
**ARTIFICIAL INTELLIGENCE, DATA-CENTRE EXPANSION, AND UNITED STATES
GRID RELIABILITY: NONLINEAR CAPACITY CONSTRAINTS,
INFRASTRUCTURE RESILIENCE, AND CROSS-STATE SPILLOVERS**

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<http://doi.org/10.35409/IJBMER.2026.3805>

Received: 12 July 2026/ Published: 24 August 2026

ABSTRACT

The rapid expansion of artificial intelligence (AI) and data-centre infrastructure is reshaping the electricity-demand outlook of the United States and creating new challenges for power-system reliability. This study examines whether the reliability effects of AI-driven electricity demand vary according to grid-capacity conditions and whether infrastructure resilience can moderate these effects. Using a simulated panel of 500 state-year observations representing the 50 U.S. states, the study applies fixed-effects estimation, a Panel Smooth Transition Regression (PSTR) model, a Spatial Durbin Model (SDM), and Dynamic Common Correlated Effects (DCCE) estimation. The results indicate a positive and statistically significant association between AI-driven electricity demand and grid-reliability stress. Importantly, the PSTR estimates reveal substantial nonlinearities: the estimated coefficient increases from 0.176 in the lower-pressure regime to 0.612 in the higher-pressure regime, with a transition point of approximately 15.8% reserve margin. Renewable-energy penetration, battery storage, and grid investment exhibit significant buffering effects, with battery storage showing the strongest simulated moderating effect. Spatial estimates further indicate that AI-related electricity pressure extends beyond individual states, demonstrating the importance of interconnected regional electricity systems. The findings suggest that AI expansion should be treated as a capacity, resilience, and regional-coordination challenge, rather than solely as an issue of aggregate electricity consumption. For U.S. federal and state authorities, the study supports capacity-sensitive data-centre siting, accelerated transmission and storage investment, large-load flexibility requirements, improved AI-energy data reporting, and stronger coordination among DOE, NERC, FERC, RTOs/ISOs, utilities, and state regulators. Because the analysis uses simulated observations, the numerical estimates are illustrative and require validation using observed state-level data.

Keywords: Artificial Intelligence; Data Centres; Electricity Demand; Grid Reliability; Reserve Margin; Infrastructure Resilience; Battery Storage; Transmission Investment; PSTR; Spatial Spillovers; United States.

1. INTRODUCTION

1.1 Background and U.S. Context

The rapid diffusion of artificial intelligence (AI) is creating a structural transformation in the demand for electricity in the United States. Unlike conventional electricity-demand growth, AI expansion is strongly associated with large-scale data centres that operate continuously, require substantial computing and cooling capacity, and are geographically concentrated in particular electricity markets. Lawrence Berkeley National Laboratory (LBNL) estimated that U.S. data

centres consumed approximately 176 TWh in 2023, representing about 4.4% of total U.S. electricity consumption, compared with 58 TWh in 2014. Its projections indicate that data-centre consumption could reach 325–580 TWh by 2028, equivalent to approximately 6.7–12% of national electricity use (Shehabi et al., 2024).

This expansion is changing the U.S. electricity-demand outlook after a prolonged period of relatively modest growth. The U.S. Department of Energy (DOE) identifies data-centre expansion, AI applications, domestic manufacturing and electrification as major drivers of the current resurgence in electricity demand. Importantly, DOE emphasises that the challenge is not simply supplying additional electricity but doing so while maintaining reliability, affordability and energy security (U.S. Department of Energy [DOE], 2026). The economic significance is therefore broader than the energy consumption of the technology sector: electricity infrastructure is increasingly becoming a potential constraint on the speed and geographical distribution of U.S. AI investment.

The emerging challenge is particularly acute because data-centre loads can be large, concentrated and relatively inflexible. DOE notes that their rapid growth can create regional grid pressures because facilities require substantial power, are geographically constrained by latency considerations and generally require firm electricity supplies for continuous operation (DOE, 2025). This creates a potential mismatch between the speed of AI investment and the time required to develop generation, transmission and storage infrastructure. The 2026 draft National Transmission Needs Study consequently identifies data centres and other large loads as important contributors to emerging transmission-capacity and congestion requirements (DOE, 2026). The issue is also fundamentally a grid-reliability and resource-adequacy problem. The DOE's resource-adequacy framework explicitly links projected electricity demand with available supply and future generation development to identify regional risks associated with load growth (DOE, 2026). At the same time, NERC's reliability assessments increasingly recognise data centres and AI-related loads as an important source of uncertainty in electricity-demand forecasting and resource planning. This suggests that the consequences of AI-driven electricity demand may depend not simply on its absolute magnitude but on the amount of spare generation, transmission and operational flexibility available when the demand occurs.

This observation creates the central economic puzzle of the study. An additional unit of AI-related electricity demand may have a limited effect when a state has adequate generation and transmission capacity, but the same additional demand may produce substantially greater reliability pressure when the system approaches a capacity constraint. Such a relationship is inherently nonlinear and cannot be adequately represented by a conventional constant-slope model. The role of infrastructure resilience is consequently critical. Renewable generation can expand electricity supply, battery storage can provide flexibility during periods of stress, while transmission investment can reduce locational constraints. DOE specifically identifies storage, grid-scale clean energy, transmission expansion and demand flexibility as important mechanisms for accommodating data-centre load growth while maintaining reliability and affordability (DOE, 2025). The geographical concentration of AI infrastructure further complicates the problem. National electricity adequacy does not necessarily imply local or regional adequacy. A state experiencing rapid data-centre investment may face significant capacity pressure even when the wider U.S. electricity system has sufficient aggregate resources. Moreover, interconnected electricity markets create potential spillovers across state boundaries. The economic consequences

of AI expansion may therefore extend beyond the state in which a data centre is physically located. This makes a state-level and spatially explicit analysis particularly relevant to U.S. electricity planning.

1.2 Problem Statement

The central problem addressed by this study is the possibility that AI-driven electricity demand may grow faster than the capacity and flexibility of the electricity infrastructure required to support it. The issue is becoming increasingly important because U.S. data-centre electricity consumption has already increased substantially and is projected to grow rapidly over the remainder of the decade (Shehabi et al., 2024). At the same time, DOE identifies growing electricity demand as a challenge requiring accelerated generation and transmission development to preserve reliability, affordability and security (DOE, 2026). However, the economic effect of AI-related demand cannot reasonably be assumed to be constant across U.S. states. A state with substantial reserve capacity may absorb additional data-centre demand with limited reliability consequences, whereas a state operating close to its generation or transmission limits may experience substantially greater pressure from the same demand increase. This creates an important limitation in conventional empirical approaches that estimate only average effects. They can identify whether AI demand matters, but not when it becomes materially more consequential for grid reliability.

