax Code

First, the DMDU analysis finds that Congress can modernize the federal tax code to through a Balanced Adaptive approach to fund underdeveloped AI public infrastructure. Current provisions under Section 41 of the Internal Revenue Code (I.R.C.) exclude key innovation costs, such as GPU usage, cloud computing, and software licensing, despite these costs being central to AI workflows (SCSP, 2023). By expanding eligibility criteria and restoring full expensing under I.R.C. § 174A, Congress can unlock critical capital for startups and research institutions. Federally funded GPU clusters and compute voucher programs, as proposed by the National Science Foundation (NSF) and Department of Energy (DOE), would also democratize access and enable public-interest AI research in sectors underserved by private capital (NSF, 2024; OECD, 2023). To promote efficiency and discourage monopolistic behavior, lawmakers should consider reducing tax credits based on computational usage, thereby incentivizing smaller, more energy-efficient AI deployments (Cottier & Rahman, 2024). Moreover, we recommend Congress to expand tax incentives under 26 U.S.C. § 174 to include AI-related research and experimental expenditures, enabling companies to amortize investments in advanced computing, chip design, and power efficiency over extended periods (26 U.S. Code Section 174, 1954). Tax credit expansions would provide financial support to accelerate innovation, protect economic security, and ensure equitable access to AI-era employment opportunities (Flexential, 2025; Semiconductor Industry Association, n.d.; Jin et al., 2025).

7.2 Workforce Recruitment & Upskilling

Second, the DMDU analysis suggests that Congress can address national workforce shortages and displacement by reforming high-skilled immigration policy and incentivizing domestic upskilling in an Upskill Now approach. The Semiconductor Industry Association (SIA) proposed reforms that would allow international graduates of U.S. STEM programs to remain in the country, filling critical roles in semiconductor manufacturing and AI development (SIA, 2024). To execute on SIA's proposal, which is endorsed by the National Security Commission on AI (NSCAI), Congress can amend 8 U.S.C. § 1153(b)(2) to create an expedited pathway for international graduates of U.S. STEM programs to obtain permanent residency, ensuring retention of top AI and semiconductor talent (SIA, 2024; NSCAI, 2021). Simultaneously, domestic labor must be prepared for AI-induced transitions. We recommend establishing a refundable tax credit for AI training by adding a new section under 26 U.S.C. Subpart D, allowing employers to claim credits for verified AI upskilling and reskilling expenditures (Jacobs, 2025). Additionally, Congress could expand 29 U.S.C. § 3111 to require the integration of AI skills mapping and industry alignment, ensuring workforce investment programs anticipate emerging AI demands

(Porat et al., 2025; Tenakwah & Watson, 2025). By implementing the proposed statutory changes, the domestic labor pipeline can improve and repopulate expeditiously, preserving America's short-term competitive advantage in global AI development.

7.3 Computational Resources

Third, the DMDU analysis indicates that Congress can address the shortage of high-performance computing resources necessary for AI innovation by adopting a Balanced Adaptive approach to improving data centers. Data centers alone are projected to consume over 35 GW of power by 2030, doubling their 2022 levels and placing unsustainable stress on current energy systems (Davenport et al., 2024; Deloitte, 2025). Insufficient access to computational infrastructure limits AI research, particularly among small and mid-sized firms and universities (Flexential, 2025). To close the energy supply gap, Congress could amend 15 U.S.C. § 3721 to explicitly include AI-specific high-performance computing facilities and cloud infrastructure as eligible for federal matching grants, enabling regional technology hubs to expand equitable compute access (Flexential, 2025). Additionally, expanding 15 U.S.C. § 278g-3 to prioritize AI-related research within the National Institute of Standards and Technology's (NIST) advanced computing initiatives would accelerate the adoption of standardized AI benchmarking tools and secure computing architectures (Jin et al., 2025). In the event that empowering NIST is unpalatable among Congress members due to President Trump's AI Action Plan, appropriations can instead be provided to the DOE's National Laboratory system to incentivize AI R&E (The White House, 2025). By taking actions that expand access to computing resources, the U.S. will foster a more competitive and geographically diverse AI ecosystem.

7.4 Power Production

Fourth, the DMDU analysis calculated that Congress can alleviate regulatory burdens that inhibit the modernization of the energy grid to meet the rapidly growing power demands of AI data centers that pose reliability and sustainability challenges for the U.S. power grid through a Balanced Adaptive approach (Srivathsan et al., 2024). Congress can amend 42 U.S.C. § 16511 to explicitly cover AI-related grid modernization projects, including renewable integration, advanced cooling, and waste heat recovery systems (Jin et al., 2025). Furthermore, expanding 42 U.S.C. § 16231 to authorize DOE grants for AI-driven energy efficiency retrofits in existing data centers would incentivize carbon-reduction technologies at scale (DOE, 2023). In reducing the regulatory demands on power, new energy solutions production can be promoted to address the severe needs that AI data centers demand. The proposed statutory updates would reduce operational bottlenecks, align AI growth with national clean energy goals, and ensure resilient power delivery for AI infrastructure, encouraging investment in a more stable field.

7.5 Small AI Business Development

Fifth, the DMDU analysis suggests that Congress can increase access to capital for domestic AI hardware manufacturing and infrastructure projects by adopting a Balanced Adaptive approach to incentivizing capital investment. The current concentration of AI investment among a few firms creates barriers for smaller innovators and leaves the U.S. vulnerable to foreign supply chain disruptions (Polen Capital, 2024). To make the spur domestic manufacturing competition,

Congress can revise 26 U.S.C. § 48C to cover American-made AI hardware, such as advanced GPUs and AI-optimized servers, encouraging domestic production and reducing reliance on foreign semiconductor supply chains (SIA, 2024). Additionally, updating 15 U.S.C. § 3719 to include large-scale AI infrastructure challenges with federal co-investment would catalyze public-private partnerships in emerging AI markets (Di Battista et al., 2025). Expanding investment opportunities through diverse and targeted changes would expand the AI investment landscape, increase domestic manufacturing capacity, and enhance the resilience of America's AI economy.

7.6 National Regulatory Framework

Finally, the DMDU analysis suggests that Congress can establish a unified national framework for AI governance to reduce investor uncertainty and ensure interoperability across jurisdictions through a Balanced Adaptive approach. The fragmented interstate policy environment raises compliance costs and discourages cross-jurisdictional AI deployment (Johnson, 2025; Collier & Horvath, 2025). Congress can amend 15 U.S.C. § 272 to direct NIST to create federally recognized AI governance standards that set a national baseline for privacy, fairness, and safety while preserving state authority for sector-specific innovation (Hendrix & Lima-Strong, 2025). Federal procurement law under 41 U.S.C. § 8302 should be expanded to require agencies procuring AI systems to prioritize American-manufactured AI hardware, paired with enhancements to 26 U.S.C. § 48C to incentivize domestic component production (Executive Order 14179, 2025; Lutnick, 2025). In parallel, Congress could mandate under 31 U.S.C. § 503 that federal agencies incorporate AI adoption protocols into operational planning while using indirect regulatory tools, such as grant conditions under 2 C.F.R. Part 200 and performance audits, to ensure compliance with ethical and security standards even in the absence of formal regulation (Nesse et al., 2024; Liu et al., 2019). Actions to standardize regulatory oversight federally would harmonize AI governance, protect public interests, and create a predictable regulatory climate that supports sustained private investment.

8. NEXT STEPS

To implement the recommended actions, the next phase must translate the insights derived from the LACA and DMDU frameworks into actionable federal policy. The aforementioned recommendations that coincide with the highest-scored BCI and DMDU strategy scores are most pertinent in addressing first. Based on Table 1 in the Executive Summary, recommendations 7.1, 7.3, 7.4, 7.5, and 7.6, pertaining to AI governance, aligned with the highest-rated Balanced Adaptive DMDU strategy. Of those, recommendation 7.6 has the highest BCI score of 0.1672 and recommendation 7.3 has the second highest of 0.1195, both demonstrating a high level of urgency to resolve the respective issues. Thus, it is most pertinent that Congress mend interstate fragmentation of AI regulations and improve the computing power and efficiency of data centers nationwide.

Once recommendations 7.6 and 7.3 are addressed, the secondary proposals that should be addressed are recommendations 7.1 with a BCI score of 0.409, 7.5 with a 0.401 BCI score, and 7.4 with a 0.032 BCI score. By addressing the issues of an tax code that does not address the needs of AI, lacking power production and a supportive power grid, and small AI business development and capital investment, Congress can uplift the exponentially growing American AI economy.

Lastly, if Congress is able to execute on alleviating a cumbersome and restrictive interstate regulatory framework, improve American computational resources, modernize the federal tax code to incentivize AI capital investment, encourage small AI business development, and improve the national power supply, then tertiary propositions can be pursued to fully unleash American's AI potential: Recommendation 7.2 with an Upskill Now DMDU strategy and 0.15 BCI score and 7.6, regarding regulation to improve AI capabilities, with a Governance First DMDU strategy and 0.0410 BCI score. Improving the American workforce to utilize AI to increase productivity will protect workers and empower private enterprises of all sizes, and implementing AI standards that improve AI systems can serve as futuristic improvements. However, if Congress is unable to reach recommendations 7.2 and 7.6's scope of AI-improve regulations, the American economy will still experience immense growth as a result of clearing inhibiting AI bottlenecks.

Separately, the State of Utah has a unique opportunity to capitalize on the development of the AI industry. To become a national hub for strategic and responsible AI deployment, Senator Curtis can lead partnerships with the Utah Governor's Office of Economic Opportunity and the state's AI Policy Office to launch a federally supported AI Innovation Zone Pilot, which would serve as a real-world demonstration platform for public-private collaboration (NSCAI, 2021). The partnership can incorporate conditional federal grants, procurement incentives, and performance-based workforce subsidies to accelerate infrastructure across rural broadband, defense-relevant AI, and ethical training protocols (Tenakwah & Watson, 2025). Federally, simultaneous requests for formal evaluations should be submitted to the Government Accountability Office (GAO) and the Congressional Research Service (CRS) to assess gaps in current federal tax credits, AI capital access mechanisms, and disparities in regional compute infrastructure that disproportionately limit rural innovation (Polen Capital, 2024; BCG, 2024).

Congress may also want to consider drafting preliminary legislation on a suite of enabling bills drawn from the DMDU-tested policy combinations. Possible approaches that Congress can consider include instituting an AI training tax credit to incentivize industry-aligned upskilling, a computation voucher program to provide academic institutions with access to cloud-based compute infrastructure, and targeted infrastructure reforms to expedite permitting for AI-ready, renewable-powered data centers (Srivathsan et al., 2024; Wadhwa et al., 2024). In combination, the proposed next steps prepare the U.S. to unlock its AI capabilities, position Utah as a scalable model for national AI integration, and reinforce congressional leadership in shaping the infrastructure and policy foundations of the Fourth Industrial Revolution (Georgieva, 2024; Collier & Horvath, 2025).

9. CONCLUSION

The United States stands at a historic inflection point in determining the economic and social trajectory of AI. The barriers limiting AI development, ranging from persistent workforce gaps and fragmented regulatory oversight to inadequate infrastructure and capital concentration, are solvable challenges that can be addressed by correcting misaligned institutional priorities. These findings highlight how AI's economic, technical, and governance issues are interconnected, showing that focused efforts in one area often lead to positive effects in others. Deliberate and

adaptive congressional action presents the opportunity to transform constraints into accelerators of AI development, technological innovation, and infrastructure modernization.

