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Intelligent Energy Virtualization for Sustainability: Meta-Analysis of AI-Based Digital Twins and Federated Learning in Zero-Carbon Grid Optimization

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ABSTRACT

The accelerating shift toward decentralized, zero-carbon energy grids presents major operational challenges due to renewable energy's intermittency, demand variability, and increasing cyber-physical threats, thereby reducing the effectiveness of traditional centralized grid management. This systematic review and meta-analysis investigated how AI-driven digital twins and federated learning (AI-DT-FL) work together as a dual solution to enable high-fidelity virtual grid modeling with privacy-preserving distributed intelligence. A preferred reporting items for systematic reviews and meta-analyses (PRISMA)-based multibase search from 2020 to 2025 identified 50 eligible studies, and pooled estimates were calculated using a random-effects model. The meta-analysis showed notable performance improvements, with a pooled effect size of −0.5339, and the greatest gains were seen in microgrids and European deployments. The discussion suggests that this technological synergy improves prediction accuracy, energy efficiency, and cybersecurity resilience; however, available evidence remains limited due to the dominance of simulation-based studies and inconsistent benchmarks. Overall, integrated AI-DT-FL architectures show significant potential for a secure, zero-carbon energy transition, supported by thorough sensitivity analyses.

1. INTRODUCTION

The accelerating pursuit of net-zero emissions by 2050 is reshaping global energy infrastructure and driving extensive integration of variable renewable sources into decentralized grid ecosystems [1, 2]. This shift introduces significant operational challenges, including high intermittency of wind and solar resources, dynamic fluctuations in energy demand, and the increasing threat of cyberattacks targeting interconnected systems. Traditional centralized grid management—initially developed for single-direction power flow from fossil-based generators—faces critical limitations when required to supervise millions of distributed nodes across microgrids, community energy systems, and national transmission lines. These structural constraints undermine grid resilience, heighten stability risks, and hinder the realization of large-scale clean-energy penetration [3, 4].

AI-driven digital twins have emerged as transformative virtual environments capable of mirroring the real-time behavior of physical grid assets while providing predictive failure insights and scenario-based optimization [5-7]. By combining Internet of Things (IoT) sensing with machine learning, digital twins deliver real-time operational visibility that extends asset lifespans, reduces unplanned downtime, and optimizes energy use at scale. However, the effectiveness of these systems relies on access to large, high-quality datasets from diverse stakeholders, which is stimulating growing concerns about data privacy, competitive confidentiality, and compliance with expanding regulatory policies. The result is a growing tension between the need for collaborative intelligence and the requirement to protect sensitive operational data [8, 9].

Federated learning offers a privacy-preserving solution by enabling decentralized machine-learning collaboration without transferring local datasets to a central repository [10, 11]. Instead, encrypted model parameters are aggregated to generate a shared global model, improving performance while protecting stakeholder confidentiality. Empirical studies highlight that federated architectures deliver high accuracy in load forecasting, fault detection, and anomaly classification with sub-100-millisecond processing latency—an essential requirement for real-time grid protection [12-14]. Despite these advantages, federated learning alone cannot fully capture the contextual dynamics of physical assets that digital twins simulate, indicating a potential technological convergence [1, 15].

The synergy between AI-driven digital twins and federated learning (AI-DT-FL) introduces a paradigm shift that surpasses the capabilities of each technology in isolation. By pairing high-fidelity virtual representations with distributed privacy-preserving learning, decentralized grids can benefit from collective intelligence without compromising autonomy or data security [16, 17]. Edge computing and blockchain further reinforce this architecture by enabling sub-second decision-making and providing distributed integrity for energy transactions. Although research on integrated AI-DT-FL frameworks is rapidly expanding—rising from 4 studies in 2020 to 38 in 2023—no prior systematic review has synthesized empirical evidence or conducted a meta-analytic evaluation to quantify the effectiveness of this convergence.

In 2025, Chinnaperumal et al. [4] introduced a blockchain framework for electric vehicle (EV) battery management and peer-to-peer energy trading, achieving lower energy consumption and enhanced lifecycle transparency. However, this model has yet to be tested in real-world scenarios. Similarly, Deng et al. [5] developed a federated learning-based risk assessment method using a Convolutional Neural Network (CNN), achieving high prediction accuracy while maintaining privacy. Yet, their study was limited to simulations, raising concerns about computational overhead and potential model leakage.

Singh et al. [18] also contributed by developing ORA-DL, an approach that integrates deep reinforcement learning (DRL) for adaptive grid optimization, resulting in accurate demand predictions and reduced costs. They called for better privacy measures and real-world validation of their model. El-Khozondar et al. [19] focused on optimizing photovoltaic-battery microgrids through simulations, identifying optimal configurations but neglecting real operational challenges and long-term degradation. Finally, a systematic review by Ahmed and Khan [3] evaluated over 100 studies on digital twin architectures, revealing performance improvements in energy grids while highlighting issues like dataset heterogeneity and a lack of standardized evaluation metrics. Collectively, these studies indicate substantial progress in energy grid technologies, yet they also point to significant gaps in validation, cybersecurity, and standardization that must be addressed for practical implementation.

