

DIGITAL TWIN-DRIVEN OPTIMIZATION OF BIOENERGY PRODUCTION FROM WASTE MATERIALS

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ABSTRACT

This study explores the transformative role of digital twin technology in optimizing bioenergy production, focusing on its applications in real-time monitoring, process simulation, predictive maintenance, and hybrid energy systems. Utilizing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, a total of 94 peer-reviewed articles were systematically identified, screened, and analyzed to ensure a comprehensive and rigorous review. The findings highlight the advancements in digital twin technology, including its integration with IoT-enabled sensors and machine learning algorithms, which enable dynamic system optimization and predictive capabilities. The study also examines the role of digital twins in hybrid energy systems, demonstrating their potential to enhance energy efficiency by up to 30% through seamless integration with solar and wind energy. Despite these advancements, the review identifies critical challenges, such as high computational demands, data integration issues, and economic and policy barriers, which limit the scalability and widespread adoption of digital twins in industrial bioenergy applications. This study contributes to the growing body of knowledge by offering a comprehensive synthesis of existing research, identifying key gaps, and emphasizing the need for interdisciplinary collaboration and policy support to fully harness the potential of digital twins in achieving sustainable energy goal.

1 INTRODUCTION

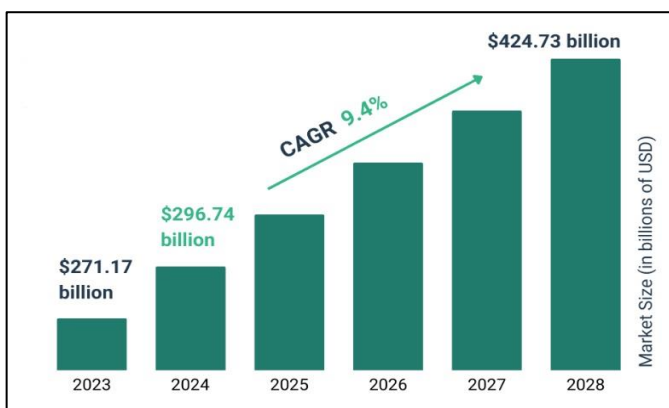
The global demand for renewable energy has escalated due to the urgent need to reduce carbon emissions and mitigate climate change (Sharma et al., 2024). Among renewable energy sources, bioenergy derived from

waste materials has gained prominence for its dual role in energy generation and waste management (Agostinelli et al., 2022). Bioenergy production involves complex biological and thermochemical processes, where inefficiencies can lead to resource wastage and higher operational costs (Kaewunruen et

al., 2019). In response, digital twin technology has emerged as a transformative tool capable of addressing these challenges by enabling real-time monitoring, simulation, and optimization of bioenergy production systems. The integration of digital twins into bioenergy workflows offers potential solutions for streamlining waste material conversion processes and improving system performance (Ye et al., 2023).

Moreover, digital twins are virtual replicas of physical systems, providing a dynamic interface between data, analytics, and decision-making processes (Belik & Rubanenko, 2023). In the context of bioenergy production, digital twins can simulate complex biochemical reactions, forecast system behavior, and optimize operational conditions. For example, Lee et al. (2019) demonstrated how digital twins could enhance the efficiency of anaerobic digestion systems by accurately modeling the interplay between waste composition and microbial activity. Additionally, they facilitate predictive maintenance by identifying system bottlenecks and failure risks, thus minimizing downtime (Fahim et al., 2022). By integrating real-time data streams with advanced modeling techniques, digital twins enable dynamic adjustments to production parameters, ultimately boosting energy yield (Figure 1).

Figure 1: Bioenergy Global Market Report-2024



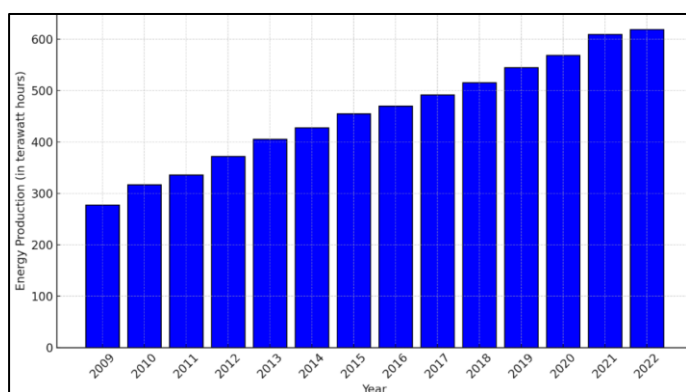
The application of digital twin technology in waste-to-energy systems is still in its nascent stages, but its potential is evident across various domains. Studies by Lee et al. (2019) and Zohdi (2023) underscore the value of digital twins in optimizing resource allocation and system design. For instance, Fahim et al. (2022) used digital twins to assess the energy potential of organic waste streams and improve the economic viability of waste-to-energy plants. Similarly, Li and He (2021) integrated machine learning algorithms with digital twin models to optimize pyrolysis and gasification