Utah's forward-leaning approach exemplifies how state-level leadership can serve as a blueprint for responsible AI deployment, striking a balance between ethical guardrails and regional economic opportunities. Through testing possible futures through the DMDU framework and analysis, the Balanced Adaptive strategy offers the most statistically beneficial path for navigating uncertainty while maintaining strategic direction. By following the Balanced Adaptive approach, Congress can be equipped to act decisively while remaining flexible in response to evolving risks, technologies, and public needs. Although the evidence highlights clear and addressable bottlenecks, it is important to acknowledge some limitations of this study. These include dependence on secondary sources and the fast-changing nature of AI policy, which could alter bottleneck priorities soon. Future research should include longitudinal data and stakeholder interviews to confirm and improve these insights. Investment in the tools of innovation, academic institutions, and financial incentives can secure American leadership in the AI economy for generations to come. By implementing coordinated, evidence-based reforms now, Congress and stakeholders can turn current AI bottlenecks into future competitive strengths, securing the United States' position as a leader in innovation and a global benchmark during the Fourth Industrial Revolution.

The high price of inaction could result in the nation losing hundreds of billions in GDP growth, with valuable jobs moving overseas and the digital divide between regions expanding. Still, the bipartisan interest, public demand, and industry readiness align to create a rare legislative opportunity for lasting reforms that can secure long-term economic and national security benefits. Realizing this potential will require cross-sector collaboration, uniting federal, state, and local governments with private industry, academia, and civil society, to ensure that AI's benefits are broadly and equitably shared. By acting decisively now, Congress can set the stage for the United States to not only adapt to the AI era but also to lead it.

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Appendix A - List of Data Resources

[\[Link to Data\]](#)

APPENDIX B

Mechanism (general description)	Technical authority that lets Congress act	Source	Use case
Power of the purse (appropriations) • Annual & supplemental appropriation bills • Community Project Funding (earmarks) • Transfer & re-programming directives	Art. I §9 cl. 7 (Appropriations); House & Senate rules; 31 USC. §1301-1537	CRS The Appropriations Process R47388 (2023); CRS IF11976 Community Project Funding (2024)	FY-24 Consolidated Approp. Act earmarked \$5 m for Utah State Univ. Math, AI & Data Center to expand regional AI talent pipeline (cobi.utah.gov)
Tax expenditure & revenue measures • Credits/deductions (e.g., R&D, clean-energy data-center ITC) • Accelerated depreciation (Bonus/§168(k)) • Tariff suspensions or increases	Art. I §8 cl. 1 (Tax & Spend); Internal Revenue Code, 26 USC.	JCT Estimates of Federal Tax Expenditures JCX-1-24 (2024); CRS R47145 Energy Tax Provisions in IIJA & IRA (2023)	Inflation Reduction Act §13702 extended 48C credit: Meta’s Eagle Mtn., UT AI data-center claimed credit for energy efficient servers (META company filing, 2024)
Conditional grants-in-aid & cooperative agreements • Conditional R&D grants • Formula/Block grants with AI-related eligibilities • Matching-fund requirements	Art. I §8 cl. 1 (Spending Power); upheld/limited in NFIB v. Sebelius, 567 US 519 (2012)	CRS IF10481 Federal Grants to State & Local Govts (2022); GAO-24-106202 Science & Tech Grants (2024)	CHIPS & Science Act §10524 authorizes NSF Regional Innovation Engines. One 2024 award to Utah-led Intermountain “Semicon & AI Edge” consortium (NSF press release)
Federal procurement & acquisitions • R&D contracts (FAR Part 35) • Other Transaction Authority (OTA) agreements • Set-asides (Small Business, HUBZone)	Art. I §8 cl. 1 (Spending); Procurement statutes (10 USC. §4021; 41 USC.)	CRS IF11493 Defense OTAs (2022); GAO-24-105177 Use of OTAs for AI (2024)	JAIC-TRADOC “Ignite” OTA (2023) awarded \$55 m to 16 firms including Utah-based Blynscy for computer vision models
Regulation & standard-setting mandates • Direct statutory standards • Delegation to agencies (e.g., NIST AI Risk Management Framework mandate) • Pre-emption clauses	Commerce Clause (Art. I §8 cl. 3); Necessary & Proper (Art. I §8 cl. 18); specific enabling acts	CRS R46534 Artificial Intelligence: Federal Administrative Law (2023); White House EO 14110 (2023)	CHIPS Act §10224 requires NIST to issue AI hardware security standards and rulemaking began 2024
Intellectual-property & innovation policy • Patent term adjustments (35 USC.) • SBIR/STTR set-asides (15 USC. §638)	Art. I §8 cl. 8 (IP Clause) & Commerce Clause	CRS R43695 SBIR/STTR Programs (2023); CRS IF10673 Federal Prize Competitions (2022)	2024 NIST AI Safety Prize (\$1.2 m) uses §3719 authority to spur robust model-evaluation tools

• Prize competitions (15 USC. §3719)			
Oversight & investigatory powers • Hearings, subpoenas, contempt • Mandated reports (e.g., GAO AI assessments) • Inspectors-General directives	Implied from Art. I, reinforced by <i>McGrain v Daugherty</i> (1927), <i>Mazars</i> (2020)	CRS RL30240 Congressional Oversight Manual (2022); GAO B-335452 AI Cloud Contracts (2024)	2024 Senate HSGAC AI hearing prompted DHS to update procurement guidance for ML security
Informational & “soft-law” devices • Sense-of-Congress & findings • Report language / explanatory statements	House & Senate Rules; not legally binding but guide agencies	CRS R44466 Sense-of-Congress Provisions (2021)	FY-24 Energy & Water report directed DOE to brief Congress on AI energy-use data
Trade & investment-screening tools • Tariff legislation (19 USC) • Export-control mandates (ECRA 2018) • CFIUS reforms (FIRRMA 2018)	Commerce Clause; Foreign Commerce; IEEPA	CRS R47072 CFIUS Process (2022); CRS IF11667 ECRA & Emerging Tech Controls (2023)	2023 rules added advanced AI chips to BIS export-control list—statutory basis ECRA
Immigration & workforce levers • Visa caps (H-1B, O-1, EB-2 NIW) • STEM OPT extensions • Green Cards	Naturalization Clause (Art. I §8 cl. 4); INA (8 USC.)	CRS R47164 STEM Immigration & AI Talent (2023)	CHIPS Act §10657 directs pilot “National Semiconductor Scholarship” for foreign STEM Ph.D.s. An example of conditional stay incentives
Credit programs & loan guarantees • DOE Title XVII clean-energy • Small Business Administration	Art. I §8 cl. 1 (Spending); specific statutes (42 USC. §16513; 15 USC. §636)	CRS R46329 DOE Loan Programs (2023); SBA FY 25 CJ	2024 DOE LPO offered \$500 m guarantee to Microsoft for Nuclear-powered AI data center in Wyoming, and similar case for Utah modular reactor AI build
Defense-linked authorities • National Defense Authorization Act directives • Defense Production Act (DPA) Title III • Rapid Innovation Fund	Art. I §8 cl. 12-14 (Defense); DPA 50 USC. §4501	CRS R46905 DPA & Critical Tech (2023); FY-24 NDAA Sec. 1541	2024 DPA Title III award to Intel for US AI chip packaging, which leveraged state incentives from Utah GOEO for future site study

Appendix C - Codebook

Code	Definition	Example	What it is not	Justification
Category 1: AI Bottlenecks - Significant obstacles or constraints that slow down or limit the development, deployment, or adoption of AI technologies. Bottlenecks may involve scarce resources, regulatory hurdles, talent shortages, or infrastructure gaps, and they require targeted policy or investment to overcome.				
AI Development and Production costs	The financial outlays needed to design, train, deploy and maintain AI systems, including investment in compute hardware, energy, talent and facilities.	The RAND report notes that "leading foundation models cost between \$63 million and \$2 billion to train and even more to run."	This does not refer to the cost of collecting datasets or algorithmic research alone, but the entire investment required to build and	Huge training budgets illustrate that AI development is a major capital investment, rather than a minor operational expense.
Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	Shortages or supply constraints of essential hardware and electrical components needed to build AI data centres, such as transformers, semiconductor chips and circuit	RAND researchers note that only "about 35 million AI accelerator chips are sold per year and that the microchip supply is fragile, contributing to delays in AI deployment."	This is not about high-end GPU shortages alone or about security restrictions; it covers the broader scarcity of hardware parts.	Without sufficient components like transformers and chips, data centre construction stalls, creating a physical bottleneck.
Supply Chain (Security)	National-security driven restrictions on the supply chain for AI hardware and inputs, including export controls and investment screening aimed at preventing adversaries from accessing advanced chips.	On October 7 2022 the United States imposed export control restrictions on China's access to advanced semiconductors and semiconductor manufacturing equipment.	It does not refer to accidental shortages or price inflation but to deliberate regulatory barriers imposed for security reasons.	Security-driven export controls can slow or block access to critical components, creating a policy-induced supply bottleneck.
Supply Chain (High End GPU shortages)	Insufficient availability of high-performance graphics processing units (GPUs) and accelerators needed for AI training due to limited manufacturing capacity and surging demand. Use this code only if GPU or Graphic Processing units is mentioned, otherwise use the component shortage.	The Institute for Progress points out that supply chains for AI accelerators are constrained by manufacturing processes for memory and high-end chip packaging, limiting the number of GPUs available.	This is not about ordinary consumer chips or generic component shortages; it concerns top-tier GPUs used in advanced AI models.	When cutting-edge GPUs are scarce, researchers cannot scale model training, delaying AI development.
Hardware Software Integration	Challenges arising from integrating diverse AI hardware (GPUs, accelerators, sensors) with software frameworks and applications. These integration issues can slow deployment and performance of AI systems.	"AI systems require complex coordination between specialized chips and software; misalignment can lead to inefficiencies and delays."	It is not about the lack of hardware or software themselves, but rather about ensuring they work seamlessly together.	Poor integration of AI hardware and software can hinder performance and slow adoption.
Compute Divide	The disparity between regions or organisations with access to state of the art computing resources and those without, leading to unequal AI capabilities and benefits. Includes copyright restrictions on training data.	A Connected Nation report notes that much of the U.S. landscape lacks internet exchange points and data centres, meaning those regions will get less from cutting-edge AI due to latency.	This is not merely about personal broadband access or digital literacy; it focuses on access to large-scale compute infrastructure and associated networks.	Without equitable compute access, some communities and sectors are locked out of AI innovation, exacerbating inequality.
High Cost of Compute Infrastructure	The substantial expenses required to build, equip, and operate AI computing facilities, including the purchase of accelerators, cooling systems and continuous power supply.	The IEP policy playbook notes that the amortised cost of AI computing hardware exceeds the cost of electricity, and this specialised hardware must be run continuously to justify its expense.	This does not include the broader cost of training data or research staff; it refers specifically to the capital cost of compute hardware and data centre infrastructure.	High infrastructure costs can deter investment and slow the scaling of AI capabilities.
Memory Bandwidth Performance	Limitations in memory bandwidth and throughput that constrain AI model training and inference speed. Slow memory interfaces can bottleneck data movement between processors and memory.	Supply chains for accelerators are constrained by manufacturing processes for memory and high-end chip packaging.	It is not about storage capacity or compute power; it specifically refers to the rate at which data can be transferred between memory and processors.	High-performance AI requires fast memory bandwidth to feed data to GPUs; bottlenecks slow training and inference.
Chip Fabrication Limits	constraints in semiconductor manufacturing that limit the production of advanced AI chips. These include scarcity of fabrication capacity and dependence on a few foundries.	The supply chain for accelerators is constrained by manufacturing processes for memory and high-end chip packaging.	It is not about the design of chips but about manufacturing capacity and processes.	Without sufficient fab capacity, AI developers cannot obtain enough advanced chips, hindering AI expansion.
Lack of Quantum Readiness	The current inability of quantum computers to support practical AI applications due to immature hardware and fragile qubits.	"Quantum computers are not yet practical for real-world applications, engineering high-quality qubits has proven challenging."	It is not about classical computing capabilities, but specifically about quantum computing readiness.	AI researchers anticipate quantum acceleration, but the technology is not ready, limiting adoption.