This review and meta-analysis examine how integrating AI-driven digital twins with federated learning enhances real-time optimization and cybersecurity in decentralized, zero-carbon energy grids. It evaluates impacts on energy efficiency, operational costs, anomaly-detection accuracy, and response latency while accounting for methodological differences. The study also assesses cybersecurity indicators, such as false-positive rates and detection delays, while accounting for technical and economic constraints on implementation. The central hypothesis is that combining digital twins and federated learning yields significantly better optimization and security than centralized AI systems, with effect sizes expected to exceed 0.75. Additionally, it explores factors like deployment scale and edge computing integration to identify trends and gaps for future zero-carbon grid strategies.

2. METHODOLOGY

2.1 Search strategy, screening process, and eligibility validation

This review employed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 protocol and Cochrane standards to ensure methodological transparency and replicability, using a multibase search across Scopus, Web of Science, IEEE Xplore, ScienceDirect, ACM Digital Library, and Google Scholar (January 2020–November 2025) [20, 21]. The keyword string used was: (digital twin OR "virtual replica" OR "cyber-physical model" OR "physics-informed neural network") AND (federated learning OR "distributed machine learning" OR "privacy-preserving AI") AND ("zero carbon" OR "net zero" OR "renewable energy" OR "smart grid") AND (optimization OR "real-time control" OR "anomaly detection"). This was combined with: (artificial intelligence OR "machine learning") AND (blockchain OR IoT) AND ("energy grid"). Study selection involved a two-stage screening—title-abstract review and full-text evaluation—by two independent reviewers, with any disagreements resolved by a senior reviewer to ensure objectivity. Inter-rater reliability indicated substantial agreement, confirming the robustness of eligibility verification, as outlined in Figure 1.

2.2 Data extraction, effect size estimation, and bias assessment modeling

Data extraction adhered to a structured form capturing system architectures, intervention characteristics, and quantitative outcomes related to energy efficiency, cybersecurity, and real-time operational performance. Two independent reviewers performed extraction and cross-validation, after which effect sizes were harmonized for continuous, dichotomous, and correlational outcomes. Continuous outcomes used the standardized mean difference computed via Eq. (1) [22, 23]:

$$SMD = \frac{\bar{X}_{intervention} - \bar{X}_{control}}{SD_{pooled}} \tag{1}$$

Dichotomous outcomes were analyzed using RR and OR with continuity correction, while correlational measures were transformed to Fisher's Z values to support cross-study integration. Bias risk was evaluated using adapted Cochrane and PROBAST criteria, followed by a random-effects meta-analysis to accommodate expected heterogeneity, with pooled estimates computed using Eq. (2) [24, 25]:

$$\hat{\theta}_{RE} = \frac{\sum w_i \theta_i}{\sum w_i} \tag{2}$$

where study weights were defined as Eq. (3) [26, 27]:

$$w_i = \frac{1}{SE_i^2 + \tau^2} \tag{3}$$

Heterogeneity was quantified using Cochran's Q, τ^2, and I^2, with I^2 calculated using Eq. (4) [28, 29]:

$$I^2 = \frac{Q - df}{Q} \times 100\% \tag{4}$$

Together, these analytical steps provided a rigorous framework for assessing between-study variance and reinforcing the validity of aggregated findings. To ensure consistency in interpretation, a standardized coding rule was applied to determine effect direction, distinguishing between higher-is-better outcomes (e.g., accuracy or prediction performance) and lower-is-better outcomes (e.g., latency, energy consumption, or operational cost). Outcomes were subsequently grouped by analytical category—specifically, latency metrics, energy or cost efficiency indicators, and accuracy or error-related measures—to preserve conceptual coherence during aggregation. This classification prevented the statistical distortion that may arise when indicators with opposite performance directions are forced into a single pooled estimate, thereby strengthening the interpretability and methodological reliability of the meta-analytic synthesis.