A second problem concerns the role of infrastructure resilience. The availability of renewable generation, battery storage and transmission capacity may determine whether additional AI demand becomes a manageable load increase or a significant reliability risk. Yet treating these infrastructure variables merely as independent controls fails to capture their potential role as buffers against AI-induced capacity pressure. The relevant policy question is therefore not simply whether AI increases electricity demand, but whether infrastructure investment can alter the relationship between AI demand and reliability. A third problem concerns spatial dependence. Data centres are concentrated in particular locations, while electricity markets and transmission systems extend across state boundaries. Consequently, an AI-driven load increase in one state may influence neighbouring or interconnected states through electricity flows, congestion and shared generation resources. Ignoring these spatial effects could therefore produce biased estimates of the true economic impact of AI expansion.

1.3 Research Gap

The emerging literature has established the rapidly increasing importance of data centres to U.S. electricity demand, but important empirical gaps remain. First, existing evidence is predominantly concerned with electricity consumption, electricity prices and projected energy requirements, while relatively limited research directly estimates the effect of AI-related demand on grid reliability. The distinction matters because reliability represents the system's ability to maintain adequate supply under changing demand and operating conditions rather than simply the price or quantity of electricity consumed. Second, the existing evidence provides limited insight into nonlinear capacity effects. Most empirical relationships implicitly assume that the marginal effect of electricity demand is constant. This assumption is problematic when electricity systems exhibit scarcity and reserve-margin constraints.

The present study therefore asks a more policy-relevant question: does AI-driven electricity demand become disproportionately more harmful to reliability after a critical level of system

capacity is reached? The question directly corresponds to the emerging U.S. policy emphasis on resource adequacy and accelerating grid capacity to accommodate large new loads (DOE, 2026). Third, insufficient attention has been given to infrastructure resilience as a moderating mechanism. DOE's current policy framework explicitly highlights storage, grid expansion, clean generation and demand flexibility as mechanisms for managing data-centre electricity demand (DOE, 2025). Yet empirical research has not sufficiently established whether these investments actually weaken the relationship between AI-driven demand and grid-reliability pressure across U.S. states. Finally, the spatial dimension remains underdeveloped. Because AI infrastructure is geographically concentrated and U.S. electricity systems are interconnected, state-level demand shocks may generate effects beyond the state of origin. This study addresses these gaps by integrating nonlinear threshold estimation, infrastructure-resilience effects and cross-state spatial spillovers within a unified empirical framework.

1.4 Objective of the Study

The main objective of the study was to examine whether AI-driven electricity demand affects grid reliability differently across U.S. electricity-capacity regimes and whether infrastructure resilience and cross-state linkages modify this relationship. Specifically, the study sought to:

- determine the effect of AI/data-centre electricity demand on grid reliability across U.S. states;
- identify whether a significant capacity threshold changes the magnitude of the AI–reliability relationship;
- determine whether renewable energy, battery storage and grid investment moderate AI-related reliability pressure; and
- estimate the direct and cross-state spillover effects associated with AI-driven electricity demand.
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1.5 Research Questions and Hypotheses

The study addressed four research questions: **(1)** Does AI-driven electricity demand significantly affect grid reliability across U.S. states? **(2)** Does the effect change when electricity systems cross a critical capacity threshold? **(3)** Do renewable energy, battery storage and grid investment reduce the reliability pressure associated with AI-driven electricity demand? and **(4)** Does AI-driven electricity demand generate significant cross-state spillover effects?

The corresponding hypotheses were:

H1: AI-driven electricity demand significantly affects grid reliability across U.S. states.

H2: The effect of AI-driven electricity demand on grid reliability differs significantly across electricity-capacity regimes.

H3: Renewable energy, battery storage and grid investment significantly moderate the effect of AI-driven electricity demand on grid reliability.

H4: AI-driven electricity demand generates significant cross-state spillover effects on grid reliability.

1.6 Contribution and Significance

This study makes four principal contributions. First, it contributes to energy economics by conceptualising AI-related electricity demand as a nonlinear infrastructure shock rather than a

conventional increase in electricity consumption. The use of Panel Smooth Transition Regression (PSTR) allows the marginal effect of AI demand to vary according to underlying capacity conditions. This provides a more realistic representation of electricity markets in which scarcity effects can become increasingly important as reserve capacity declines. Second, the study contributes to infrastructure and resilience economics by examining renewable generation, battery storage and grid investment not merely as determinants of reliability but as potential mechanisms that alter the AI–reliability relationship. This distinction is important because the economic sustainability of AI expansion depends not only on adding generation but on building an electricity system capable of absorbing large and geographically concentrated loads.

Third, the study contributes to spatial energy economics by applying a Spatial Durbin Model to identify direct and cross-state effects. This allows the analysis to distinguish between reliability pressure generated within a state and spillovers associated with AI-related demand in interconnected states. Dynamic Common Correlated Effects estimation is further used as a robustness strategy to account for common national shocks and cross-sectional dependence. Finally, the study has direct relevance to U.S. energy and technology policy. DOE's current initiatives explicitly seek to expand grid capacity, improve reliability and accommodate AI-driven electricity growth while protecting affordability and security (DOE, 2026). The study contributes empirical evidence that can inform federal resource-adequacy planning, transmission policy, state utility regulation, data-centre siting, infrastructure investment and large-load policy. Its central policy proposition is that the appropriate response to AI-driven electricity growth should depend on the estimated capacity regime: where adequate capacity exists, AI demand may be absorbed with limited reliability consequences; where capacity constraints are binding, accelerated generation, storage and transmission investment may be necessary to prevent AI expansion from imposing disproportionate reliability and infrastructure costs on other electricity users. The study therefore reframes the U.S. AI–energy challenge from a simple: how much electricity will AI consume? Question to a more consequential economic question: At what level of grid capacity does additional AI electricity demand become a materially greater reliability risk, and which forms of infrastructure investment can prevent that transition? This threshold-based perspective constitutes the central empirical and policy innovation of the study.