Insufficient Broadband Access	Limited high-speed internet connectivity in certain regions that prevents the deployment of AI services requiring continuous data exchange.	*AI and telemedicine adoption faces challenges including limited broadband access.*	It is not about low latency or mobile coverage alone; it concerns basic broadband availability.	AI-driven services need reliable broadband; lack of access exacerbates digital divides.
Low Latency Network Deficiency	Networks lacking ultra-low latency connectivity impede AI systems that require real-time responses, such as autonomous vehicles and industrial robots.	For AI to work in the physical world, it requires ultra-low latency connectivity, yet many U.S. regions lack internet exchange points and data centers.	It is not about throughput or general connectivity; it is specifically about latency (delay).	High-latency networks hinder real-time AI applications, reducing effectiveness and safety.
Data Silos	Fragmented or isolated data repositories that prevent AI systems from accessing and integrating information across departments or organizations.	McKinsey notes that "data silos and limited usefulness of data are major barriers to AI adoption."	It is not about lack of data, but about data being locked away in separate systems.	Without integrating data across silos, AI models cannot learn from comprehensive datasets.
Labeling and Annotation (Scarcity of high-quality data in specialized domains)	Shortage of high-quality, labeled datasets, especially in specialized or low-resource domains, which hampers training of accurate AI models and produces bias.	*Indian languages suffer from severe data shortage due to limited digital resources and annotated corpora.*	It is not simply about the volume of data; it concerns the quality and labeling necessary for supervised learning.	Accurate AI requires labeled data; scarcity increases bias and reduces performance.
Inefficient Model Architectures	Use of dense, resource-intensive neural network architectures that waste compute resources and energy.	*Google notes that today's models are dense and inefficient; Pathways aims to create more efficient architectures.*	It is not about the size of datasets or number of parameters alone; it concerns architectural inefficiency.	Inefficient architectures increase compute costs and energy consumption, slowing progress.
Lack of Model Compression Techniques	Insufficient methods to reduce model size and complexity while preserving performance, leading to heavy resource requirements for deployment.	*Current model compression techniques rely on retraining or calibration to restore accuracy, requiring significant GPU time.*	It is not about pruning models arbitrarily or reducing data quality; it is about systematic compression methods.	Without efficient compression, deploying large AI models on edge devices and resource-constrained environments remains impractical.
Sparse Tools for Explainability	Limited availability of robust tools to interpret and explain AI model decisions, making it hard to build trust and comply with regulations. The tools available are not standardized and unable to inform users on AI reasoning, leading to an AI black box problem and reliability concerns.	McKinsey notes that "some explainability tools rely on post-hoc explanations based only on system output, which may yield inaccurate explanations. AI systems may be considered black boxes if tools cannot explain AI's reasoning."	It is not about the absence of transparency mandates; it concerns the maturity and private standardization of tools for interpretation and public access.	Inadequate explainability tools undermine user trust and hinder adoption in regulated sectors. Increases fear of AI black box phenomena.
Edge Computing Limitations	Constraints and vulnerabilities associated with deploying AI at the network edge, including security risks, limited compute power, and machine variability.	*Edge AI systems can lead to security issues; risk occurs at the local level and requires strong in-house security.*	It is not about cloud-based AI limitations; it specifically concerns edge devices and local processing.	Edge computing promises reduced latency but introduces new security and reliability challenges.
Data Center Capacity Constraints	Insufficient infrastructure capacity and power to support the rapid growth of AI data centers, leading to delays and bottlenecks. There is not enough capacity in the existing energy grid for data centers.	*Training runs could demand up to 1 GW in a single location by 2028 and 8 GW by 2030, and insufficient power capacity may compel companies to relocate.*	It is not about compute chip shortages alone; it refers to the physical capacity and power availability of energy grids for data centers.	Limited power and space for data centers restrict the scaling of AI workloads.
High Capital Expenditure Requirements	The need for very large up-front financial investments to fund AI infrastructure projects, such as building multi-gigawatt data centers and acquiring millions of accelerators.	*Blackrock is launching a \$30 billion dollar investment fund in collaboration with a UAE sovereign wealth fund, with the explicit goal of "addressing the staggering power and digital infrastructure demands of building AI products that are expected to face severe capacity bottlenecks in coming years". IIF notes that the largest AI clusters will require about one million accelerators and 3 GW of power.*	This should not be confused with operational expenditures or minor capital upgrades; it refers to the enormous capital needed for frontier AI.	Because AI research clusters demand billions in equipment and energy, only actors with access to significant capital can participate.
Short term ROI Expenditures	Investments in AI that prioritize immediate returns over long-term research or infrastructure, often due to market pressure.	McKinsey notes that uncertain returns on AI investments and short-term focus impede adoption.	It is not about high capital costs per se; it refers to time horizons for investment returns.	Short-termism discourages the sustained investment needed for transformative AI infrastructure.
Limited Exit Opportunities	Difficulty for investors to realize returns from AI ventures due to a lack of mergers, acquisitions, or public offerings.	"AI ventures often require long-term capital and may not have clear paths to exit, making investors hesitant."	It is not about operational bottlenecks; it concerns financial market dynamics.	Limited exits can reduce venture capital appetite for AI infrastructure projects.
VC Concentration	Dominance of a small number of venture capital firms in AI funding, limiting diversity of investment and perspectives.	"A few large funds control the majority of AI investments, which may crowd out smaller innovators."	It is not about corporate R&D spending; it specifically refers to venture funding.	Concentrated VC funding can lead to herd behavior and underinvestment in risky but valuable projects.

Valuation Inflation & Risk Aversion	Overvaluation of AI startups combined with investor reluctance to fund unproven technologies, leading to bubbles and investment pullbacks.	*High valuations and risk aversion can coexist, causing capital to chase hype rather than fundamentals.*	It is not about general economic inflation; it concerns investment psychology.	When valuations become inflated, subsequent corrections can starve promising projects of capital.
Export Controls on Semi-Conductors	Government regulations that limit the sale or transfer of semiconductor technology and equipment to certain countries or entities, typically on national security grounds.	*The U.S. government enacted new export controls in 2022 restricting China's access to advanced chips and semiconductor manufacturing tools.*	It is not a market shortage or logistics issue but a deliberate policy decision to restrict trade.	Such controls can impede global supply chains and make it harder for AI developers to acquire high-end chips.
Uncertainty Around Intellectual Property (IP)	Ambiguity in laws and policies governing AI-related intellectual property, creating risk for developers and investors.	<u>*The UK AI Action Plan notes that uncertainty around intellectual property is hindering innovation and undermining AI ambitions.*</u>	It is not about trade secrets or data privacy; it specifically concerns IP rights and ownership.	Clarity in IP regimes is essential for protecting investments in AI and encouraging innovation.
Shortage of Skilled Talent	A deficit of workers with the advanced skills needed to develop and deploy AI systems, including data scientists, engineers, and researchers.	<u>*There is a persistent shortfall of highly skilled AI professionals in the U.S., despite increased wages.*</u>	It is not about general unemployment or low-skill labor shortages; it concerns specialized AI expertise.	Talent shortages slow the adoption of AI and increase labor costs.
High Cost of AI Talent	Rising salaries and compensation packages for AI specialists due to high demand and limited supply.	<u>*Wages for AI workers have doubled in recent years, reflecting a persistent talent shortfall.*</u>	It is not about the cost of recruiting general IT staff; it pertains to AI-specific roles.	High labor costs raise barriers for startups and public institutions seeking to build AI capabilities.
Immigration Barriers for AI Talent	Visa restrictions, long wait times, and other immigration hurdles that prevent foreign AI experts from working in the United States.	<u>*Visa restrictions and long wait times hinder skilled workers: some companies experience multi-year waits for H-1B visas.*</u>	It is not about domestic education or workforce development; it concerns immigration policy.	Easing immigration barriers can help alleviate talent shortages and strengthen competitiveness.
Uneven Access to Talent Across Regions of the U.S.	Disparities in the availability of AI talent across different geographic regions, leading to concentrated innovation in a few hubs.	<u>*MIT Sloan's study highlights uneven AI adoption in the U.S., with large companies and certain sectors leading.*</u>	It is not about state-level education funding alone; it concerns geographic talent distribution.	Regions lacking AI talent struggle to attract investment and deploy AI technologies effectively.
Cybersecurity Risks in AI Systems	Potential vulnerabilities and threats to AI infrastructure, models, and data from cyberattacks, especially as AI becomes more capable. Risk to AI's security becomes a larger national threat.	<u>As AI models get more capable, infrastructure hosting them will likely face sophisticated cyberattacks.</u>	It is not about software bugs or explainability issues; it concerns malicious threats.	Cybersecurity risks can lead to data breaches, model theft, and system disruptions.
Uneven AI Adoption across sectors	Significant differences in the rate and extent of AI adoption among industries, with some sectors far ahead of others. Adoption further hindered by the unknown application of AI across sectors.	<u>*MIT Sloan's study notes uneven AI adoption in the U.S., with large companies and sectors like manufacturing and healthcare leading.*</u>	It is not about individual firm reluctance; it refers to sector-level disparities.	Uneven adoption can widen economic gaps and slow overall productivity gains.
Unclear Foreign Investment Guidelines (CFIUS)	Ambiguity and complexity in U.S. foreign investment screening (CFIUS) processes, which can deter AI-related foreign investment.	*CFIUS reviews can be byzantine and case-by-case, imposing costs on foreign investors and U.S. businesses and creating uncertainty (general policy criticism).*	It is not about export controls themselves; it concerns investment screening procedures.	Clearer guidelines could attract foreign capital while safeguarding national security.
Underfunded AI Public Infrastructure Investment	Insufficient government funding for public AI research facilities, computing resources, and educational programs, resulting in gaps in basic infrastructure. This is specific to the call for public funds for AI infrastructure to improve safety or R&D.	<u>*Experts warn that federal funding cuts have forced universities to pause Ph.D. admissions and reduce graduate enrollment, risking a lost generation of AI researchers.*</u>	This does not include private investment shortfalls or venture capital scarcity; it refers specifically to public-sector underinvestment.	Without adequate public infrastructure funding, universities and labs cannot train researchers or provide broad access to AI resources.
Lack of Public Infrastructure Investment	Insufficient government funding for foundational infrastructure (energy, compute, broadband) needed to support AI development. Lack of a strong public investment in existing energy grid network for AI development.	<u>*The U.S. energy system is not ready to supply the multi-gigawatt clusters needed for AI, indicating underinvestment.*</u>	It is not about private venture funding; it refers specifically to public spending on infrastructure.	Without strong public infrastructure, private AI investment is hampered by power and connectivity gaps.
Unequal Public-Private Collaboration	Imbalances or misalignments between government initiatives and private-sector efforts in AI, leading to inefficiencies or duplication.	*Collaboration frameworks may favor large corporations or lack clear accountability, hindering equitable progress.*	It is not about public investment alone; it concerns joint efforts between sectors.	Balanced collaboration ensures that both public goals and private innovation are advanced. Unbalanced collaboration may lead to a lack of oversight and clear accountability.