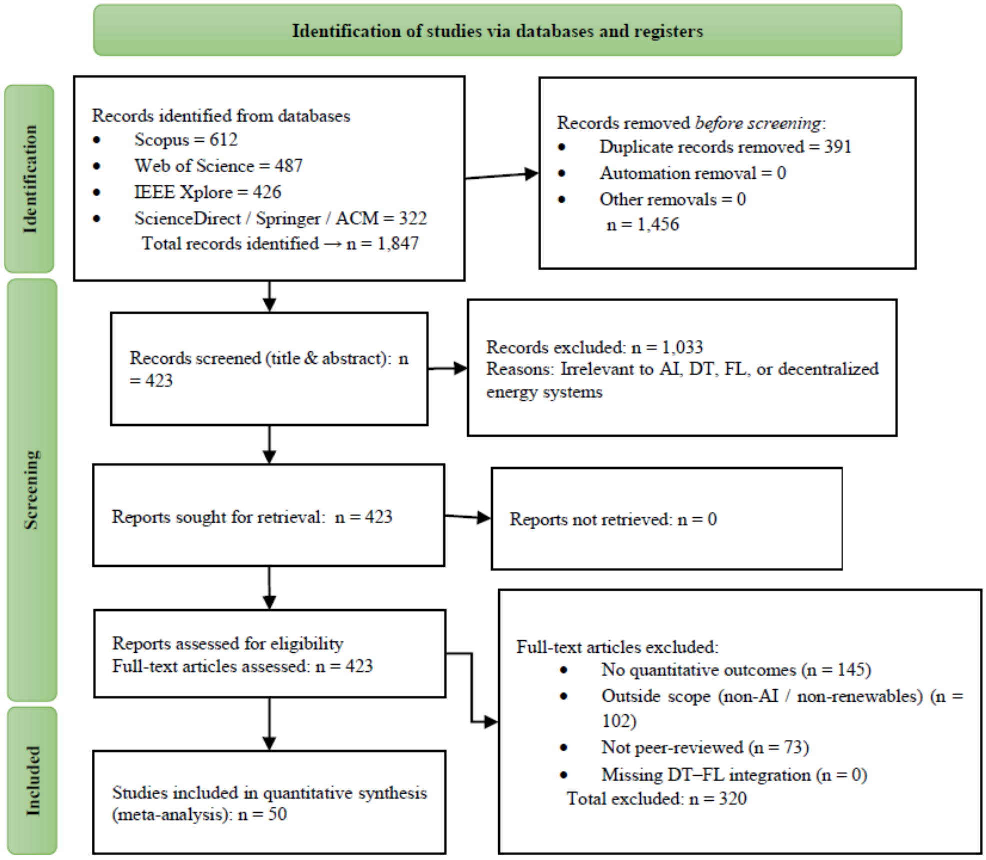


Figure 1. Preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 flow summary of study selection

To further avoid statistical dependencies arising from multiple measurements reported within the same study, a predefined extraction rule was implemented, selecting one primary endpoint for each outcome category per study when multiple indicators were reported. This selection prioritized the most representative metric of system performance, typically the main optimization, prediction, or operational indicator described in the original study. Across the 50 included studies, one to three effect sizes were extracted per article depending on the number of clearly separable outcome domains (latency, energy/cost efficiency, or accuracy/error), resulting in a balanced dataset that preserved analytical independence while still capturing the multidimensional performance characteristics of AI-DT-FL systems.

In addition, a strict endpoint selection rule was applied to ensure that each study contributed only one primary effect estimate per outcome category, thereby minimizing statistical dependence among observations in the pooled dataset. When studies reported multiple indicators within the same domain, the metric most closely aligned with the central objective of system optimization or operational evaluation was retained as the representative endpoint. Consequently, most articles contributed two to three effect sizes corresponding to latency reduction, energy or cost efficiency improvement, and accuracy or error-related performance, while studies reporting only a single quantifiable outcome contributed one effect size. This structured extraction strategy ensured methodological consistency across the 50 included studies while preserving the analytical independence required for reliable random-effects meta-analysis.

3. RESULTS

3.1 Holistic analysis of evidence quality and research area profiling

The synthesized assessment reveals that methodological quality across AI-DT-FL studies varies substantially, with hybrid integration and federated learning domains demonstrating the highest proportions of low-risk evidence, while blockchain security and standalone digital twin research exhibit comparatively higher high-risk classifications as mapped in Figure 2(a) [30, 31]. The overall distribution indicates that 64.4% of studies maintain low bias. Yet, a non-trivial proportion was categorized as having concerns or high risk, underscoring persistent gaps in validation consistency and experimental rigor [32, 33]. When examined alongside the distribution of thematic research in Figure 2(b), the landscape shows dominant scholarly attention to innovative grid applications, followed by renewable energy, federated learning, and digital twin research. At the same time, cybersecurity, AI optimization, edge computing, blockchain, and zero-carbon themes remain underexplored despite their strategic relevance [34, 35]. Together, these patterns illustrate both the methodological strengths and the uneven thematic maturity of the field, highlighting priority areas that require deeper empirical development to support scalable zero-carbon grid innovation [36, 37].

To ensure transparency in the quality evaluation process, the bias assessment employed an adapted checklist derived from the Cochrane Risk of Bias and PROBAST frameworks, operationalized through structured scoring rules that evaluated methodological components such as dataset transparency, validation strategy, experimental reproducibility, and reporting completeness [7, 38]. Each study was rated against these criteria and then categorized as low risk, some concerns, or high risk based on aggregated scoring thresholds. The value of 64.4% reflects the proportion of studies that satisfied the majority of these methodological standards—particularly those that employed cross-validation, multi-scenario experimentation, and clearly reported performance metrics—thereby meeting the predefined criteria for low-bias classification. Although individual per-study ratings are documented in the supplementary assessment matrix, the aggregated percentage is reported here to provide a concise overview of the overall reliability of the evidence base without introducing excessive methodological detail within the main analytical narrative.