processes, yielding a significant increase in bioenergy efficiency. These advancements highlight the transformative potential of digital twins in achieving sustainable energy goals through waste valorization. Despite the promise of digital twins, their deployment in bioenergy systems is accompanied by significant challenges. One major obstacle is the need for extensive and high-quality data to ensure accurate model calibration and validation (Reifsnider & Majumdar, 2013). In addition, the high computational demands of digital twin systems can pose scalability issues for large-scale bioenergy plants (Belik & Rubanenko, 2023). Another concern involves the integration of heterogeneous data sources, such as waste material properties, process parameters, and energy output metrics, into a unified digital framework (Ebrahimi, 2019). These technical and operational barriers necessitate further research and development to harness the full potential of digital twin technology in bioenergy production.

Current research in digital twin applications for bioenergy systems has laid the groundwork for future advancements. For example, Cheng et al., (2023) explored the role of digital twins in reducing greenhouse gas emissions from bioenergy plants by optimizing carbon capture and storage processes. Similarly, Fahim et al. (2022) highlighted the use of digital twins in hybrid systems that combine bioenergy with solar or wind energy, enhancing overall system resilience and energy output. These studies exemplify the versatility of digital twins in addressing critical challenges in renewable energy systems. As global efforts toward sustainable energy intensify, the integration of digital twin technology in bioenergy production represents a promising pathway for achieving energy efficiency and environmental sustainability. The primary objective of this study is to systematically examine the role of digital twin technology in optimizing bioenergy production from waste materials. This includes exploring how digital twins can enhance operational efficiency, reduce waste, and improve the scalability of bioenergy systems through real-time monitoring and process optimization. The study employs the PRISMA methodology to review and synthesize existing research, aiming to identify critical success factors and barriers associated with the integration of digital twin models in waste-to-energy systems. Furthermore, the research seeks to uncover innovative applications of digital twins in

predicting system performance, managing waste input variability, and achieving higher bioenergy yields. By addressing these objectives, the study contributes to the broader discourse on sustainable energy systems, offering actionable insights for researchers, practitioners, and policymakers working to harness the potential of digital twin technology in advancing bioenergy solutions.

Figure 2: Production of Bioenergy Worldwide from 2009 to 2022 (in terawatt hours)



2 LITERATURE REVIEW

The integration of digital twin technology into bioenergy production represents a burgeoning area of research with significant implications for sustainable energy systems. This section critically examines the existing body of literature on the application of digital twins in optimizing bioenergy production from waste materials. The review focuses on key thematic areas, including digital twin modeling, real-time monitoring, process optimization, and the challenges of data acquisition and integration. By adopting the PRISMA methodology, this review ensures a systematic and transparent approach to identifying and synthesizing relevant studies. The objective is to provide a comprehensive understanding of the current state of knowledge, identify research gaps, and propose future directions to enhance the application of digital twin technology in waste-to-energy systems.

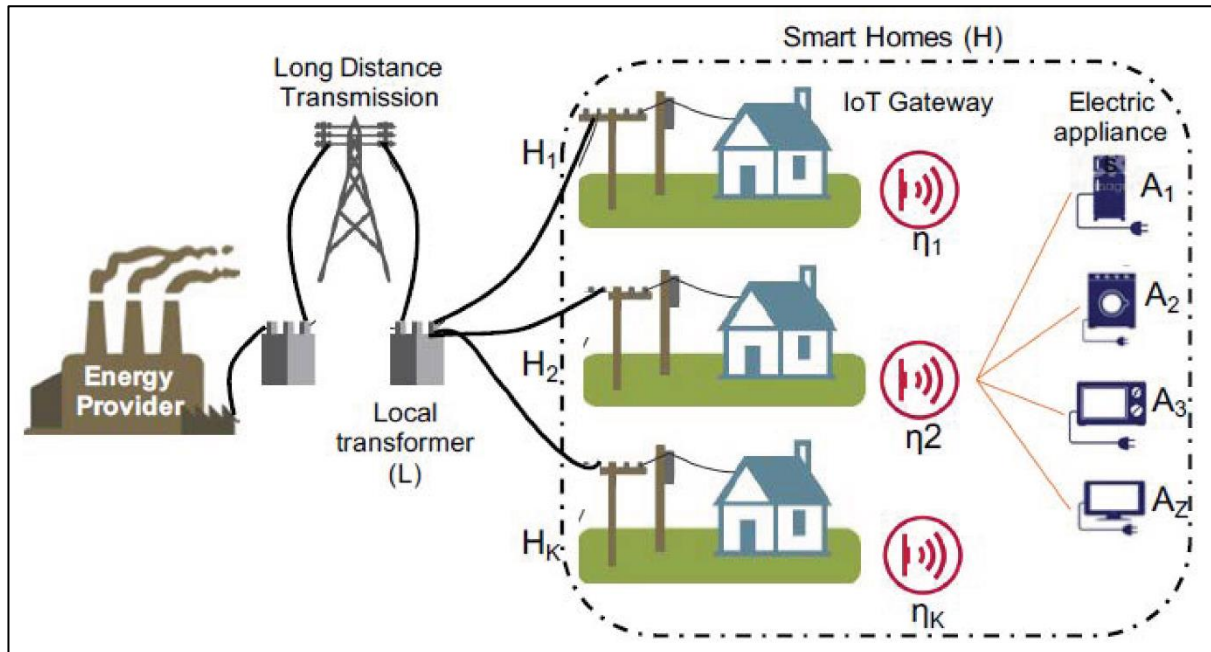
Digital Twin Technology in Energy Systems