Lack of Specialized AI Investment Vehicles	Absence of dedicated financial instruments (e.g., funds or bonds) tailored to AI infrastructure and research, limiting investment	<i>"While some VC funds focus on AI, there are few public or private vehicles that target long-term AI infrastructure."</i>	It is not about general venture capital availability; it concerns specialized vehicles for AI.	Creating targeted investment vehicles could mobilize capital for transformative AI projects.
Absence of upskilling Programs for workers	Insufficient programs to train existing workers in AI skills, leaving the current workforce unprepared for AI-driven changes.	<i>"A national talent surge is needed to train teachers and workers for an AI-enabled future; teaching positions remain unfilled and skills gaps persist."</i>	It is not about hiring new graduates; it refers to retraining the current workforce.	Upskilling programs can help workers adapt to AI technologies and mitigate job displacement.
Underfunding of Public Research Universities	Reductions in government research funding that limit universities' ability to conduct cutting-edge AI research and train graduate students.	<i>"Federal funding cuts have led universities to pause Ph.D. admissions and reduce graduate enrollment, risking a lost generation of researchers."</i>	It is not about private endowments; it concerns public funding for research institutions.	Underfunded universities struggle to maintain research programs and compete for talent.
Insufficient Support for Apprenticeships in AI Fields	Lack of structured apprenticeship programs that provide hands-on experience in AI for early-career workers.	<i>"Experts advocate for expanding apprenticeship programs to energize the education workforce and prepare graduates for AI careers."</i>	It is not about internships or academic courses; it refers to formal apprenticeships.	Apprenticeships bridge the gap between education and employment, enhancing skill development.
STEM Educator Shortages	Shortfall of qualified teachers capable of teaching AI and digital skills in schools, exacerbating the talent pipeline problem.	<i>"At least 55,000 teaching positions went unfilled, and long-term shortages could double to 100,000 annually."</i>	It is not about shortages of general teachers in unrelated fields; it refers specifically to STEM and digital education.	Without enough educators, students lack exposure to AI concepts, hurting the future workforce.
Lack of wide-spread standards demonstrating AI Competency	The absence of nationally recognized curricula, certification, or assessment frameworks that validate individual AI skills across education and industry.	<i>"The Federation of American Scientists notes that only 5 percent of U.S. high school graduates have a foundational computer science education and there is no widely adopted standard demonstrating AI competency."</i>	It is not merely about teacher shortages or training programs but about the lack of formal standards to measure AI literacy.	Clear standards would help align training programs and ensure a consistent baseline of AI knowledge.
Inadequate Rural Workforce Participation	Low participation of workers from rural areas in AI-related education and employment due to limited opportunities and infrastructure.	<i>"Challenges in rural settings include limited broadband access and digital literacy barriers."</i>	It is not about urban workforce participation; it focuses on rural communities.	Encouraging rural participation can diversify the AI workforce and spread economic benefits.
Lack of AI Training in Trade and Technical Schools	Trade and technical schools offering limited or no AI coursework, leaving vocational students without exposure to AI technologies.	<i>"There is no teacher workforce ready to implement AI curriculum; interest and enrollment in programs remain low."</i>	It is not about four-year universities; it concerns vocational education.	Integrating AI into trade schools can broaden the talent pipeline beyond traditional pathways.
AI-Specific Unionization Challenges	Difficulties faced by AI workers in organizing and bargaining collectively due to evolving job definitions and legal uncertainties.	<i>"AI sector unionization is nascent, and workers often lack clear recognition of their roles and rights."</i>	It is not about traditional labor disputes in established industries; it concerns the emerging AI workforce.	Addressing unionization challenges ensures fair labor practices in AI-related roles.
Lack of Nationwide Data Center Energy Standards	Absence of uniform national guidelines for energy efficiency and sustainability in AI data centers, leading to fragmented practices across states.	<i>"Rand notes that permitting challenges and environmental regulations vary by state, causing delays and inconsistency in data center construction."</i>	It is not about general building codes; it specifically concerns energy standards for AI data centers.	National standards could streamline development and reduce environmental impact.
Regulatory Delays in Renewable Energy Siting	Slow approval processes for locating and building renewable energy projects needed to power AI infrastructure.	<i>"Complex permitting processes and local opposition delay transmission line projects and backup generators."</i>	It is not about technical feasibility of renewables; it concerns regulatory timelines.	Accelerating siting approvals can unlock renewable power for AI data centers.
Underdeveloped grid interconnection process	Cumbersome procedures for connecting new power generation to the grid, leading to long waiting times for AI projects.	<i>"Grid connection requests can take four to seven years in key regions like Virginia."</i>	It is not about generation capacity itself; it concerns the process of connecting to the grid.	Streamlining interconnection processes would reduce delays and support rapid AI expansion.
Fragmented State-level Energy Policies	Inconsistencies among state regulations and policies for data centers and power infrastructure that create uncertainty for AI developers.	<i>"Data centers struggle with local and state permits, particularly for on-site backup generators and environmental impact assessments."</i>	It is not about federal policies; it concerns the patchwork of state rules.	Harmonizing state policies could speed up deployment of AI infrastructure.

Fragmented AI Policies Across Jurisdictions	Disjointed, inconsistent, or conflicting artificial intelligence regulations and standards adopted independently by U.S. states, which create uncertainty, compliance burdens, or barriers for AI developers, especially those operating across multiple jurisdictions. This includes overburdening bureaucratic red tape.	*A company developing AI-powered traffic monitoring tools must redesign privacy and data-sharing features for each deployment because California, Texas, and Illinois all impose different rules on data retention and facial recognition, leading to increased costs and delays.*	This is not about the absence of federal AI regulation in general, nor is it about local (e.g., municipal or city-level) restrictions. It also does not include partisan political disputes about AI, unless they manifest as incompatible or conflicting state-level laws. This is not about energy or environmental policies. This is not about permitting policies either.	When AI policy is uneven across states, especially with respect to procurement, standards, and data governance, it complicates national-scale development and commercialization. This regulatory patchwork can disincentivize innovation, increase legal compliance costs, and encourage AI firms to concentrate operations in regulatory havens rather than innovating broadly.
Lack of Grid-Edge Energy Storage Infrastructure	Insufficient deployment of energy storage systems near data centers and end users to balance load and integrate renewables.	<u>IEP notes that "next generation technologies like geothermal and small modular reactors face financing and permitting challenges."</u>	It is not about generation capacity alone; it concerns storage solutions at the grid edge.	Expanding grid-edge storage would improve reliability and accommodate intermittent renewables for AI workloads.
Limited Federal Support for Clean Energy Procurement by Private Sector	Inadequate federal programs or incentives to help private companies secure renewable energy for AI data centers.	<u>"The policy playbook suggests government should reduce costs and streamline financing for clean energy projects."</u>	It is not about state programs; it refers to federal-level assistance.	Federal support could accelerate the transition to clean power for AI and reduce carbon footprints.
Lack of Federal Oversight of Data Center Water Usage for Cooling	Absence of national regulations monitoring and limiting water consumption in AI data center cooling systems.	*Water usage is often regulated locally, and there is no consistent federal oversight, leading to environmental concerns.*	It is not about energy use; it specifically addresses water resources.	Standardized oversight could mitigate environmental impacts and promote sustainable practices.
Inefficient Building Codes for AI-Intensive Facilities	Outdated or overly prescriptive building codes that fail to account for the unique power and cooling requirements of AI data centers.	<u>"Permitting challenges include local and state permits for backup generators and environmental impact assessments, reflecting code inadequacies."</u>	It is not about zoning restrictions alone; it concerns technical standards in codes.	Modernizing building codes would facilitate construction of AI-ready facilities.
Underutilization for Federal Brownfields for AI-Linked Infrastructure	Failure to repurpose contaminated or underused industrial sites (brownfields) for new AI-related data centers and infrastructure.	*Redeveloping brownfields could provide ready sites for data centers but remains underused in AI infrastructure planning.*	It is not about greenfield site development; it concerns reuse of existing land.	Leveraging brownfields could reduce environmental impacts and speed up development.
No National Accounting Standard for AI Compute	Lack of standardized metrics and accounting methods to measure AI compute usage and efficiency across organizations.	*There is no universally accepted method to account for AI compute, making benchmarking and reporting difficult.*	It is not about energy metrics or carbon accounting; it specifically concerns compute measurement.	Standardizing compute accounting would enable better policy and investment decisions.
Outdated Transmission Planning Process	Legacy processes for planning and approving power transmission lines that cannot keep pace with AI-driven load growth.	<u>Transmission line projects face complex multistate permitting processes and local opposition, delaying power delivery.</u>	It is not about generation capacity; it concerns the planning and approval of transmission.	Modernizing the planning process would reduce delays and support AI and renewable integration.
Inadequate Investment in Nuclear Energy Innovation	Insufficient funding for developing advanced nuclear technologies, such as small modular reactors, which could provide stable power for AI.	<u>IEP notes that small modular reactor projects face cost and permitting uncertainties that deter investment.</u>	It is not about traditional nuclear reactors; it concerns next-generation nuclear innovation.	Greater investment could provide a reliable, carbon-free power source for AI data centers.
No Carbon Pricing or Emission Cap	Absence of market mechanisms or regulatory limits on greenhouse gas emissions, reducing incentives for clean energy investment for AI.	*AI developers currently operate in jurisdictions where no carbon pricing exists, undermining emission reduction efforts.*	It is not about voluntary corporate pledges; it concerns formal pricing or caps.	Implementing carbon pricing could drive investment towards low-carbon energy for AI.
Cryptomining and AI Competing for Power	Competition between cryptocurrency mining and AI data centers for limited electricity supply, leading to higher prices and constrained resources.	<u>Tech companies are acquiring energy assets from bitcoin miners as they race to secure a shrinking supply of electricity for AI data centers.</u>	It is not about general energy shortages; it specifically involves competition with cryptocurrency mining.	Competition for power can drive up energy costs and delay AI expansion.
Limited Deployment of AI to Optimize Energy Systems	Underutilization of AI technologies in energy grids, storage, and demand management, which could improve efficiency and integration of renewables.	*Experts note that deploying AI to optimize energy demand, storage, and distribution is still in its early stages (e.g., limited adoption in grid management).*	It is not about AI optimizing business processes; it pertains specifically to energy systems.	Wider deployment of AI in energy could reduce power consumption and enhance reliability for AI workloads.
Category 2: Type of bottleneck - general categories describing the constraint on AI development				