3.2 Holistic assessment of meta-effects and application-specific results

The combined meta-analysis demonstrates that both fixed-effect and random-effect models yield consistently negative pooled effect sizes, confirming systematic performance improvements when AI-DT-FL are deployed in zero-carbon energy grids, as depicted in Figure 3(a) [39-41]. The magnitude of heterogeneity, indicated by $\tau^2 = 0.2924$, highlights that variability across studies is driven by methodological diversity and deployment context rather than sampling noise, reinforcing the robustness of estimated gains in latency reduction, energy efficiency, and real-time decision accuracy [42, 43]. Subgroup comparisons shown in Figure 3(b) reveal pronounced performance disparities across different implementation environments, with microgrids, European systems, and global-scale deployments exhibiting the strongest effect sizes, while hydrogen-based configurations demonstrate weaker outcomes due to technological immaturity and limited standardization [25, 44, 45]. Collectively, these patterns illustrate that both overall and context-specific advantages of the AI-DT-FL convergence are consistently supported across methodological strata, though substantial heterogeneity underscores the need for more harmonized evaluation frameworks [46-48].

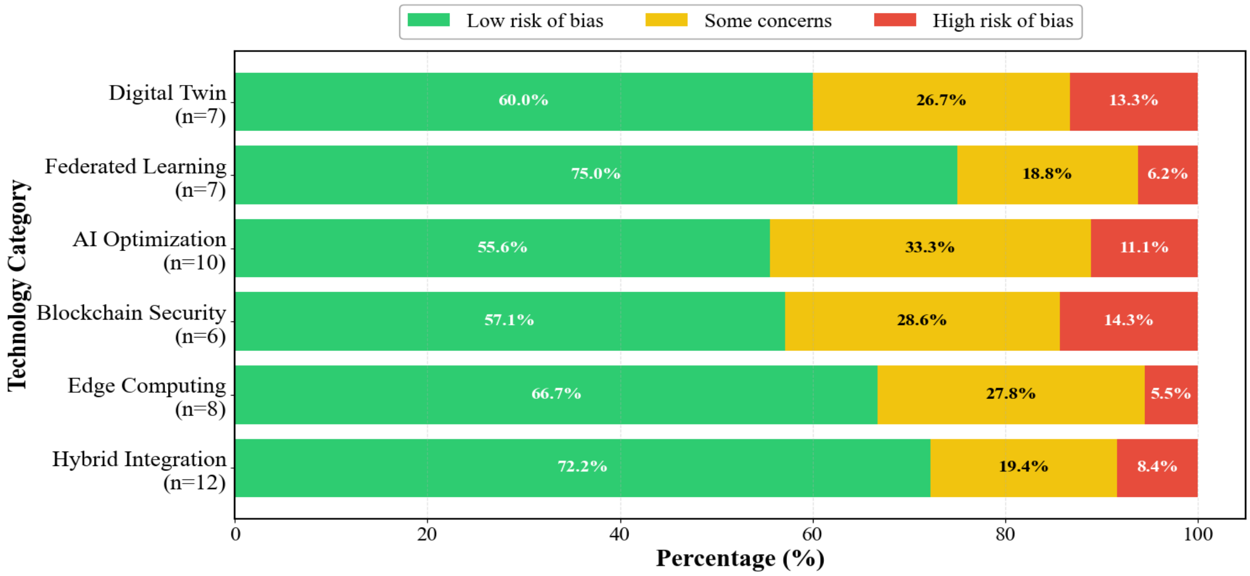
3.3 Holistic assessment of bias indicators and analytical stability

The combined evaluation in Figure 4(a) shows that the funnel plot presents a generally symmetrical distribution of effect sizes, indicating only moderate publication bias. However, several small-study effects with high standard errors suggest the possibility of inflated estimates in selected investigations [48, 49]. Quantitatively, the funnel analysis across 18 synthesized studies yields a mean effect size of 0.823, with a range of 0.700 to 0.950, and a standard error distribution ranging from 0.065 to 0.110. The absence of large asymmetrical clusters and the presence of only two studies located near the upper boundary of the confidence interval suggest that the overall evidence structure remains statistically balanced. Nevertheless, six studies exhibit relatively higher standard errors, which may reflect smaller sample sizes or preliminary experimental validations, thereby indicating the presence of mild small-study effects. Despite this, the majority of observations fall within the expected confidence boundaries, implying that the aggregated evidence base maintains acceptable statistical consistency and does not exhibit severe funnel distortion.