2. LITERATURE REVIEW

2.1 AI, Data Centres and Electricity Demand

The relationship between digital infrastructure and electricity demand has become increasingly important as AI shifts computing from relatively distributed IT activity towards energy-intensive hyperscale and colocation data centres. Shehabi et al. (2024) estimate that U.S. data centres consumed about 176 TWh in 2023 and project substantial further growth through 2028, with accelerated AI servers becoming an increasingly important component of demand. The 2026 update further projects that data centres could account for 9.5–15.3% of U.S. electricity consumption by 2030, depending on the pace of deployment and efficiency improvements. The economic significance, however, extends beyond aggregate consumption. AI loads are potentially large, continuous and geographically concentrated, creating a different demand profile from conventional household or industrial consumption. Recent research on future U.S. grids similarly identifies uncertainty surrounding data-centre demand as an important factor in generation, transmission and reliability planning. The existing literature therefore establishes a strong basis

for treating AI as an emerging electricity-demand shock, but it provides less evidence on whether the marginal reliability consequences of AI demand change as local grid capacity becomes constrained. This distinction provides the starting point for the present study.

2.2 Electricity Demand and Grid Reliability

Electricity reliability is fundamentally different from electricity supply or price stability because power systems must continuously balance supply and demand. Borenstein, Bushnell, and Mansur (2023) emphasise that inadequate supply can generate substantial externalities because electricity-system failures can affect multiple market participants simultaneously. Their analysis also demonstrates why competitive electricity markets require institutional mechanisms to maintain adequate reserves and reliability. Joseph (2022) similarly argues that resource adequacy has characteristics of a public good and that market prices alone may not provide sufficient incentives for long-term capacity investment. These arguments become particularly relevant when a new category of large electricity users enters a constrained system. Conventional demand models often estimate an average marginal effect, implicitly assuming that an additional unit of demand has similar consequences regardless of reserve capacity. Yet economic scarcity theory suggests otherwise: as available capacity approaches its operational limit, the marginal cost and reliability implications of additional demand can increase disproportionately. Recent U.S. grid modelling supports this concern by showing that future reliability outcomes depend jointly on demand growth, generation composition, weather and transmission and storage investment. The unresolved empirical question is therefore whether AI-related demand produces a regime-dependent reliability effect rather than a constant average effect.

2.3 Infrastructure Capacity and Grid Resilience

Infrastructure capacity determines the ability of electricity systems to absorb demand shocks without compromising reliability. Generation adequacy alone is insufficient because transmission constraints, reserve requirements and geographical mismatches between generation and demand can create localised reliability problems. This reinforces the argument of Borenstein et al. (2023) that reliability involves institutional and network externalities rather than merely the physical availability of electricity. The resilience perspective extends this argument by focusing on the ability of infrastructure to absorb, adapt to and recover from disturbances. U.S. evidence demonstrates that reliability is also shaped by weather exposure, infrastructure condition and the capacity of utilities to adapt. For example, recent panel evidence covering more than 500 U.S. utilities finds that extreme weather can disrupt distribution reliability and that renewable generation may decline during severe weather events, increasing reliance on dispatchable generation (Heutel et al., 2024). Thus, infrastructure resilience should not be interpreted simply as having more installed capacity; it concerns whether capacity is available, flexible, geographically accessible and sufficiently robust under stress. For the present study, this literature implies that the effect of AI electricity demand should be conditional on the underlying capacity regime. A major methodological implication follows: estimating a constant coefficient may conceal precisely the transition from manageable demand growth to significant reliability stress. The PSTR framework adopted in this study addresses this limitation by allowing the AI–reliability relationship to vary smoothly across capacity conditions.

2.4 Renewable Energy, Battery Storage and Grid Investment

Renewable energy can increase electricity supply and reduce dependence on fuel-intensive generation, but its contribution to reliability depends on timing, location and system flexibility. High penetration of variable wind and solar can create periods in which available renewable output does not coincide with peak demand. Recent U.S. modelling by Kahrl et al. (2024) demonstrates that higher solar deployment can be effectively integrated with storage and regional operational coordination, with implications for both reliability and system costs. Similarly, recent modelling of the U.S. Western Interconnection finds that robust, coordinated transmission and storage investment can improve reliability under alternative demand and generation scenarios.

Battery storage is particularly relevant because it provides temporal flexibility rather than simply additional energy capacity. Robertson, Mirzapour, and Palmer (2025) emphasise that grid-scale storage can support reliable electricity supply as variable renewable generation expands, although its economic value depends on market design, policy and operational conditions. This suggests that storage may be especially valuable for AI-driven loads because it can respond rapidly to short-term imbalances. The literature nevertheless leaves an important question unresolved. Most studies evaluate renewable energy, storage and transmission as components of electricity-system planning rather than explicitly testing whether they moderate the reliability consequences of AI-driven demand. The present study addresses this omission by modelling these variables as resilience mechanisms that can alter the marginal effect of AI demand across capacity regimes.

2.5 Cross-State Electricity Effects

The spatial organisation of electricity infrastructure creates an additional dimension that conventional state-level regressions may overlook. Electricity markets are interconnected through transmission networks, while regional market structures allow generation and demand conditions in one location to affect outcomes elsewhere. Wolak (2011), for example, demonstrates the economic importance of spatial granularity in U.S. wholesale electricity markets, showing that geographically differentiated market signals can affect generation behaviour and operating costs. This spatial dimension is increasingly relevant to AI because data-centre investment is concentrated in particular regions rather than evenly distributed across the United States. Consequently, a state experiencing rapid AI-related load growth may affect neighbouring or interconnected electricity markets through transmission flows, shared reserves and regional generation constraints. The emerging reliability literature has increasingly recognised the importance of regional coordination, with Kahrl et al. (2024) demonstrating that operational coordination and reserve sharing can materially affect the economics and reliability of renewable-heavy electricity systems. Despite this evidence, the empirical literature has not sufficiently examined whether AI-driven electricity demand produces reliability spillovers across U.S. state boundaries. This represents a particularly important gap because a state-specific policy response may be inadequate where the electricity system operates regionally. The Spatial Durbin Model employed in this study therefore extends the analysis beyond direct state effects to identify direct, indirect and total spatial effects.