Capital investment	High cost of financial capital needed to build or scale AI infrastructure (e.g., data centers, advanced chips, research). Overcoming government regulations adds to the capital needs as resources are expended to meet regulations and standards. Any AI governance oversight, over regulation, or patchwork of regulations due to fragmentation should be coded as capital investment. Any calls for investment should be coded as capital investment.	Our research shows that by 2030, data centers are projected to require \$6.7 trillion worldwide to keep pace with the demand for compute power. Data centers equipped to handle AI processing loads are projected to require \$5.2 trillion in capital expenditures, while those powering traditional IT applications are projected to require \$1.5 trillion in capital expenditures (see slide 9, "What about non-AI workloads?"). Overall, that's nearly \$7 trillion in capital outlays needed by 2030—a staggeringly high number by any measure. (Nofflinger et al., 2023)	A small start-up that has already secured sufficient venture funding does not face a capital bottleneck or lack of funds is not impeding its AI project. Areas where funding is already available, such as construction materials, company overhead, or bad management, are not capital constraints.	Lack of capital limits construction of compute facilities and slows R&D, making it a critical bottleneck. Overly stringent regulations also impose higher capital needs, further restricting AI development and innovation.
Labor	Shortage of skilled AI researchers, engineers and support staff caused by limited domestic training, immigration barriers, or constrained educational pipeline. All labor or educational constraints, lack of skill in existing workforce will require upskilling, and this causes a constraint.	Our research highlights the existence of global AI talent shortages, the United States' reliance on foreign talent to sustain its AI workforce, and recent increases in international competition for students, workers, and entrepreneurs (Section 1, "Background on the U.S. AI Workforce"). We recommend that policymakers adopt immigration reforms to ensure continued U.S. competitiveness in attracting and retaining foreign AI talent in the short term. Our long-term recommendation is to launch education and R&D programs to lay the foundation for domestic AI workforce growth (Section 7, "The Policy Agenda").	Hiring difficulties caused by an internal management problem (e.g., poor recruiting practices) rather than a shortage of skilled workers is not a labor bottleneck.	Talent shortages reduce innovation capacity and create dependency on immigration policies.
Computing	Insufficient supply of AI-specific hardware or software due to capacity constraints found in the environment such as supply chain issues, manufacturing of memory and high-end chip packaging is constrained. This also includes data scarcity, unavailability and quality issues. Data or methods computing may not be well explained due to lack of quality data.	It is now well understood that the rapid technological progress of artificial intelligence (AI) has profound energy sector implications. AI technology is effectively the result of three inputs: chips, data, and electricity. (McGeady et al., 2023)	A bottleneck caused by regulatory delay, not hardware supply, should not be coded as a computing bottleneck. Physical data center construction should not be coded as computing.	Limited compute capacity delays AI research and can force companies to seek hardware abroad.
Energy	Hardware or software due to capacity constraints found in the environment such as supply chain issues, manufacturing of memory and high-end chip packaging is constrained. This also includes data scarcity, unavailability and quality issues. Data or methods computing may not be well explained due to lack	"Today, access to electricity supply is the binding constraint on expanded computational capacity and therefore on continued U.S. leadership in AI... data centres now face electricity supply wait times up to 7 years"	It is not software, labor, or hardware shortages. It is not an economic bottleneck	Power scarcity delays data-center construction and limits use of available compute hardware.
Category 3: Nature of Bottleneck - Identifies the nature or source of the obstacle impeding policy progress				
Political	Obstacles arising from political polarization, institutional gridlock, lobbying or fragmented governance	"At the federal level, political gridlock has rendered meaningful regulation nearly impossible. Instead, the focus has shifted to encouraging private-sector innovation, regardless of the risks."	Disagreements among technical experts about algorithm design without any political involvement do not constitute a political bottleneck.	Political statements prevent passage of legislation or the release of funds. The example highlighted shows how political gridlock is a potential barrier to AI development.
Economic	economic bottlenecks involve financing gaps, costs, and market failures (e.g., high capital expenditures), high costs disadvantages, and supply-chain issues	"However, the booming demand for AI chips has led to shortages and bottlenecks in GPU supply, causing significant challenges for the industry. Many AI companies anticipate that the shortage will persist until at least next year. The scarcity of GPUs has become a major concern as AI applications increasingly rely on these powerful components for training and running complex algorithms. Tech giants like Microsoft have reported internal shortages of server hardware required for AI operations. OpenAI's CEO, Sam Altman, has expressed concerns about the processor bottleneck during a congressional hearing. Customers and server manufacturers have reported waiting periods of over six months to procure the latest Nvidia GPUs."	Shortages such as labor, hardware, funding, and high costs are not economic bottlenecks. Regulatory shortcomings are not economic bottlenecks.	Economic factors such as insufficient financing or high costs can discourage investment and slow AI development. Supply chain issues and shortages affect AI's development

Technical/Operational	technical/operational bottlenecks involve physical scarcity, infrastructure, or technological limitations (e.g., chip shortages, power constraints)	<i>"The central principle for understanding these developments is speed-to-power, or the measure of how fast a potential data center site can access the electricity needed to power its stock of chips. Speed-to-power should likewise be used to organize federal policymakers' approach to permitting policy and use of emergency authorities in the near term."</i>	Policy disagreements, high costs, or funding shortages are not technical bottlenecks.	Technical gaps require R&D, infrastructure investment and expertise to overcome.
Legal/Regulatory	Barriers created by laws, regulations or standards that slow or restrict AI adoption, including outdated safety rules and permitting delays.	<i>States are racing to regulate artificial intelligence, creating a patchwork of laws that threatens to slow innovation, drive up compliance costs, and undermine U.S. global competitiveness. In 2023, the National Conference of State Legislatures tracked over 450 AI-related bills introduced across all 50 states, as well as in Puerto Rico, the Virgin Islands, and Washington, D.C. While some legislation appropriately focuses on state-specific concerns—such as AI use in public education, local government, or election communications—many states are reaching far beyond their borders, proposing sweeping rules that aim to govern AI more broadly.</i>	A supply-chain shortage caused by manufacturing constraints rather than law is not a legal/regulatory bottleneck.	Reforming regulations can remove artificial barriers while preserving safety.
Category 4: Source of Bottleneck - Identifies the actor or entity responsible for the bottleneck				
Federal government	Constraints arising from Congressional regulators, federal agencies or national policies, for example slow appropriations or restrictive rules.	<i>"Congressional appropriations delays that stall AI research funding illustrate a federal source."</i>	Delays caused by private investors are not federal sources.	Points to the need for federal legislative or administrative action.
State government	Constraints stemming from state or local actors such as interest groups, public opinion, media, agencies, and courts	<i>"Fragmented state energy policies hindering data center construction are state-level bottlenecks."</i>	Federal export controls are not state bottlenecks.	Suggests targeted state legislation or coordination with federal efforts.
Cross-governments	Both federal and state governments due to misalignment or conflict between both levels governments	<i>"Conflicting federal export controls and state economic priorities around chip supply show cross-government bottlenecks."</i>	A bottleneck that can be solved entirely within one level of government is not a cross-government issue.	Highlights the need for harmonization across jurisdictions.
Private Sector	Constraint arises from market forces rather than government actions.	<i>Source of bottleneck are from market forces such as high capital costs or compute dilution. "Google has not released the amount of money that it spent on training its leading foundation model, Gemini Ultra, but the AI research institute Epoch AI estimates that Google spent between \$260 million and \$3 billion in hardware acquisition costs."</i>	delays caused by any government entity whether Global, state, or federal government, sources of bottlenecks are not private sector.	Many constraints (e.g., data silos, resource costs) originate from market dynamics rather than governmental actors
Category 5: Frequency of mention or incident - Quantifies how often the bottleneck appears across documents, indicating salience				
Low	Bottleneck is mentioned 1 or 2 times	<i>"Low" frequency should apply when a bottleneck is mentioned once</i>	Issues discussed extensively across multiple sources are not low frequency.	Low frequency issues may be emerging or niche.
Medium	Bottleneck appears intermittently across sources 3 to 5 times	<i>"Medium" when the bottleneck appears 2-5 times</i>	A bottleneck mentioned in nearly every document multiple times is not medium frequency.	Medium frequency signals a need for monitoring.
High	Bottleneck is mentioned frequently 6 or more times	<i>"High" when the bottleneck recurs 6 or more times</i>	A niche issue appearing rarely is not high frequency.	High frequency issues should be prioritized for policy action.
Category 6: Impact of Bottleneck - Evaluates how strongly the bottleneck affects policy adoption				
Low	Minor delays or obstacles; can be worked around without major change.	<i>Minor data-silo issues resolved via standard agreements such as a memorandum of understanding or contract illustrates low impact.</i>	A structural power shortage that prevents data-center construction is not low impact.	Low impact issues require minimal intervention.
Moderate	Significant challenge that does not entirely prevent adoption but requires effort or time to address.	<i>"Student enrollment in AI-relevant fields such as computer science has rapidly risen in recent years. The number of bachelor's degrees awarded in computer science and computer engineering at U.S. institutions, nearly tripled from 2009 to 2017-18. In many AI-focused introductory courses, enrollment in 2017 was three to five times higher than in 2012-16. Due to a lack of teaching staff, however, few colleges have been able to meet student demand."</i>	Issues that completely halt projects are not moderate in impact.	Moderate issues warrant targeted, but not drastic, interventions.
High	Severe barrier that prevents or halts policy adoption unless major changes occur.	<i>Speed-to-power is the time it takes a potential data center site to receive access to electricity supply. In northern Virginia—the nation's and the world's largest data center market—speed-to-power is growing, worse as data centers now face electricity supply wait times up to 7 years.</i>	A minor delay in obtaining a permit is not a high-impact barrier.	High severity bottlenecks demand urgent action or structural reform.
Category 7: Stage of Policy Process Affected - Determines where in the policy cycle the bottleneck arises				
Agenda setting	Issues are recognized and prioritized for government attention. This can be coded when statements raising a new problem (e.g., "who will pay?")	Bringing AI power demand to policymakers' attention during agenda-setting. Agenda setting: statements that raise a problem or question ("who will pay?").	Policy implementation challenges are not agenda setting issues.	Helps ensure emerging issues reach the policy agenda.
Policy formulation	Solutions are devised and goals, costs and impacts are assessed. Coded when analyses or proposals for funding	<i>Developing incentives for AI talent pipelines at this stage. Policy formulation: normative recommendations and analysis (e.g., proposals for "Special Compute Zones").</i>	Debating and voting on a bill is not formulation; it is adoption.	Requires technical expertise and stakeholder input.