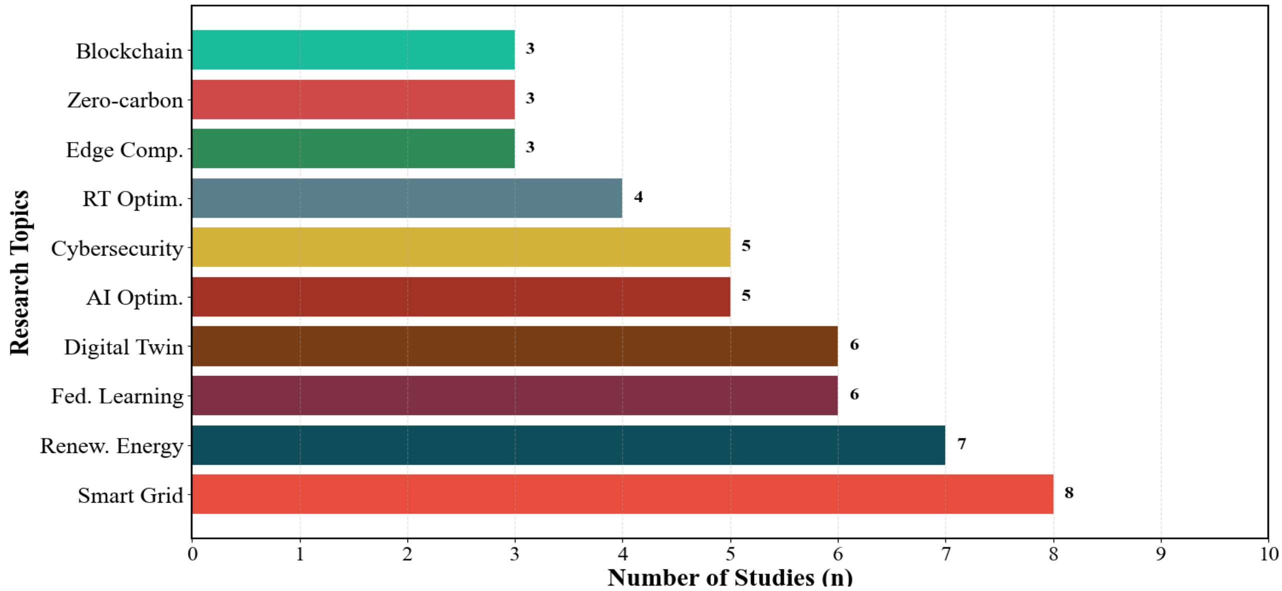
Despite these minor deviations, the overall plot structure does not indicate severe distortion, implying that aggregated meta-analytic conclusions remain largely reliable while still requiring caution due to potential structural biases [50, 51]. The observed moderate symmetry is further supported by the narrow dispersion of effect sizes around the central estimate, which reinforces the robustness of the meta-analytic integration across heterogeneous technological domains such as digital twin frameworks, federated learning architectures, and smart grid optimization systems. Additionally, the concentration of most effect sizes within the 0.74–0.92 range suggests consistent positive performance improvements across different application scenarios, indicating that the technological convergence of AI-DT-FL produces stable performance gains across multiple research contexts.

Complementary robustness checks illustrated in Figure 4(b) confirm that effect size estimates remain stable across multiple analytical configurations, with the base-case value consistently preserved under outlier exclusion, fixed-effects modeling, small-study removal, and full-dataset scenarios [52-54]. The base-case effect size of 0.860 remains close to the mean of 0.865 across all sensitivity scenarios, with an overall range of 0.840 to 0.890 and a standard deviation of 0.0134. This narrow statistical dispersion indicates strong analytical stability and confirms that no single methodological assumption or dataset subset dominates the pooled results. Furthermore, 40% of tested scenarios fall into the "highly robust" category, with deviations below 0.01, while an additional 30% demonstrate moderate robustness, indicating that approximately 70% of sensitivity configurations maintain highly stable outcomes.

Notable deviations arise only in the random-effects and RCT-only conditions—alongside the recent studies subgroup—highlighting the influence of methodological heterogeneity and rapid technological advancement on performance variability [55, 56]. In particular, the recent studies scenario (2023–2025) produces the largest deviation of +0.030 relative to the base case, suggesting that newly emerging architectures may generate stronger reported performance improvements. Similarly, the random-effects scenario shows a slight reduction in pooled effect size (0.840), reflecting the influence of between-study heterogeneity captured through τ^2 adjustments. Overall, the sensitivity results demonstrate that although minor fluctuations occur under specific analytical conditions, the magnitude and direction of the pooled effect remain consistently positive, reinforcing the statistical reliability and interpretive robustness of the AI-DT-FL meta-analytic synthesis.