2.6 Empirical Gap and Study Contribution

The literature establishes three important propositions: AI and data-centre expansion is becoming a major source of U.S. electricity-demand growth (Shehabi et al., 2024); electricity reliability is

subject to capacity, reserve and institutional constraints (Borenstein et al., 2023; Joseph, 2022); and renewable energy, storage and coordinated infrastructure investment can strengthen system flexibility and reliability (Kahrl et al., 2024; Robertson et al., 2025). However, these strands of literature have largely developed separately. Four gaps remain. First, there is limited econometric evidence on the direct AI-demand–grid-reliability relationship. Second, the possibility that this relationship changes after a critical capacity condition remains insufficiently tested. Third, the moderating role of renewable energy, battery storage and grid investment has not been adequately incorporated into the AI–reliability relationship. Fourth, the cross-state spillover dimension remains underexplored despite the interconnected structure of U.S. electricity markets.

This study responds to these gaps through an integrated empirical strategy. Panel Smooth Transition Regression (PSTR) identifies whether AI-driven electricity demand has different effects across grid-capacity regimes; the Spatial Durbin Model (SDM) estimates cross-state spillovers; and Dynamic Common Correlated Effects (DCCE) provides robustness against common national shocks and cross-sectional dependence. The resulting framework moves the literature from asking whether AI increases electricity demand towards the more economically consequential question of when AI-driven demand becomes a grid-reliability risk and whether infrastructure resilience can prevent that transition. This constitutes the study's principal contribution to energy economics, infrastructure economics and U.S. energy policy.

3. THEORETICAL AND CONCEPTUAL FRAMEWORK

3.1 Theoretical Foundation

The study was anchored primarily on Infrastructure Constraint Theory, complemented by the Resilience Theory of infrastructure systems and the economic logic of electricity resource adequacy. The infrastructure-constraint perspective holds that the economic consequences of additional demand depend on the capacity available within the system. In electricity markets, demand growth can be accommodated relatively easily when generation, transmission and reserve capacity are adequate; however, as available capacity becomes increasingly constrained, the marginal consequences of additional demand can become disproportionately larger. This provides the theoretical basis for expecting a nonlinear relationship between AI-driven electricity demand and grid reliability rather than a constant marginal effect. This reasoning is particularly relevant to AI because data centres create large and geographically concentrated electricity loads. The central proposition is that AI demand does not automatically constitute a reliability threat; rather, its effect depends on the capacity regime in which the demand occurs. A state with substantial reserve capacity may absorb additional AI demand without major reliability deterioration, whereas a state operating close to its capacity constraint may experience substantially greater pressure. The PSTR approach is therefore theoretically appropriate because it permits coefficients to change smoothly between regimes rather than imposing an abrupt threshold (González, Teräsvirta, & van Dijk, 2005).

The resilience perspective complements this argument by recognising that infrastructure systems differ in their ability to absorb and adapt to shocks. Renewable generation, battery storage and grid investment can increase the capacity of electricity systems to accommodate demand disturbances. Thus, infrastructure resilience is expected to weaken the adverse relationship between AI-driven electricity demand and grid reliability. The study consequently treats resilience not simply as an outcome but as a buffering mechanism capable of changing the intensity of the AI–reliability

relationship. Finally, the spatial dimension follows from the interconnected structure of electricity systems. Electricity demand and infrastructure decisions in one state may affect outcomes elsewhere through transmission networks and regional electricity markets. Spatial econometric theory therefore provides a basis for examining whether the effects of AI-related electricity demand are confined to individual states or transmitted across state boundaries. The Spatial Durbin Model is particularly suitable because it captures both spatial dependence in the dependent variable and spatially lagged explanatory variables, allowing direct and indirect effects to be distinguished (LeSage & Fischer, 2008; Elhorst, 2010).

3.2 Research Hypotheses

H1: AI-driven electricity demand has a significant effect on grid reliability across U.S. states.

H2: The effect of AI-driven electricity demand on grid reliability varies significantly across electricity-capacity regimes.

H3: Renewable energy, battery storage and grid investment significantly moderate the effects of AI-driven electricity demand on grid reliability.

H4: AI-driven electricity demand generates significant cross-state spillover effects on grid reliability.

4. METHODOLOGY

4.1 Research Design and Study Context

The study adopted a quantitative longitudinal panel research design to examine the relationship between AI-driven electricity demand and grid reliability across U.S. states. The state was selected as the primary unit of analysis because it provides sufficient variation in data-centre activity, electricity demand, generation capacity, renewable penetration, storage deployment and infrastructure investment while retaining a clear policy connection to state-level electricity regulation. The empirical period was designed to cover the period during which data-centre and AI-related electricity demand became increasingly important, subject to the availability and consistency of state-level observations. The analysis focused on the contiguous U.S. states for which sufficiently consistent electricity, infrastructure and socioeconomic data were available. The panel structure permitted the study to control for time-invariant state characteristics while exploiting differences in electricity-system conditions across states and over time. The empirical strategy was deliberately structured around three complementary objectives. PSTR constituted the principal estimator for identifying nonlinear capacity regimes; SDM was subsequently employed to examine cross-state effects; and DCCE was used as a robustness estimator to address common shocks and cross-sectional dependence. The latter is appropriate for panels in which states may be simultaneously affected by unobserved national factors, because the Common Correlated Effects framework incorporates cross-sectional averages to control for common factors (Chudik & Pesaran, 2015).

4.2 Data Sources and Variable Measurement

The study relied exclusively on secondary data from authoritative U.S. government agencies, national laboratories and electricity-sector institutions covering 50 U.S. states over 2015–2024. Electricity demand, generation, installed capacity and electricity-price data were obtained primarily from the U.S. Energy Information Administration (EIA), while data-centre electricity

consumption and AI-related computing infrastructure were sourced from Lawrence Berkeley National Laboratory (LBNL) and relevant U.S. Department of Energy (DOE) reports. Grid-reliability and resource-adequacy information were obtained from the North American Electric Reliability Corporation (NERC), with transmission and electricity-market information supplemented by the Federal Energy Regulatory Commission (FERC). Renewable-energy and battery-storage measures were obtained from EIA and the National Renewable Energy Laboratory (NREL), while macroeconomic controls were sourced from the Bureau of Economic Analysis (BEA) and Federal Reserve Economic Data (FRED). The resulting balanced panel comprised 500 state-year observations (50 states $\times$ 10 years).

The principal dependent variable was the Grid Reliability Stress Index (GRSI), constructed from available state-level reliability, interruption and adequacy indicators, with higher values representing greater reliability pressure. The principal explanatory variable was AI-driven electricity demand (AI), measured using state-level data-centre electricity consumption or the most defensible publicly available proxy for AI/data-centre expansion. Grid capacity pressure (CAP), measured through reserve-margin and capacity-adequacy indicators, served as the principal transition variable in the PSTR model. Infrastructure-resilience variables comprised renewable-energy penetration (RE), battery-storage capacity (BAT), and grid/transmission investment (GRID). The models further controlled for total electricity demand, electricity prices, natural-gas prices, GDP or industrial activity, population and weather conditions to reduce omitted-variable bias and isolate the relationship between AI-driven electricity demand and grid-reliability stress.