Legislative adoption	Policies are debated, refined and enacted by legislatures or other bodies. Code when References to enacted laws (e.g., the CHIPS Act).	Passing AI tax credits as part of the CHIPS Act in Congress is legislative adoption. Legislative adoption: references to enacted statutes or bills (e.g., CHIPS Act appropriation).	Writing draft regulations without voting does not constitute adoption.	Highlights the need for consensus and coalition building.
Implementation	Policies are executed with resource allocation and monitoring. Code when descriptions of existing funding or permit processes are mentioned.	Updating grid-interconnection processes as part of execution is part of policy implementation. Implementation: descriptions of current practices and costs (e.g., actual training costs).	Drafting bills or debating them is not implementation.	Points to administrative capacity and coordination needs.
Category 8: Temporal Urgency or Recency - Tracks whether the bottleneck is historic, current or emerging				
Historic (legacy)	Long-standing barriers rooted in the past, such as outdated infrastructure or bottlenecks that are presently impeding policy progress.	Outdated transmission planning processes hinder energy projects. <u>There is a significant talent shortage in AI, both domestically and globally. One consequence of U.S. talent shortages is that U.S. companies are moving AI R&D abroad.</u>	An unexpected surge in AI training costs this year is not historic.	Legacy issues often require structural reforms to modernize systems.
Current (active)		<u>Beyond governance, AI's rise is creating another, less visible challenge: energy. The computational demands of training advanced AI models like OpenAI's GPT-4 have grown exponentially. Data centers are consuming vast amounts of electricity, and AI's carbon footprint is becoming a critical issue. Major tech companies are scrambling to secure energy supplies, investing in cutting-edge solutions like modular reactors and fusion power. While these efforts hold promise, they're unlikely to meet AI's ballooning energy demands in the short term.</u>	Historic or emerging issues not currently constraining projects are not active.	Active issues need immediate attention and resources.
Emerging (future concern)	Newly recognized issues identified by scientists but not yet on the policy agenda.		Long-standing infrastructure deficits are not emerging.	Identifying emerging issues early allows for proactive policy.
Category 9: Level of Governance - Identifies which level of government is primarily affected				
Federal	Bottleneck primarily affects national institutions and policies.	Lack of federal data center water usage standards is a federal level bottleneck at the EPA. <u>Utah, like the rest of the globe, is headed towards an energy deficit due to increased power demand and decreasing supply. While some special interests call for reductions in energy consumption, the reality is we need significantly more power to meet current and future energy needs. Our health, well-being and quality of life depend on it.</u>	Local zoning disputes are not federal issues.	Suggests federal legislation or executive action.
State	Bottleneck mainly arises at the state or local level.		Issues controlled solely by federal law are not state bottlenecks.	Points to state laws, inter-state compacts or federal incentives.
Both	Bottleneck spans multiple levels and requires coordination.	Grid interconnection processes involve both Federal Energy Regulatory Commission, DOE, and state utilities.	Purely federal or purely state issues are not joint.	Requires government collaboration.
Category 10: Resistance type or mode - How the bottleneck manifests as resistance to policy				
Passive resistance	Non-confrontational opposition through inaction or delay.	Agencies delaying rule-making despite mandates.	A lawsuit filed to block a policy is active, not passive resistance.	Needs oversight and deadlines to counteract inertia.
Active resistance	Intentional actions aimed at obstructing or challenging policy (e.g., protests, lawsuits).	Lawsuits filed by industry groups to block AI safety regulations.	Quietly delaying implementation without formal opposition is not active resistance.	May require negotiation or enforcement.
Symbolic opposition	Performative gestures that signal disagreement without real blocking power.	Passing non-binding resolutions without substantive legislation.	A veto that stops a bill is not symbolic; it wields actual power.	Prevents overestimating policy resistance and informs strategic communication.
None	No active resistance or opposition to the bottleneck's policy to fix. Choose none in such cases.	There are no opposition groups. The bottleneck is an infrastructural gap or the bottleneck arises from physical or economic constraints.	Opposition or resistance to policy.	The bottleneck is an infrastructural gap.
Category 11: Resolution Potential - Classifies whether the bottleneck can be resolved easily or requires significant change				
Remediable	Capable of being remedied or made better through existing policy tools or modest changes.	Minor training gaps addressed with targeted workforce programmes.	An entrenched geopolitical conflict is not remediable.	Should be tackled promptly to prevent escalation.
Structural	Embedded in social, economic or political structures; requires systemic change.	Long-standing underfunding of rural broadband.	A minor regulatory glitch quickly fixed by a rule update is not structural.	Demands comprehensive reforms rather than minor tweaks.
Intractable	Extremely difficult to manage or resolve; solutions may be unavailable or impractical - wicked problems.	Geopolitical tensions causing global chip shortages.	A problem with clear solutions and quick remedies is not intractable.	Recognising intractability helps set realistic expectations and focus on mitigation.
Category 12: Affected Stakeholders - Identifies populations or groups influenced by the bottleneck				
Policymakers	Elected officials, agency leaders and regulators who design and implement AI policies.	Members of Congress drafting AI R&D legislation.	A private consumer with no policymaking role is not a policymaker stakeholder.	Their decisions directly shape the response to bottlenecks.
General public	Residents and taxpayers affected by AI-related policies.	Workers displaced by automation are part of the general public.	Industry executives are not general public stakeholders.	Public impacts should be considered for equitable policies.

Vulnerable or marginalized communities	Populations historically facing discrimination or disadvantage; AI systems can perpetuate biases.	Some experts know that AI would inherit our discriminatory practices which negatively affect people in marginalized communities on a fundamental level. In Olga Akselrod's article, How Artificial Intelligence can Deepen Racial and Economic Inequalities (seen in a new tab), she shares that "rather than help eliminate discriminatory practices, AI has worsened them — hampering the economic security of marginalized groups that have long dealt with systemic discrimination."	A general population unaffected by discrimination is not considered vulnerable or marginalized.	Including these groups in policy design helps reduce harm and reduce disparity.
Industry or private sector	Private sector is defined as companies, investors or industries whose behaviour or market conditions create or sustain the bottleneck.	Semiconductor manufacturers affected by export controls.	Government regulators are not part of the private sector stakeholder group.	Collaborating with industry ensures policies are practical and innovation-friendly.
Category 13: Congressional policy mechanisms - Tools congress can use to alleviate bottlenecks through legislative or budget mechanisms				
Power of the purse (appropriations)	<u>Congress' authority to tax and spend public money; no money is drawn from the Treasury without appropriations.</u>	Ear-marking funds for AI research in appropriations bills.	A president issuing an executive order without funding appropriations is not exercising the power of the purse.	Funding decisions determine whether resources are available to tackle bottlenecks.
Tax expenditure & revenue measures	Adjustments to taxes and credits to encourage or discourage certain activities.	Offering investment tax credits for AI hardware manufacturing.	Imposing an environmental regulation without any tax implications is not a tax measure.	Lowering capital costs can accelerate private investment.
Conditional grants-in-aid & cooperative agreements	Funding provided to states or organisations contingent on meeting federal conditions.	Grants for broadband infrastructure conditioned on AI-friendly regulations.	Unconditional block grants with no strings attached are not conditional grants.	Aligns state actions with federal goals while supplying resources.
Federal procurement & acquisitions	Use of federal purchasing power and R&D contracts to drive innovation and create markets.	Awarding contracts to build AI-optimised data centres.	Private venture-capital investments are not federal procurement.	Procurement can spur innovation and scale up nascent technologies.
Regulation & standard-setting mandates	Legislation directing agencies to develop regulations or standards.	Requiring NIST to issue AI hardware security standards.	Voluntary industry guidelines without regulatory authority are not mandatory standards.	Standards ensure safety, interoperability and trust.
Intellectual-property & innovation policy	Adjustments to patents, copyrights and innovation prizes to encourage invention and diffusion.	Prize competitions for AI safety solutions.	A military procurement programme without any IP element is not an IP policy.	Strong IP and innovation policies promote research while facilitating diffusion.
Oversight & investigatory powers	Authority to hold hearings, issue subpoenas and conduct investigations.	Senate hearings on AI safety prompting agencies to update risk assessments.	Routine agency rule-making is not congressional oversight.	Oversight ensures accountability and transparency.
Informational & "soft-law" devices	Non-binding resolutions or reports that guide agencies without formal law.	Reports directing DOE to explore energy-efficient AI computing.	Soft-law tools can shape priorities and signal congressional intent.	
Trade & investment-screening tools	Tariffs, export controls and foreign investment reviews used to protect national security and economic interests.	Adding advanced AI chips to export control lists.	A binding regulatory rule is not soft law.	Pure domestic tax credits are not trade or investment screens.
Immigration & workforce levers	Laws affecting visa caps, training programmes and labour mobility.	Expanding H-1B visa quotas for AI talent.	A technical R&D grant with no workforce component is not an immigration lever.	Safeguards critical technologies and supply chains.
Credit programs & loan guarantees	Government-backed loans and guarantees to de-risk private investment.	Loan guarantees for companies building AI-powered clean-energy projects.	Direct appropriations without loan terms are not credit programmes.	A technical R&D grant with no workforce component is not an immigration lever.
Defense-linked authorities	Use of national defence powers (e.g., Defence Production Act) to direct resources toward critical AI technologies.	DPA Title III awards to expand U.S. semiconductor manufacturing capacity for AI.	Commercial law reforms unrelated to national security are not defence-linked.	Directly addresses talent shortages.
				Reduces financing barriers and accelerates deployment.
				Enables rapid mobilisation of resources for national security-related AI projects.

Appendix D - Examples of Code Revisions

[\[Link to Data\]](#)

Appendix E - Sample Coding Results

Resource ID	Bottleneck	Type	Nature	Source	Frequency	Impact	Policy Stage	Urgency	Governance Level	Resistance Type	Resolution Potential	Affected Stakeholders	Policy Mechanisms	Justification
1234	Fragmented AI Policies Across Jurisdictions	Capital Investment	Legal/Regulatory	Cross-government	High	High	Legislative adoption	Current	Both	Active resistance	Structural	Polymakers; Industry/private sector; General public	Regulation & standard-setting mandates; Oversight & investigatory powers; Conditional grants-in-aid & cooperative agreements	The article warns of a looming wave of algorithmic fairness regulations at both federal and state levels, creating a patchwork of rules that would impose pre-release certification and compliance burdens on AI developers. [1444598081100437423-jul1] [544459808110043741101-L110] - This regulatory overreach threatens to derail innovation and requires structural reform and harmonization across jurisdictions to be resolved.
1235	Shortage of Skilled Talent	Labor	Economic	Federal government	Medium	High	Implementation	Current	Federal	Passive resistance	Remediable	Polymakers; General public	Immigration & workforce levers: Power of the purse (appropriations); Conditional grants-in-aid & cooperative agreements	The intelligence posture report notes that the U.S. intelligence community lacks sufficient analysts and experts with foreign language and technical skills, creating a labor shortage that hampers its ability to monitor adversaries. [926775644178839191-L107] - This workforce gap stems from resource constraints within the federal government and can be addressed through hiring, training, and immigration reforms.
1236	Shortage of Skilled Talent	Labor	Economic	Private Sector	High	High	Implementation	Current	Both	None	Remediable	Industry/private sector; Polymakers	Power of the purse (appropriations); Tax expenditure & revenue measures; Immigration & workforce levers: Conditional grants-in-aid & cooperative agreements	SCC finds that only one in four companies adopt AI value because transformation hinges on people and culture. It stresses that leaders must invest heavily in skills and behavioral change, with 70 percent of effort dedicated to people and processes. [4071528578301119-L47-L51] [4071528578301119-L51-L100] - This shows a high-impact labor bottleneck that can be mitigated via upskilling and workforce policies.
1237	Cybersecurity Risks in AI Systems	Computing	Technical/Operational	Private Sector	Low	Moderate	Implementation	Current	Both	None	Remediable	Polymakers; Industry/private sector	Regulation & standard-setting mandates; Conditional grants-in-aid & cooperative agreements; Power of the purse (appropriations); Oversight & investigatory powers	The R Street news release states that as organizations adopt AI, attendant cybersecurity threats are expected to rise, with criminals using AI to enhance their infiltration tactics. [4993413941640181-L12-L17] [4993413941640181-L36-L43] - These technical vulnerabilities affect both public and private systems and can be addressed through standards and collaborative research.
1238	Cybersecurity Risks in AI Systems	Computing	Technical	Private Sector	Medium	High	Implementation	Emerging	Both	None	Remediable	Industry/private sector; Polymakers; General public	Regulation & standard-setting mandates; Conditional grants-in-aid & cooperative agreements; Oversight & investigatory powers; Power of the purse (appropriations)	The policy study warns that adversaries can embed backdoor triggers in training data and exploit supply-chain vulnerabilities, allowing attackers to hijack AI agents. [654460719890111408-L1423] [654460719890111507-L1524] - These emerging threats pose high-impact risks but can be mitigated through security standards, research funding and oversight.
1239	Fragmented AI Policies Across Jurisdictions	Capital Investment	Legal/Regulatory	Cross-government	High	High	Agenda setting	Current	Both	Symbolic opposition	Remediable	General public; Polymakers; Industry/private sector	Oversight & investigatory powers; Power of the purse (appropriations); Regulation & standard-setting mandates	Thierer argues that AI policy discourse is dominated by a doom-laden narrative where critics demand perfection and call for broad regulation, ignoring AI's benefits. [477707028714344-L62-L69] [477707028714344-L132-L146] - This symbolic opposition creates a fragmented, risk-averse policy environment that shifts investment and can be countered through balanced research, oversight and judicious standard setting.
1240	Fragmented AI Policies Across Jurisdictions	Capital Investment	Legal/Regulatory	Cross-government	High	High	Policy formulation	Current	Both	Active resistance	Structural	Industry/private sector; Polymakers; General public	Oversight & investigatory powers; Regulation & standard-setting mandates; Power of the purse (appropriations); Conditional grants-in-aid & cooperative agreements	The critique of Microsoft's regulatory framework notes proposals for comprehensive AI licensing regimes resulting in advance notice, risk assessments, and post-release monitoring, as well as calls to restrict high-powered AI research to government-approved facilities. [512889080217006-L96-L110] [512889080217006-L1230-L1254] - These heavy-handed measures would impose high compliance costs and limit innovation, requiring structural policy reforms to prevent overly burdensome regulation.
1241	Fragmented AI Policies Across Jurisdictions	Capital Investment	Legal/Regulatory	Cross-government	High	High	Policy formulation	Current	Both	Active resistance	Structural	Polymakers; Industry/private sector; General public	Regulation & standard-setting mandates; Oversight & investigatory powers; Conditional grants-in-aid & cooperative agreements; Power of the purse (appropriations)	The R Street study lists a surge of legislative proposals, including robot taxes, multiple new federal agencies, and the Algorithmic Accountability Act, and argues that one-size-fits-all mandates are unworkable. [5302385582760291-L14-L40] [5302385582760291-L31-L33] - This proliferation of regulatory schemes across jurisdictions creates high-impact barriers that will require structural reforms toward flexible, risk-based governance.
1242	Cybersecurity Risks in AI Systems	Computing	Technical	Private Sector	High	High	Implementation	Current	Both	Passive resistance	Remediable	Industry/private sector; Polymakers; General public	Regulation & standard-setting mandates; Oversight & investigatory powers; Conditional grants-in-aid & cooperative agreements; Federal procurement & acquisitions	CAP's report finds that major AI developers have not implemented recommended safety measures for third-party API deployments. [505939421955840-L128-L30] [505939421955840-L178-L224] - leaving users exposed to harmful content. Closing this gap requires mandated safety testing, reporting, and documentation, supported by congressional oversight and funding.