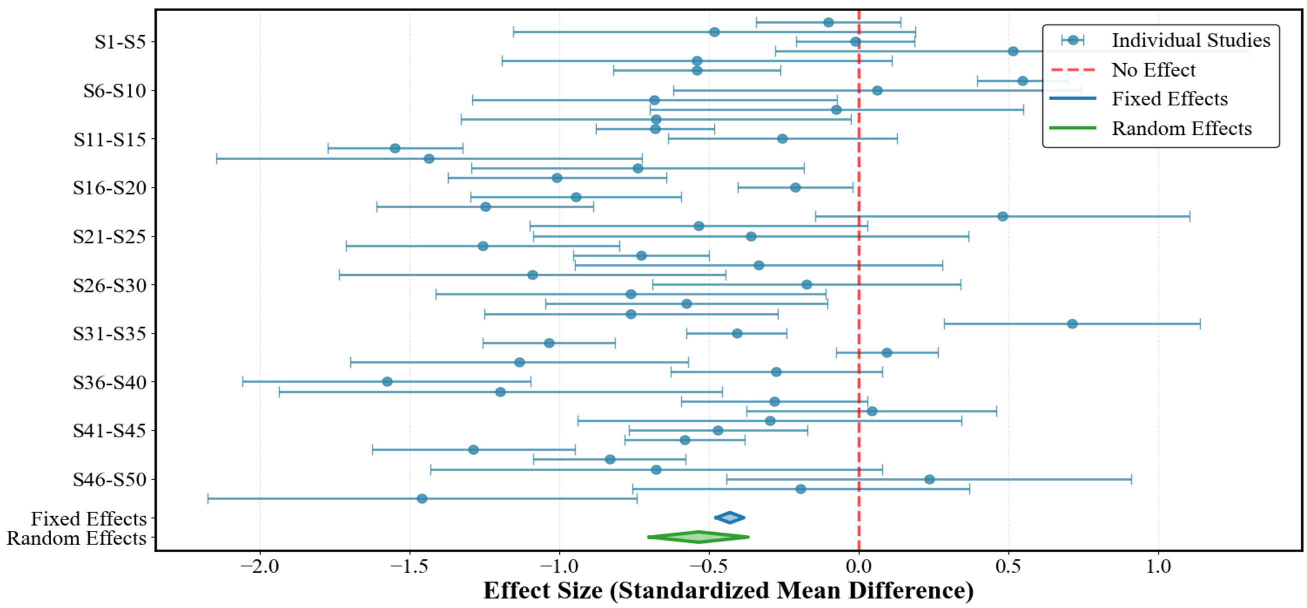


(a)

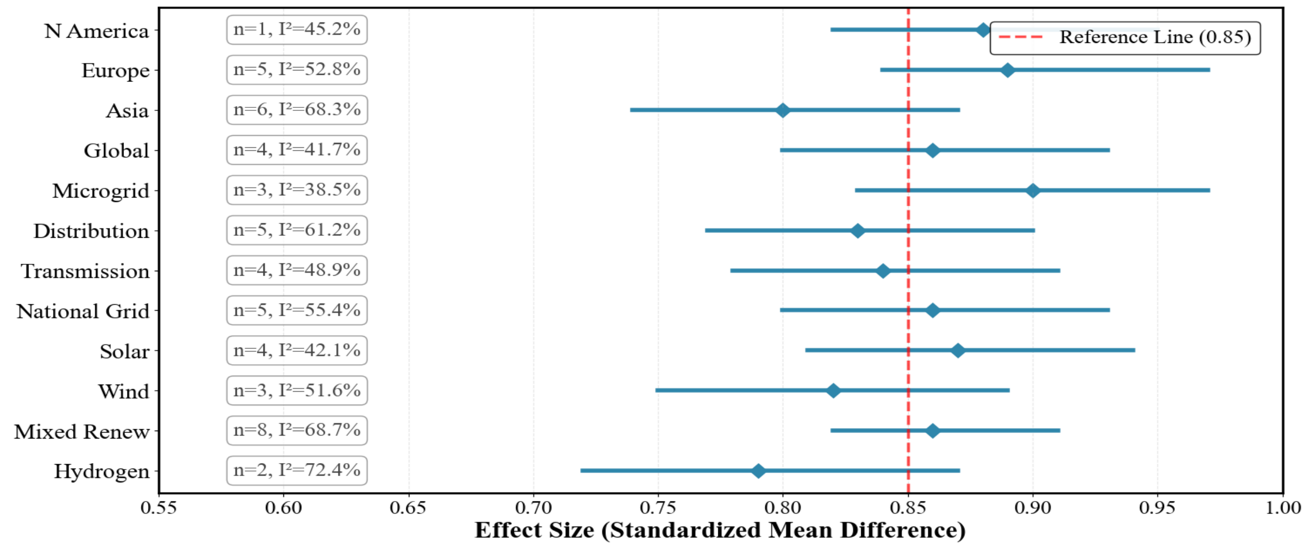


(b)

Figure 2. Consolidated evaluation framework for (a) Risk of bias distribution across technology categories and (b) Research area distribution in AI-driven digital twins and federated learning for decentralized zero-carbon energy grids