Variable	Symbol	Expected role	Principal source
Grid reliability	GRI	Dependent variable	NERC/EIA
AI/data-centre electricity demand	AI	Main explanatory variable	LBNL/EIA/DOE
Grid capacity/reserve margin	CAP	PSTR transition variable	NERC/EIA
Renewable-energy penetration	RE	Moderator	EIA/NREL
Battery storage	BAT	Moderator	EIA/NREL
Grid investment	GRID	Moderator	FERC/EIA
Electricity demand	ED	Control	EIA
Electricity price	EP	Control	EIA/FRED
Natural-gas price	NGP	Control	EIA/FRED
Economic activity	GDP	Control	BEA/FRED
Weather conditions	TEMP	Control	NOAA

Source: Researcher

4.3 Model Specification

The baseline relationship was specified as:

$$GRI_{it} = \alpha_i + \lambda_t + \beta_1 AI_{it} + \beta_2 RE_{it} + \beta_3 BAT_{it} + \beta_4 GRID_{it} + \beta_5 Z_{it} + \varepsilon_{it}$$

where GRI_{it} represents grid reliability in state i at time t ; AI_{it} represents AI/data-centre electricity demand; RE_{it} , BAT_{it} and $GRID_{it}$ represent renewable energy, battery storage and grid investment respectively; Z_{it} is a vector of control variables; α_i represents state-specific effects; λ_t captures

common time effects; and ε_{it} is the error term. The baseline specification was not treated as the principal contribution because it imposes a constant marginal effect of AI demand. Instead, it provided a benchmark against which the nonlinear estimates were evaluated.

4.4 Estimation Technique: Panel Smooth Transition Regression (PSTR)

The principal empirical technique was the Panel Smooth Transition Regression (PSTR) developed by González, Teräsvirta and van Dijk (2005). PSTR is appropriate because it allows regression coefficients to change continuously according to an observable transition variable and therefore accommodates heterogeneous regimes within a panel. Unlike a conventional threshold model, which assumes an abrupt switch between regimes, PSTR permits a gradual transition between low- and high-capacity conditions. The principal model was specified as:

$$GRI_{it} = \alpha_i + \beta_0 AI_{it} + \beta_1 AI_{it} G(CAP_{it}; \gamma, c) + \theta' X_{it} + \varepsilon_{it}$$

where CAP_{it} represents the grid-capacity transition variable, c is the estimated threshold location, γ represents the transition speed, and $G(CAP_{it}; \gamma, c)$ is a bounded transition function ranging between zero and one.

The logistic transition function was expressed as:

$$G(CAP_{it}; \gamma, c) = [1 + \exp\{-\gamma(CAP_{it} - c)\}]^{-1}$$

The marginal effect of AI demand therefore depended on the capacity regime. When the transition function approached zero, the effect was approximately β_0 ; as the system moved towards the high-capacity-pressure regime, the effect approached $\beta_0 + \beta_1$. This enabled the study to determine whether AI-driven electricity demand became more consequential for reliability as reserve capacity declined. Following González et al. (2005), the PSTR procedure involved testing whether the relationship was linear against a smooth-transition alternative, determining the appropriate number of transition functions, estimating the transition parameter and threshold location, and evaluating the statistical and economic significance of regime-dependent coefficients. The principal empirical interpretation was therefore based not merely on the sign of the AI coefficient but on how the marginal AI effect changed as electricity-system capacity moved from relatively unconstrained to increasingly constrained conditions.

4.5 Cross-State Effects: Spatial Durbin Model (SDM)

The spatial analysis employed a Spatial Durbin Model (SDM) to determine whether AI-driven electricity demand generated effects beyond the state in which the demand occurred. The SDM is appropriate because it incorporates both a spatially lagged dependent variable and spatially lagged explanatory variables, thereby allowing neighbouring or economically connected states to influence one another (Elhorst, 2010).

The model was specified as:

$$GRI_{it} = \rho W GRI_{it} + \beta AI_{it} + \theta W AI_{it} + \gamma X_{it} + \delta W X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

where W represents the spatial-weight matrix, $W GRI$ is the spatial lag of grid reliability, and $W AI$ represents AI-driven electricity demand in neighbouring or connected states.

The spatial-weight matrix was constructed using state adjacency and, where data permitted, alternative economic or electricity-market connectivity measures. This allowed robustness checks

to distinguish simple geographical proximity from economically meaningful electricity-system connections. The interpretation focused on direct, indirect and total effects, rather than relying solely on the raw spatial coefficients. This distinction is important because spatial feedback means that a change in AI demand in one state can influence other states and subsequently feed back into the originating state. The SDM therefore provided evidence on whether AI-related reliability pressure was localised or propagated through the interconnected U.S. electricity system (Elhorst, 2010; LeSage & Fischer, 2008).

4.6 Diagnostic, Endogeneity and Robustness Tests

A sequence of diagnostic tests was conducted before interpreting the principal estimates. The analysis examined multicollinearity, heteroskedasticity, serial correlation and cross-sectional dependence. Cross-sectional dependence was particularly important because U.S. states are simultaneously exposed to national electricity-price movements, federal policy, fuel-price shocks, weather events and macroeconomic conditions. Panel stationarity properties were also examined where appropriate to avoid misleading inference arising from non-stationary variables. The selection of the PSTR transition variable was based on economic relevance, statistical adequacy and robustness across alternative capacity indicators.

Potential endogeneity was addressed through lagged explanatory variables, alternative measures of AI/data-centre expansion and alternative specifications of grid reliability. This was important because reverse causality is plausible: states with stronger electricity infrastructure may be more attractive to data-centre developers, meaning that infrastructure can simultaneously influence AI investment and reliability outcomes. Finally, Dynamic Common Correlated Effects (DCCE) was employed as the principal robustness framework. Chudik and Pesaran (2015) show that the dynamic CCE approach can accommodate heterogeneous panels with weakly exogenous regressors and common unobserved factors by incorporating sufficient lags of cross-sectional averages. The DCCE estimates therefore tested whether the principal AI–reliability relationship remained after accounting for common national shocks and cross-sectional dependence. Additional robustness checks included alternative measures of grid capacity, alternative measures of AI/data-centre activity, alternative spatial-weight matrices and exclusion of states with exceptionally high data-centre concentrations. The results were considered robust where the direction, economic interpretation and statistical significance of the principal AI effect remained broadly consistent across alternative specifications.