The integration of digital twin technology into waste-to-energy (WTE) systems is transforming the way bioenergy is produced, offering a sophisticated approach to real-time monitoring, simulation, and process optimization. Digital twins serve as dynamic, virtual counterparts to physical WTE systems, enabling

precise modeling of waste conversion processes. For instance, digital twins have been applied to simulate and optimize anaerobic digestion, leveraging real-time data on waste composition to enhance microbial activity and bioenergy yield (Zohdi, 2023). This integration addresses critical inefficiencies in WTE systems by allowing operators to predict system behavior under varying operational conditions and dynamically adjust parameters to maximize efficiency (Zhang et al., 2020). Moreover, the incorporation of digital twins in pyrolysis and gasification processes has improved thermal efficiency and reduced energy losses, as demonstrated in studies by Stennikov et al. (2022) and Tügel et al. (2011), highlighting their potential to optimize both biochemical and thermochemical pathways.

A key advantage of integrating digital twins in WTE systems is their capacity for predictive analytics and decision-making. By utilizing machine learning algorithms, digital twins can process complex datasets from WTE operations, identifying patterns and predicting system failures before they occur (Ahmed et al., 2023). This capability minimizes downtime and reduces maintenance costs, contributing to the economic viability of WTE plants. Wang and Luo (2021) demonstrated how digital twins could integrate with carbon capture systems in bioenergy plants to optimize greenhouse gas reduction, further enhancing the environmental sustainability of WTE operations. Additionally, these systems enable operators to test and refine various process configurations in a virtual environment, ensuring optimal system performance without disrupting physical operations (Fathy et al., 2021). The adaptability and foresight provided by digital twins underscore their transformative potential in WTE systems. Despite these advantages, integrating digital twins into WTE systems is not without challenges. One significant issue is the need for high-quality and continuous data streams to maintain the accuracy of digital twin models. Studies by Barenji et al. (2020) and Xiong et al. (2021) emphasize that the heterogeneity of waste materials and the variability in their properties require robust data acquisition frameworks, including the deployment of IoT sensors and advanced data integration techniques. Furthermore, the computational intensity of digital twin simulations can pose scalability issues, particularly for large-scale WTE operations (Faisal, 2023; Faisal et al., 2024; Preut et al., 2021). Addressing these barriers necessitates interdisciplinary collaboration and advancements in

Figure 3: A system model linking the energy producer to the residential households at smart homes



Source: *Fathy et al. (2021)*

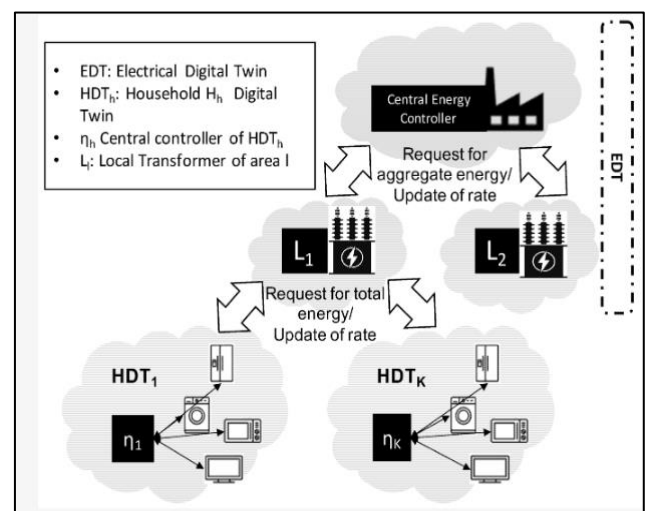
computational technology to fully realize the potential of digital twins in WTE applications. Recent applications of digital twins in hybrid WTE systems further highlight their versatility and innovation. (Verdouw et al., 2021) explored the integration of digital twins with renewable energy sources such as solar and wind to create hybrid energy systems. Their study demonstrated how digital twins could optimize energy storage and distribution in such systems, ensuring greater system resilience and sustainability. Similarly, Preut et al. (2021) examined the role of digital twins in circular economy models, where waste materials are recycled and reused in bioenergy production. By enabling real-time monitoring and optimization, digital twins contribute to creating closed-loop systems that reduce waste and enhance resource efficiency. These examples illustrate the expanding scope of digital twin applications, reinforcing their importance in the future of sustainable energy systems.