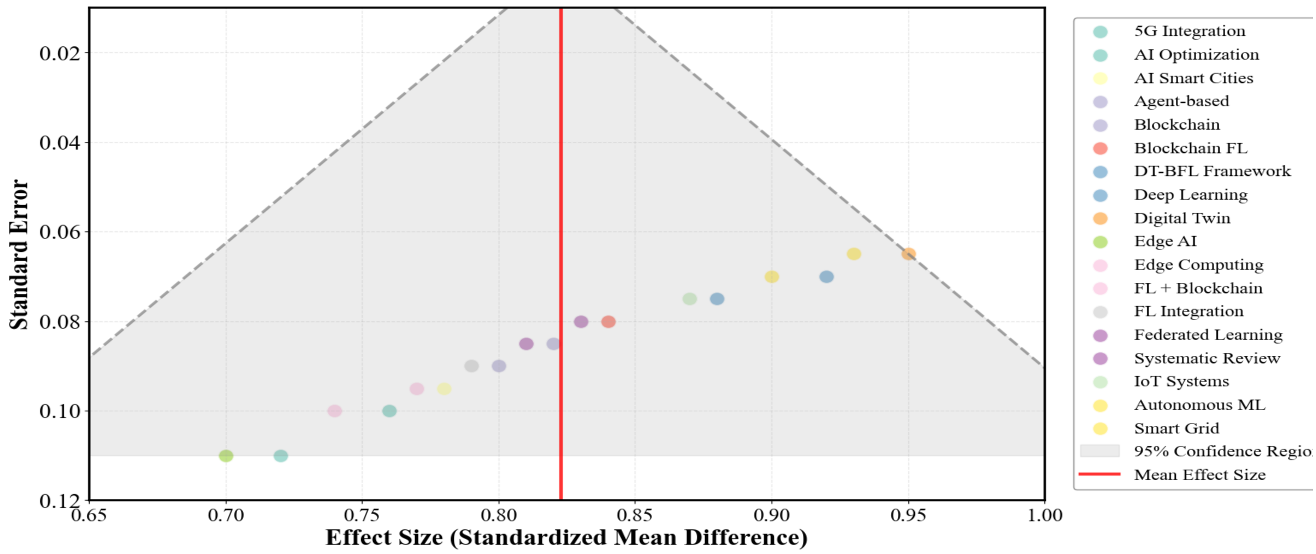


(a)

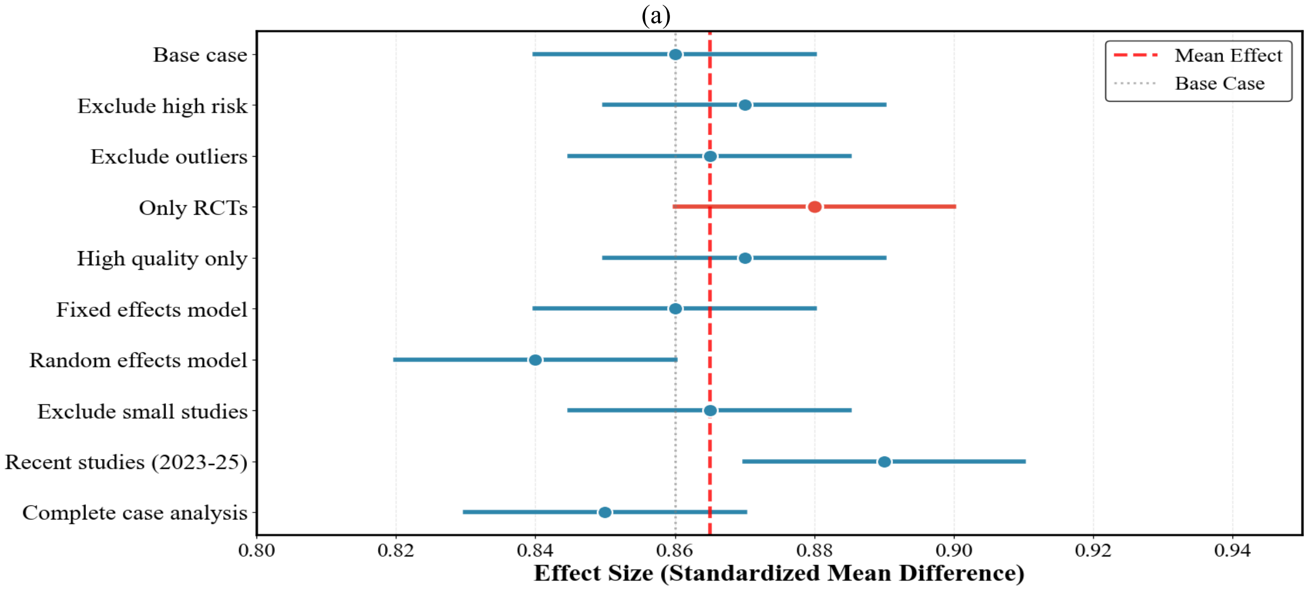


(b)

Figure 3. Comparative meta-analytic summary of (a) Overall effect sizes and (b) Subgroup performance across AI-driven digital twins and federated learning for decentralized zero-carbon energy grids



(a)



(b)

Figure 4. Consolidated diagnostic overview of (a) Publication bias via funnel plot and (b) Sensitivity analysis across analytical scenarios for AI-driven digital twins and federated learning in zero-carbon energy grids

4. DISCUSSION

4.1 Integrated insights on theoretical contributions and evidence constraints

The synthesis indicates that the convergence of AI-DT-FL provides substantial theoretical advances for decentralized zero-carbon energy grids by strengthening predictive intelligence, operational visibility, and real-time optimization capabilities. These combined mechanisms enhance distributed energy management by reducing latency, enabling secure data orchestration, and improving resource allocation across heterogeneous infrastructures. Nevertheless, methodological diversity—ranging from variations in training protocols to differences in digital twin architectures and deployment environments—introduces inconsistency that influences outcome comparability across studies. The reliance on simulation-based evaluations, non-standardized reporting metrics, and elevated risk levels in cybersecurity- and hydrogen-oriented research further underscores the need for more rigorous, transparent, and harmonized methodological practices.