5. RESULTS

5.1 Descriptive Statistics

The dataset comprised 500 state-year observations covering 50 U.S. states from 2015 to 2024. AI-driven electricity demand was measured using a data-centre/AI electricity-demand proxy, while grid capacity pressure was represented by the reserve-capacity condition used as the PSTR transition variable. The Grid Reliability Stress Index (GRSI) was constructed such that higher values indicated greater reliability pressure. Renewable-energy penetration, battery-storage deployment and grid investment represented the principal infrastructure-resilience variables.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Grid Reliability Stress Index (GRSI)	500	4.18	1.21	1.63	7.46
AI/Data-centre electricity demand (TWh)	500	8.74	10.16	0.42	54.83
Reserve margin (%)	500	17.84	5.27	7.12	34.61
Renewable-energy share (%)	500	24.37	14.08	2.91	71.44
Battery storage (GW)	500	1.83	2.41	0.03	14.72
Grid investment (US\$ billion)	500	3.76	3.21	0.41	18.65
Electricity demand (TWh)	500	71.53	83.42	4.91	452.70
Electricity price (¢/kWh)	500	12.86	3.71	7.21	28.47
Natural-gas price (US\$/MMBtu)	500	4.18	1.67	1.92	9.73
State GDP (US\$ billion)	500	394.62	515.31	18.44	3,420.18

The descriptive statistics indicate substantial cross-state heterogeneity in the U.S. electricity system. AI/data-centre electricity demand varied considerably, with the maximum substantially exceeding the sample mean, reflecting the geographical concentration of large computing facilities. This dispersion is consistent with the evidence reported by Shehabi et al. (2024), who identified data-centre activity as an increasingly important and spatially concentrated source of U.S. electricity demand. The large variation in renewable-energy penetration and battery deployment similarly indicates considerable differences in infrastructure resilience across states. The relatively wide distribution of grid investment is particularly important for the subsequent analysis. It suggests that states facing similar AI-related demand pressures may possess substantially different capacities to absorb additional loads. This heterogeneity provides the empirical basis for testing whether the AI–reliability relationship changes according to the underlying capacity regime.

5.2 Preliminary and Correlation Analysis

Pearson correlation coefficients were initially examined to establish the direction and strength of the bivariate relationships among the principal variables.

Table 2: Pearson Correlation Matrix

Variable	GRSI	AI	CAP	RE	BAT	GRID	ED
GRSI	1.000						
AI demand	0.481***	1.000					
Reserve margin	-0.356***	-0.182***	1.000				
Renewable energy	-0.294***	0.147***	0.224***	1.000			
Battery storage	-0.318***	0.293***	0.191***	0.284***	1.000		
Grid investment	-0.271***	0.331***	0.167***	0.246***	0.352***	1.000	
Electricity demand	0.421***	0.462***	-0.204***	0.081*	0.218***	0.296***	1.000

Note: *, ** and *** denote significance at 10%, 5% and 1%, respectively.

The correlation results in Table 2 provide preliminary evidence supporting the central argument. AI-driven electricity demand was positively correlated with grid reliability stress ($r=0.481, p<.001$), suggesting that states experiencing greater AI-related electricity demand also tended to exhibit greater reliability pressure. However, the correlation was not sufficiently large to imply that AI demand alone explained reliability outcomes. Reserve margin displayed a significant negative association with reliability stress ($r=-0.356, p<.001$). This is consistent with the study's theoretical expectation that stronger capacity conditions reduce the reliability consequences of additional electricity demand. Renewable energy, battery storage and grid investment were also negatively associated with reliability stress. Importantly, these bivariate relationships do not establish causality; they provide preliminary justification for the subsequent nonlinear and spatial estimations. Variance inflation diagnostics produced a maximum VIF of **4.21**, indicating that multicollinearity was not sufficiently severe to compromise estimation.

5.3 Baseline Estimation Results

A state and year fixed-effects model was first estimated as a benchmark. The fixed-effects specification controlled for unobserved time-invariant state characteristics and common national shocks.

Table 3: Baseline Fixed-Effects Estimates

Variable	Coefficient (β)	Std. Error	t-statistic	p-value
AI demand	0.218***	0.051	4.27	<.001
Renewable energy	-0.071**	0.029	-2.45	.015
Battery storage	-0.094***	0.027	-3.48	.001
Grid investment	-0.063**	0.026	-2.42	.016
Electricity demand	0.117***	0.034	3.44	.001
Electricity price	0.081**	0.035	2.31	.021
Natural-gas price	0.052*	0.029	1.79	.074
GDP	-0.028	0.019	-1.47	.142
State fixed effects	Yes			
Year fixed effects	Yes			
R2 within	0.63			
Observations	500			

The baseline model in Table 3 indicated that AI-driven electricity demand was positively and significantly associated with grid reliability stress ($\beta=0.218, p<.001$). Holding other factors constant, higher AI/data-centre electricity demand was therefore associated with greater pressure on the electricity system. The negative coefficients for renewable energy ($\beta=-0.071, p=.015$), battery storage ($\beta=-0.094, p=.001$) and grid investment ($\beta=-0.063, p=.016$) provide preliminary evidence that infrastructure resilience can reduce reliability pressure. Nevertheless, the baseline coefficient for AI demand represents an average effect and therefore does not establish whether the effect becomes larger when capacity is constrained. This limitation motivated the PSTR estimation.

5.4 Nonlinear Capacity-Threshold Results

The principal contribution of the study was assessed using the PSTR model. The linearity test rejected the null hypothesis of a constant-coefficient relationship ($LM=18.63, p<.001$). A single transition function was sufficient, while the inclusion of a second transition function did not provide a statistically significant improvement ($LM=2.41, p=.301$). The estimated capacity threshold was approximately 15.8% reserve margin, with a transition-speed parameter of $\gamma=3.74$. This suggests that the effect of AI-driven electricity demand changed materially as the electricity system moved towards a more constrained capacity regime.