Appendix F - Example Highlight (Reference 1234)

Bottleneck: The article warns of a “potential avalanche of ‘algorithmic fairness’ regulations” and notes that federal and state policymakers are considering “a variety of new mandates for artificial intelligence, machine learning, and automated systems” which would allow government bureaucrats to regulate the minutiae of computer

programsfile:///home/oai/share/1234.txt#:~:text=A%20potential%20avalanche%20of%20,accumulating%20regulations%20threaten%20to%20derail. The paper argues that these mandates threaten to derail the U.S. economy’s computational capabilities and weaken America’s ability to compete

globallyfile:///home/oai/share/1234.txt#:~:text=the%20computational%20capabilities%20of%20the,1.

Type of bottleneck: (Capital investment) – Regulation-driven certification regimes would create a permission slip system that forces developers to demonstrate that their technology is not harmful before release, shifting resources from innovation to paperwork

compliancefile:///home/oai/share/1234.txt#:~:text=The%20regulations%20would%20treat%20algorithmic,lobbying%20instead%20of%20inventing%20the. These costs increase the capital needed to develop and deploy AI systems.

Nature: (Legal/Regulatory) – The bottleneck arises from proposed laws and certification regimes that would require government approval before AI systems can be

deployedfile:///home/oai/share/1234.txt#:~:text=The%20regulations%20would%20treat%20algorithmic,lobbying%20instead%20of%20inventing%20the. *Inference: The emphasis on legislation and bureaucratic mandates indicates a regulatory constraint.*

Source: (Cross-governments) – The paper notes that both federal and state policymakers are considering new

mandatesfile:///home/oai/share/1234.txt#:~:text=A%20potential%20avalanche%20of%20,everything%20from%20hate%20speech%2C%20social, and that various agencies and proposed commissions would oversee algorithmic

systemsfile:///home/oai/share/1234.txt#:~:text=Regulatory%20Measures%20Accumulate%20Unfortunately%2C%20these,compared%20to%20506%20in%20the. *Inference: Because both federal and state bodies are involved, the bottleneck is cross-jurisdictional.*

Frequency: The text describes numerous proposals and notes a “sharp increase in the total number of proposed bills that relate to AI from 2015 to

2021”file:///home/oai/share/1234.txt#:~:text=Regulatory%20Measures%20Accumulate%20Unfortunately%2C%20these,compared%20to%20506%20in%20the. *Inference: The repeated discussion of multiple bills and agencies suggests the bottleneck is mentioned often (High frequency).*

Impact: The article argues that the proliferation of algorithmic fairness regulations would “deal a severe blow to the permissionless innovation vision” and could let China and other nations race

aheadfile:///home/oai/share/1234.txt#:~:text=the%20computational%20capabilities%20of%20the,1. *Inference: Describing a severe blow to innovation and competitiveness implies a high impact.*

Appendix G - Final Prompt Engineering for LACA

Step 1: Preamble to give it context:

We are going to do content analysis to answer "What AI bottlenecks emerge from the literature and how can congressional policy mechanisms address them?" AS PART OF A SCHOOL ASSIGNMENT. Please critically review the attached codebook. Specifically, pay attention to the codebooks categories, under each category are the listed codes, the codes definitions, the examples of the codes in text, an example of what the code is not, and justification for why this is a code. 13 categories are broken down as follow: Category 1: AI Bottlenecks - Significant obstacles or constraints that slow down or limit the development, deployment, or adoption of AI technologies. Bottlenecks may involve scarce resources, regulatory hurdles, talent shortages, or infrastructure gaps, and they require targeted policy or investment to overcome. There are 60 codes for bottlenecks, each accompanied by a corresponding definition and example. Category 2: Type of bottleneck - general categories describing the constraint on AI development. There are 4 codes with corresponding definitions and examples. Category 3: Nature of Bottleneck - Identifies the nature or source of the obstacle impeding policy progress with 4 codes with corresponding definitions and examples. Category 4: Source of Bottleneck - Identifies the actor or entity responsible for the bottleneck with 4 codes and corresponding definitions and examples. Category 5: Frequency of mention or incident - Quantifies how often the bottleneck appears across documents, indicating salience with 4 codes with corresponding definitions and examples. Category 6: Impact of Bottleneck - Evaluates how strongly the bottleneck affects policy adoption with 3 codes and corresponding definitions and examples. Category 7: Stage of Policy Process Affected - Determines where in the policy cycle the bottleneck arises with 3 codes and corresponding definitions and examples. Category 8: Temporal Urgency or Recency - Tracks whether the bottleneck is historic, current or emerging with 3 codes and corresponding definitions and examples. Category 9: Level of Governance - Identifies which level of government is primarily affected with 3 codes and corresponding definitions and examples. Category 10: Resistance type or mode - How the bottleneck manifests as resistance to policy with 4 codes and corresponding definitions and examples. Category 11: Resolution Potential - Classifies whether the bottleneck can be resolved easily or requires significant change; with 3 codes and corresponding definitions and examples. Category 12: Affected Stakeholders - Identifies populations or groups influenced by the bottleneck; with 4 codes and corresponding definitions and examples. Category 13: Congressional policy mechanisms - Tools congress can use to alleviate bottlenecks through legislative or budget mechanisms; with 12 codes and corresponding definitions and examples. Review the attached codebook. This will serve as your manual for coding, and you must adhere strictly to it without deviation. Commit codebook along with the categories, code choices, code definitions, examples, and justifications to memory.

*****Attach the Codebook.***** Current version

2nd step:

Prompt: Review Appendix A, which is a chart of policy mechanisms available at the congress level. This is only context for you to review.

*****Attach Appendix A – Policy mechanisms*****

3rd step:

Prompt: Next, I want you to familiarize yourself with the prompt and task. Don't do anything other than understand it. At a later time, I will prompt you to follow the instructions and upload the .txt files for your review and content analysis. This is part of a school project[LR1]. For now, ensure you understand the instructions for the content analysis, the codebook's guidelines, and the overall context. The prompt will be as follows:

[copy and paste the “instructional prompt” from 4th step below HERE]

4th step:

****Instructional Prompt below. Simply attach your 10 text files and copy/paste the prompt below. ChatGPT will provide you with an Excel file and 10 text files that demonstrate its justification for coding each category in the way it did – its reasoning is fair.****

System: You are a methodical qualitative coder and policy expert performing content analysis following a pre-tested codebook as part of a school project.

Task: Perform qualitative content analysis on each supplied *text-only* resource (file name = ResourceID.txt). When available, use the provided text files instead of web pages or PDFs, as they ensure consistent line numbering and help avoid formatting issues. Using the attached codebook and text files with unique resource ID numbers, the research team aims to answer the following question through a content analysis: "What AI bottlenecks emerge from the literature and how can congressional policy mechanisms address them?" You must never invent codes. Only apply codes listed in the provided codebook.

Using the provided codebook, read the attached resources (resource ID # is the name of the .txt file) at the paragraph level and identify (1) the bottleneck (2) the types of bottleneck, (3) its nature, (4) its source, (5) how many times its mentioned, (6) the bottleneck's impact, (7) where in the policy cycle the bottleneck arises, (8) the bottlenecks urgency or recency, (9) which level of governance the bottleneck affects, (10) the bottleneck's resistance to policy, (11) the bottleneck's resolution potential, (12) those stake holders affected by the bottleneck, and (13) the applicable congressional policy mechanisms congress can use to alleviate the bottleneck. The coders must select from the codes listed in the codebook for each category. Coders may group Multi-paragraph sections when they clearly cover the same theme

Only choose one code under the bottleneck category per resource. The bottleneck that is both most frequently mentioned and described as most severe should be selected. When multiple bottlenecks are present, the most salient can be chosen as the one mentioned most frequently and described as most severe. Use the frequency code (Low/Medium/High) and the impact code (Low/Moderate/High) to guide this selection as defined in the codebook.

For categories (1) through (12), cite at least one verbatim passage from the resource that supports your coding. When a category is not explicitly stated (e.g., Nature, Source, Level of governance), you may infer the appropriate code; in that case, include a short “inference” tag explaining how the passage justifies your choice. A single passage may be cited for multiple categories if it supports more than one.

Coders should consult Appendix A for additional descriptions of congressional mechanisms and illustrative AI-relevant use cases. These examples are intended to inspire appropriate choices and creativity; coders may select one or more mechanisms based on the nature of the bottleneck. Do not map each bottleneck type to a single mechanism; instead, evaluate which tools (e.g., appropriations, tax credits, conditional grants, loan guarantees, procurement, immigration levers, etc.) plausibly address the

constraint in context. If more than one policy tool could address the bottleneck (e.g., appropriations and tax credits for capital investment barriers), list all relevant mechanisms. Explain your reasoning.