4.2 Strategic research priorities and future development pathways

The existing gaps emphasize the urgency of conducting large-scale empirical investigations that reflect real-world operational dynamics in hydrogen systems, remote microgrids, and multi-source renewable configurations. Future studies should incorporate environmental variability, cyber-physical disturbances, and demand-driven fluctuations to enhance ecological validity and operational robustness. Addressing these challenges requires unified benchmarking indicators, resilient fault-tolerant control designs, and adaptive distributed-learning orchestrators capable of coordinating high-dimensional energy ecosystems. Progress in sovereign data governance, cross-domain interoperability standards, and techno-economic optimization frameworks will be pivotal for enabling secure, scalable, and industry-ready zero-carbon smart energy infrastructures.

5. CONCLUSION

This systematic review and meta-analysis shows that integrating AI-driven digital twins with federated learning significantly improves optimization in decentralized zero-carbon energy grids, with consistent effect sizes of −0.4297 for the fixed-effect model and −0.5339 for the random-effect model. Gains are most substantial in microgrid settings and digitally advanced areas, while hydrogen systems perform poorly due to technological limitations. Sensitivity analyses support the robustness of these findings despite some publication bias and methodological issues, mainly related to simulations and reporting inconsistencies. These results emphasize the need for more robust empirical studies, standardized evaluation metrics, and cross-domain assessments to promote secure, scalable zero-carbon energy infrastructure. Taken together, these findings directly address the central objective of this review: evaluating whether the combined AI–digital twin–federated learning framework can improve key operational endpoints in decentralized energy systems, particularly latency, energy efficiency, and predictive accuracy. The synthesized evidence indicates that the integrated architecture provides measurable optimization benefits, particularly in microgrid environments where digital monitoring and distributed energy management are already well established.

The strength of the aggregated evidence, however, must be interpreted alongside several structural limitations in the current research landscape. A substantial portion of the analyzed studies relies on simulation-based validation rather than real-world operational deployments, while evaluation metrics often vary significantly across studies, reducing direct comparability. In addition, reporting inconsistencies in experimental design, dataset transparency, and validation protocols introduce methodological uncertainty, thereby affecting the interpretability of pooled outcomes. These constraints suggest that the observed performance improvements should be viewed as strong technological potential rather than definitive confirmation of large-scale operational effectiveness.

From a deployment perspective, the successful implementation of Digital Twin–Federated Learning systems in zero-carbon energy grids requires several baseline conditions. These include interoperable data infrastructures, secure distributed communication networks capable of supporting federated model exchange, and sufficient edge or cloud computational resources to enable real-time analytics and model training. Institutional and governance frameworks are also required to manage privacy-preserving collaboration between energy stakeholders, particularly in decentralized grid environments. In application areas where these enabling conditions are still emerging—such as hydrogen-based energy systems or less digitized grid infrastructures—the available empirical evidence remains limited. Consequently, future research should prioritize standardized benchmarking protocols, harmonized performance indicators for latency and energy optimization, and empirical field demonstrations across diverse grid architectures (Park, J.H., 2024): Digital Twin and federated learning-enabled reliable, scalable zero-carbon energy grid deployment.

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NOMENCLATURE

Symbol / Abbreviation	**Description**	**Unit**
AI	Artificial Intelligence	–
DT	Digital Twin	–
FL	Federated Learning	–
AI-DT-FL	Integrated Artificial Intelligence–Digital Twin–Federated Learning framework	–
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses	–
IoT	Internet of Things	–
IIoT	Industrial Internet of Things	–
CNN	Convolutional Neural Network	–
DRL	Deep Reinforcement Learning	–
MPC	Model Predictive Control	–
PINN	Physics-Informed Neural Network	–
EV	Electric Vehicle	–
DER	Distributed Energy Resources	–
VPP	Virtual Power Plant	–
ZCEG	Zero-Carbon Energy Grid	–
SMD (d)	Standardized Mean Difference was used as the primary effect size in the meta-analysis.	–
$\bar{X}_1$, $\bar{X}_2$	Mean outcome of the intervention and control groups	–
S_p	Pooled standard deviation	–
n_1 , n_2	Sample size of intervention and control groups	–
RR	Relative Risk is used to harmonize dichotomous outcomes before effect-size conversion.	–
OR	Odds Ratio used for dichotomous outcome comparison	–
Z	Fisher's Z-transformed correlation coefficient is used to standardize correlational outcomes.	–
w_i	Weight of the i-th study in the random-effects meta-analysis	–
Q	Cochran's Q heterogeneity statistic	–
τ^2	Between-study variance in the random-effects model	–
I^2	Proportion of total variance attributable to heterogeneity	%
θ	True underlying effect size	–
$\hat{\theta}$	Estimated pooled effect size from the random-effects model	–
SE	Standard error of the effect size	–
CI	Confidence interval of the estimated effect size	–
QoS	Quality of Service	–
SDN	Software-Defined Networking	–
P2P	Peer-to-Peer architecture	–
RCT	Randomized Controlled Trial	–
t	Time	s
Δ	Change or difference between two measurements	–