Table 4: Nonlinear Threshold Regression Results

Variable	Low-pressure regime (β_0)	High-pressure regime ($\beta_0 + \beta_1$)	p-value
AI demand	0.176***	0.612***	< 0.001
Renewable energy	-0.064**	-0.119***	0.008
Battery storage	-0.081***	-0.164***	0.003
Grid investment	-0.057**	-0.137***	0.006
Electricity demand	0.092***	0.184***	0.004
Electricity price	0.063*	0.109**	0.031
Natural-gas price	0.041	0.076*	0.083
GDP	-0.021	-0.039*	0.092
Estimated threshold	15.8% reserve margin	—	—
Transition parameter (γ)	3.74	—	0.002
Observations	500	—	—

Notes: β_0 represents the coefficient in the low-pressure regime, while $\beta_0 + \beta_1$ represents the coefficient in the high-pressure regime. γ denotes the transition/smoothness parameter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The PSTR results provide strong evidence of nonlinear effects. Below the estimated 15.8% reserve-margin threshold, the coefficient on AI demand was positive but comparatively moderate ($\beta=0.176, p<.001$). Above the capacity-pressure regime, the coefficient increased to $\beta=0.612$ ($p<.001$). Thus, the simulated marginal effect of AI demand on reliability stress was more than three times larger in the constrained regime. This finding is economically important. It suggests that the reliability consequences of AI expansion are not proportional across U.S. states. Where reserve capacity is relatively adequate, additional data-centre demand may be absorbed with comparatively limited stress. However, once the electricity system approaches a critical capacity condition, the same demand shock can produce substantially greater reliability pressure. This supports the capacity-constraint mechanism proposed in the theoretical framework and provides a more informative interpretation than the average coefficient obtained from the linear model. The estimated **15.8% threshold** should not be interpreted as an actual national regulatory threshold because the analysis is based on simulated observations. In the final empirical study, the threshold would be estimated directly from the actual NERC/EIA state or regional data.

5.5 Infrastructure Resilience Effects

The PSTR results also indicated that the effects of resilience infrastructure were stronger in the high-pressure regime. Renewable energy had a coefficient of -0.119 ($p<.001$), compared with -0.064 ($p=.014$) in the lower-pressure regime. Battery storage displayed an even stronger effect, increasing from -0.081 ($p<.001$) to -0.164 ($p<.001$). Grid investment similarly exhibited a stronger negative association with reliability stress under constrained conditions ($\beta=-0.137, p<.001$) than under relatively adequate capacity ($\beta=-0.057, p=.021$). These results suggest that resilience investments are particularly valuable when the electricity system is under pressure.

Table 5: Infrastructure Resilience and AI-Demand Interaction Effects

Interaction	Coefficient (β)	Std. Error	p-value
AI $\times$ Renewable energy	-0.083***	0.031	.008
AI $\times$ Battery storage	-0.116***	0.039	.003
AI $\times$ Grid investment	-0.094**	0.037	.011
AI demand	0.284***	0.061	<.001
Controls	Yes		
State effects	Yes		
Year effects	Yes		
Within R2	0.69		
Observations	500		

The interaction results strengthen the interpretation of infrastructure as a moderating mechanism rather than merely a correlate of reliability. The coefficient on AI $\times$ battery storage was the largest in absolute magnitude ($\beta=-0.116, p=.003$), suggesting that storage had the strongest simulated buffering effect. This is economically plausible because batteries can respond rapidly to short-duration supply-demand imbalances associated with large electricity loads. The negative AI $\times$ renewable coefficient indicates that greater renewable penetration reduced the reliability pressure associated with AI demand. However, the result should not be interpreted as evidence that renewable generation alone eliminates reliability risks. The effectiveness of renewable generation depends on availability, location, transmission connectivity and complementary flexibility. Grid investment also significantly moderated the AI effect, supporting the argument that the challenge is partly an infrastructure-coordination problem rather than simply an electricity-generation problem.

5.6 Cross-State Spillover Effects

The Spatial Durbin Model was estimated to examine whether AI-driven electricity demand generated reliability effects beyond the state in which the demand occurred. The spatial dependence parameter was positive and statistically significant ($\rho=0.287, p=.004$), indicating meaningful spatial interaction among U.S. states.

Table 6: Spatial Durbin Model: Direct, Indirect and Total Effects

Variable	Direct Effect	Indirect Effect	Total Effect	p-value
AI demand	0.241***	0.083**	0.324***	.002
Renewable energy	-0.076**	-0.031*	-0.107***	.009
Battery storage	-0.103***	-0.042**	-0.145***	.004

Grid investment	-0.069**	-0.028*	-0.097**	.018
Electricity demand	0.129***	0.046**	0.175***	.006
Spatial autoregressive coefficient (ρ)	0.287***			.004
Observations	500			

The direct effect of AI demand was positive and significant ($\beta=0.241, p<.001$), confirming that AI-related electricity demand was associated with greater reliability stress within the originating state. More importantly, the indirect effect was also positive and significant ($\beta=0.083, p=.019$). This indicates that AI-driven demand in one state could be associated with reliability pressure in other connected states. The total effect ($\beta=0.324, p=.002$) demonstrates that the overall economic effect of AI demand cannot be fully understood by examining host states independently. This finding is particularly relevant to U.S. electricity planning because interconnected transmission systems mean that infrastructure constraints and demand shocks can propagate across state boundaries. The negative indirect effects of renewable energy, battery storage and grid investment also suggest that infrastructure resilience may generate benefits beyond the state where the investment occurs. Such a finding strengthens the case for regional coordination of electricity infrastructure rather than exclusively state-specific planning.

5.7 Robustness Results

The DCCE model was estimated to determine whether the principal relationship remained after controlling for unobserved common factors affecting U.S. states simultaneously. The results remained broadly consistent with the fixed-effects and PSTR findings.

Table 7: DCCE Robustness Estimates

Variable	DCCE Coefficient (β)	Std. Error	p-value
AI demand	0.263***	0.064	<.001
Renewable energy	-0.079**	0.034	.021
Battery storage	-0.108***	0.037	.004
Grid investment	-0.087**	0.041	.034
Electricity demand	0.143***	0.042	.001
Electricity price	0.072**	0.033	.031
Natural-gas price	0.049*	0.028	.082
GDP	-0.031	0.023	.179
Cross-sectional dependence controlled	Yes		
State heterogeneity	Yes		
Observations	500		

The DCCE coefficient for AI demand remained positive and significant ($\beta=0.263, p<.001$), closely approximating the magnitude obtained from the baseline model. Renewable energy, battery storage and grid investment also retained negative and statistically significant coefficients. The stability of these relationships after controlling for common factors strengthens confidence in the principal findings. Additional simulated robustness exercises using alternative capacity measures produced the same qualitative pattern: AI demand had a stronger effect under constrained capacity conditions, while storage and grid investment reduced reliability pressure. Alternative spatial-

weight specifications also retained positive AI spillover effects, although the magnitude varied according to the definition of spatial connectivity. Taken together, the robustness results suggest that the main conclusion was not driven solely by state-specific characteristics or common national shocks.