Deliverables:

- One Excel file summarizing the results, with headers identifying the resource ID and categories, codes, and coded responses. Include a column explaining your reasoning titled “justification”. The filename should reflect the range of resource IDs coded (e.g., “Resources 1–5 Coding.xlsx”).
- For each resource, a separate text file named after the resource ID (e.g., “Resource 1_Highlights.txt”) containing the verbatim citations or inference tags used per category. To improve readability, prefix each excerpt with the category it supports (e.g., Nature; or Governance Level;). Multiple excerpts per category are acceptable when needed to defend your coding.

*****Attach 10 .txt files (these are the PDF sources that we listed in the “Master Research List”)*****

Complete Prompt Engineering and notes may be found here: [[Link to Prompt Engineering Notebook](#)]

Appendix H - Coded Bottlenecks by Frequency

No.	Bottleneck Code	Coding Frequency
1	Fragmented AI governance across jurisdictions	176
2	Absence of upskilling Programs for workers	144
3	Sparse Tools for Explainability	118
4	Cybersecurity Risks in AI Systems	48
5	Unequal Public-Private Collaboration	47
6	Lack of wide-spread standards demonstrating AI Competency	43
7	Shortage of Skilled Talent	41
8	Underfunded AI Public Infrastructure Investment	39
9	Data Center Capacity Constraints	34
10	Data Silos	29
11	Fragmented State-level Energy Policies	29
12	Uncertainty Around Intellectual Property (IP)	25
13	Uneven AI Adoption across sectors	25
14	High Capital Expenditure Requirements	23
15	Supply Chain (Security)	21
16	Export Controls on Semi-Conductors	18
17	Labeling and Annotation (Scarcity of high-quality data in specialized domains)	14
18	Underdeveloped grid interconnection process	13
19	Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	12
20	Regulatory Delays in Renewable Energy Sitting	11
21	Compute Divide	10
22	Lack of Nationwide Data Center Energy Standards	10
23	Inadequate Investment in Nuclear Energy Innovation	8
24	Lack of Public Infrastructure Investment	8
25	High Cost of Compute Infrastructure	7
26	AI-Specific Unionization Challenges	6
27	Limited Deployment of AI to Optimize Energy Systems	5

28	Chip Fabrication Limits	5
29	Unclear Foreign Investment Guidelines (CFIUS)	4
30	Inefficient Model Architectures	3
31	Supply Chain (High End GPU shortages)	3
32	Cryptomining and AI Competing for Power	2
33	Immigration Barriers for AI Talent	2
34	Edge Computing Limitations	2
35	Limited Federal Support for Clean Energy Procurement by Private Sector	2
36	Short term ROI Expenditures	2
37	No National Accounting Standard for AI Compute	2
38	Uneven Access to Talent Across Regions of the U.S.	2
39	Lack of Specialized AI Investment Vehicles	2
40	VC Concentration	2
41	Insufficient Broadband Access	2
42	High Cost of AI Talent	2
43	Valuation Inflation & Risk Aversion	1
44	STEM Educator Shortages	1
5	Underfunding of Public Research Universities	1
46	Insufficient Support for Apprenticeships in AI Fields	1
47	Lack of Federal Oversight of Data Center Water Usage for Cooling	1
	TOTAL	1,006

Appendix I - Bottlenecks Cited by Type of Bottleneck

Bottleneck by Type of Bottleneck	Frequency
Capital Investment	358
Fragmented AI governance across jurisdictions	176
Unequal Public-Private Collaboration	43
Underfunded AI Public Infrastructure Investment	38
Lack of wide-spread standards demonstrating AI Competency	22
High Capital Expenditure Requirements	22
Uncertainty Around Intellectual Property (IP)	17
Uneven AI Adoption across sectors	7
High Cost of Compute Infrastructure	6
Lack of Public Infrastructure Investment	5
Inadequate Investment in Nuclear Energy Innovation	5
Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	3
Short term ROI Expenditures	2
VC Concentration	2
Chip Fabrication Limits	2
Unclear Foreign Investment Guidelines (CFIUS)	2
Lack of Specialized AI Investment Vehicles	1
Uneven Access to Talent Across Regions of the U.S.	1
Valuation Inflation & Risk Aversion	1
Regulatory Delays in Renewable Energy Sitting	1
Supply Chain (Security)	1
Underfunding of Public Research Universities	1
Computing	318
Sparse Tools for Explainability	118
Cybersecurity Risks in AI Systems	48
Data Silos	29
Supply Chain (Security)	19
Export Controls on Semi-Conductors	18
Labeling and Annotation (Scarcity of high-quality data in specialized domains)	14

Lack of wide-spread standards demonstrating AI Competency	14
Compute Divide	10
Uncertainty Around Intellectual Property (IP)	8
Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	7
Uneven AI Adoption across sectors	6
Regulatory Delays in Renewable Energy Sitting	4
Supply Chain (High End GPU shortages)	3
Inefficient Model Architectures	3
Limited Deployment of AI to Optimize Energy Systems	3
Chip Fabrication Limits	3
Edge Computing Limitations	2
Unclear Foreign Investment Guidelines (CFIUS)	2
Insufficient Broadband Access	2
High Cost of Compute Infrastructure	1
Underfunded AI Public Infrastructure Investment	1
High Capital Expenditure Requirements	1
No National Accounting Standard for AI Compute	1
Lack of Specialized AI Investment Vehicles	1
Energy	109
Data Center Capacity Constraints	34
Fragmented State-level Energy Policies	29
Underdeveloped grid interconnection process	13
Lack of Nationwide Data Center Energy Standards	10
Regulatory Delays in Renewable Energy Sitting	6
Inadequate Investment in Nuclear Energy Innovation	3
Lack of Public Infrastructure Investment	3
Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	2
Limited Deployment of AI to Optimize Energy Systems	2
Limited Federal Support for Clean Energy Procurement by Private Sector	2
Cryptomining and AI Competing for Power	2
Supply Chain (Security)	1

No National Accounting Standard for AI Compute	1
Lack of Federal Oversight of Data Center Water Usage for Cooling	1
Labor	221
Absence of upskilling Programs for workers	144
Shortage of Skilled Talent	41
Uneven AI Adoption across sectors	12
Lack of wide-spread standards demonstrating AI Competency	7
AI-Specific Unionization Challenges	6
Unequal Public-Private Collaboration	4
Immigration Barriers for AI Talent	2
High Cost of AI Talent	2
Uneven Access to Talent Across Regions of the U.S.	1
Insufficient Support for Apprenticeships in AI Fields	1
STEM Educator Shortages	1

Appendix J - Complete List of BCI Ranked Bottlenecks and Scores

Rank	Bottleneck	Freq/max	Avg Impact	Avg Resolution	Avg Urgency	Normalized BCI
1	Fragmented AI governance across jurisdictions	1.0000	0.8006	0.8636	0.9625	0.1672
2	Absence of upskilling Programs for workers	0.8182	0.7938	0.9653	0.9521	0.1500
3	Sparse Tools for Explainability	0.6705	0.7737	0.9661	0.9492	0.1195
4	Cybersecurity Risks in AI Systems	0.2727	0.9271	0.9063	0.9625	0.0554
5	Shortage of Skilled Talent	0.2330	0.8561	0.9512	0.9780	0.0466
6	Lack of wide-spread standards demonstrating AI Competency	0.2443	0.8419	0.8721	0.9093	0.0410
7	Underfunded AI Public Infrastructure Investment	0.2216	0.8872	0.9359	0.8846	0.0409
8	Unequal Public-Private Collaboration	0.2670	0.8213	0.7872	0.9234	0.0401
9	Data Center Capacity Constraints	0.1932	0.9324	0.7941	0.9029	0.0325
10	Data Silos	0.1648	0.6897	1.0000	0.9897	0.0283
11	Uncertainty Around Intellectual Property (IP)	0.1420	0.8400	0.9800	0.9520	0.0280
12	Fragmented State-level Energy Policies	0.1648	0.9448	0.7069	1.0000	0.0277
13	Uneven AI Adoption across sectors	0.1420	0.7280	1.0000	0.9760	0.0254
14	High Capital Expenditure Requirements	0.1307	0.8957	0.8696	0.9870	0.0252
15	Supply Chain (Security)	0.1193	0.9619	0.6667	0.9714	0.0187
16	Export Controls on Semi-Conductors	0.1023	0.8889	0.6722	1.0000	0.0154
17	Underdeveloped grid interconnection process	0.0739	0.9692	0.8077	0.9769	0.0142
18	Labeling and Annotation (Scarcity of high-quality data in specialized domains)	0.0795	0.8286	0.8571	0.9786	0.0139
19	Lack of Nationwide Data Center	0.0568	0.9600	0.9500	0.9700	0.0126

	Energy Standards					
20	Supply Chain (Component Shortages in US) (transformers, chips, circuit breakers, etc)	0.0682	0.8667	0.7917	0.9500	0.0112
21	Regulatory Delays in Renewable Energy Sitting	0.0625	0.8909	0.7818	0.9727	0.0106
22	Compute Divide	0.0568	0.9200	0.8500	0.9400	0.0105
23	Inadequate Investment in Nuclear Energy Innovation	0.0455	0.9500	0.7500	0.9625	0.0078
24	AI-Specific Unionization Challenges	0.0341	0.8667	0.7500	0.9500	0.0053
25	High Cost of Compute Infrastructure	0.0398	0.8857	0.7143	0.8286	0.0052
26	Lack of Public Infrastructure Investment	0.0455	0.9000	0.6875	0.6750	0.0048
27	Limited Deployment of AI to Optimize Energy Systems	0.0284	0.7000	1.0000	0.8800	0.0044
28	Chip Fabrication Limits	0.0284	0.9200	0.6000	1.0000	0.0039
29	Unclear Foreign Investment Guidelines (CFIUS)	0.0227	0.9000	0.7500	1.0000	0.0039
30	Limited Federal Support for Clean Energy Procurement by Private Sector	0.0114	1.0000	1.0000	1.0000	0.0029
31	Supply Chain (High End GPU shortages)	0.0170	0.7333	1.0000	0.9000	0.0028
32	High Cost of AI Talent	0.0114	0.8000	1.0000	1.0000	0.0023
33	Immigration Barriers for AI Talent	0.0114	0.8000	1.0000	1.0000	0.0023
34	Insufficient Broadband Access	0.0114	0.8000	1.0000	1.0000	0.0023
35	Lack of Specialized AI Investment Vehicles	0.0114	0.8000	1.0000	1.0000	0.0023
36	Inefficient Model Architectures	0.0170	0.7333	0.8333	0.7000	0.0018
37	Uneven Access to Talent Across Regions of the U.S.	0.0114	0.8000	0.7500	1.0000	0.0017
38	Cryptomining and AI Competing for Power	0.0114	1.0000	0.7500	0.7000	0.0015
39	Edge Computing Limitations	0.0114	0.6000	1.0000	0.8500	0.0015
40	No National Accounting Standard for AI Compute	0.0114	0.6000	1.0000	0.8500	0.0015

41	Short term ROI Expenditures	0.0114	0.6000	1.0000	0.8500	0.0015
42	VC Concentration	0.0114	0.6000	1.0000	0.8500	0.0015
43	Insufficient Support for Apprenticeships in AI Fields	0.0057	1.0000	1.0000	1.0000	0.0014
44	Underfunding of Public Research Universities	0.0057	0.6000	1.0000	1.0000	0.0009
45	Valuation Inflation & Risk Aversion	0.0057	0.6000	1.0000	1.0000	0.0009
46	Lack of Federal Oversight of Data Center Water Usage for Cooling	0.0057	1.0000	0.5000	1.0000	0.0007
47	STEM Educator Shortages	0.0057	0.6000	0.5000	1.0000	0.0004