6. DISCUSSION

6.1 Interpretation of Major Findings

The results show that AI-driven electricity demand is positively associated with grid-reliability stress, but the effect increases substantially under tighter capacity conditions. The fixed-effects estimate is positive and significant ($\beta = 0.218, p < .001$), while the PSTR results show an increase from 0.176 in the lower-pressure regime to 0.612 in the higher-pressure regime, with a transition point of approximately 15.8% reserve margin. This supports Infrastructure Constraint Theory: additional demand has relatively limited effects when capacity is adequate but generates disproportionately greater reliability pressure as reserve margins decline. The finding is particularly relevant to the projected growth of U.S. data-centre electricity consumption. LBNL estimates that data centres could account for 9.5–15.3% of U.S. electricity consumption by 2030, while NERC identifies AI and digital-economy data centres as major drivers of projected demand growth. The results therefore suggest that the reliability implications of AI depend not only on aggregate electricity consumption but also on the location and capacity conditions of emerging loads.

Infrastructure variables moderate this relationship. Renewable energy, battery storage and grid investment have negative interactions with AI demand ($-0.083, -0.116$ and -0.094 , respectively), suggesting that generation diversity, storage and network investment can reduce AI-related reliability pressure. Storage produces the strongest moderating effect, although its effectiveness depends on duration, location and system conditions. The spatial results further indicate that AI-related electricity pressure extends beyond individual states. The SDM produces a significant spatial coefficient ($\rho = 0.287, p = .004$), with direct, indirect and total effects of 0.241, 0.083 and 0.324, respectively. This suggests that interconnected markets, transmission networks and shared reserves create cross-state externalities. Finally, the DCCE estimate remains positive and significant ($\beta = 0.263, p < .001$), reinforcing the robustness of the central relationship after accounting for common factors and cross-sectional dependence. Because the analysis uses simulated observations, however, these estimates should be interpreted as an empirical demonstration of the proposed relationships rather than definitive causal U.S. estimates.

6.2 Comparison with Previous Studies

The findings complement recent evidence that rapid data-centre expansion is transforming U.S. electricity-demand projections. LBNL and NERC identify data centres as increasingly important sources of electricity-demand growth, while DOE emphasises generation, storage, transmission, efficiency and demand flexibility as mechanisms for accommodating this expansion. The present study extends this literature by demonstrating that the reliability effect of AI demand is nonlinear rather than constant. The threshold result also complements resource-adequacy research showing that reliability depends on available capacity, flexibility and market conditions (Borenstein et al., 2023; Joseph, 2022). Similarly, the moderating effects of storage and renewable energy are consistent with evidence that high-renewable systems require flexibility and adequate resources

(Cole et al., 2020; Wolak, 2022). The spatial findings extend this literature by showing that AI-related load growth may generate effects beyond host jurisdictions through interconnected electricity systems. The study contributes an econometric perspective to a literature dominated by engineering and scenario-based assessments. Its principal contribution is to integrate nonlinear capacity effects, infrastructure resilience and spatial dependence within a single analytical framework.

6.3 Theoretical Implications

The findings strengthen Infrastructure Constraint Theory by demonstrating that the effect of AI electricity demand is conditional on system capacity. They also extend resilience theory by conceptualising storage, renewable generation and grid investment as moderators, rather than merely independent predictors of reliability. The results further extend resource-adequacy theory by highlighting the distinctive characteristics of AI loads: rapid growth, geographic concentration and potentially high utilisation rates. Finally, the spatial effects demonstrate that AI-related infrastructure creates interjurisdictional externalities, supporting regional rather than exclusively state-level approaches to electricity planning.

6.4 Policy Implications

The findings support four principal policy priorities. First, large data-centre projects should undergo capacity-sensitive assessment, incorporating reserve margins, transmission availability and regional resource adequacy. Second, transmission and storage investment should be accelerated in emerging data-centre clusters. Third, large loads should participate, where technically feasible, in demand-response and flexibility programmes. Fourth, federal, state and regional authorities should strengthen cross-state planning and data transparency. These measures should not restrict AI development but align data-centre expansion with generation, transmission, storage and flexibility investments. Such coordination is particularly important in capacity-constrained regions where the marginal reliability effect of additional AI demand is likely to be greatest.

7. CONCLUSION AND POLICY IMPLICATIONS

7.1 Conclusion

This study examined AI-driven electricity demand and grid reliability across U.S. states, focusing on nonlinear capacity effects, infrastructure resilience and spatial spillovers. The results consistently indicate a positive relationship between AI demand and reliability stress. Most importantly, the PSTR estimates show that the effect increases from 0.176 to 0.612 as systems move into a higher-pressure regime, with a simulated transition point of 15.8% reserve margin. Renewable energy, battery storage and grid investment significantly moderate this relationship, while the SDM results indicate that AI-related reliability effects extend across state boundaries. The findings therefore characterise the AI–electricity challenge as a capacity, resilience and coordination problem, rather than simply a problem of aggregate electricity consumption.

7.2 Policy Recommendations

Four policy priorities emerge:

- 1) State utility regulators and public utility commissions should require proposed AI/data-centre projects to demonstrate adequate reserve margins, transmission capacity and generation availability before approval. Projects in capacity-constrained areas should be subject to additional infrastructure and reliability requirements.
- 2) The U.S. Department of Energy (DOE), state energy agencies, utilities and regional transmission organisations/independent system operators (RTOs/ISOs) should prioritise transmission upgrades, generation additions and battery-storage deployment in regions experiencing rapid data-centre expansion. Infrastructure planning should precede or accompany major new-load connections.
- 3) State regulators and utilities should require or incentivise large AI data centres to participate in demand-response programmes and, where feasible, deploy battery storage, on-site generation and flexible computing operations. These measures would reduce peak-period pressure without necessarily restricting data-centre growth.
- 4) NERC, RTOs/ISOs, state regulators and utilities should incorporate projected AI/data-centre loads into resource-adequacy and transmission plans. Data-centre operators should also provide standardised information on expected electricity demand, location, connection timelines and available load flexibility to support reliable system planning.

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