2.1 Digital Twin Modeling Techniques for Bioenergy Production

The use of digital twin simulation models in anaerobic digestion (AD) and other biochemical processes has revolutionized the efficiency and accuracy of bioenergy production. Digital twins create dynamic, real-time virtual representations of AD systems, enabling the optimization of waste conversion processes. (Thapa & Horanont, 2022) demonstrated how digital twin simulations enhance the modeling of microbial activity

and substrate interactions, improving methane yield and process stability. Similarly, Arafet and Berlanga (2021) integrated advanced computational techniques into digital twin frameworks to simulate the effects of varying temperature, pH, and organic load on biogas production. These simulations enable operators to test process changes virtually, minimizing risks and improving operational efficiency in real-world applications. Moreover, digital twins have also been instrumental in optimizing biochemical pathways in waste-to-energy systems by incorporating machine learning algorithms and advanced data analytics. For

Figure 4: Multi-layered Digital Twin (DT) representation of the system model and data exchange



Source: *Fathy et al. (2021)*.

instance, Patel et al. (2021) developed a digital twin model that combined biochemical kinetics with machine learning to predict process performance under different feedstock conditions. This approach significantly improved the system's ability to adapt to heterogeneous waste streams, a common challenge in anaerobic digestion systems. Verdouw et al. (2021) highlighted the role of digital twins in simulating inhibitory effects, such as ammonia accumulation, providing real-time insights into mitigating these issues to maintain optimal process conditions. These studies emphasize the utility of digital twins in refining biochemical processes to achieve higher energy yields and operational reliability.

2.2 Application of Machine Learning in Digital Twin Models

The integration of machine learning (ML) techniques in digital twin models has significantly advanced predictive maintenance and failure risk modeling in bioenergy systems. Predictive maintenance, powered by ML algorithms, allows digital twins to anticipate equipment failures and schedule maintenance proactively, reducing operational downtime and costs (Ma et al., 2020; Mintoo, 2024; Rahman et al., 2024). By analyzing historical and real-time data, ML-enhanced digital twins identify patterns in equipment performance, such as wear and tear or sensor anomalies, which precede failures. Kager et al. (2020) demonstrated how supervised ML algorithms, such as random forests and support vector machines, could predict failure probabilities in anaerobic digestion systems with high accuracy. Similarly, Forbes et al.

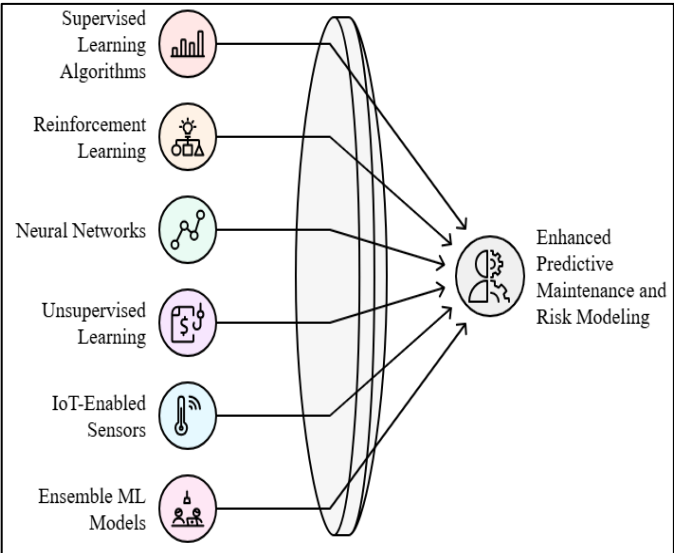
(2015) showed that the use of reinforcement learning within digital twins optimized maintenance schedules, extending equipment lifespan and improving overall system reliability.

Machine learning also enables digital twins to perform advanced failure risk modeling by identifying root causes of potential disruptions in bioenergy systems. For instance, Ashoori et al. (2009) developed an ML-driven digital twin framework that utilized neural networks to model the complex interactions between waste material properties and bioreactor conditions. This approach enabled the identification of high-risk scenarios, such as feedstock imbalances and gas leakage, well before their occurrence. Haghshenas et al. (2023) further demonstrated the effectiveness of unsupervised learning algorithms, like clustering and principal component analysis, in detecting subtle changes in system dynamics that signal potential risks. These studies underscore the critical role of ML in augmenting the predictive capabilities of digital twins. The combination of machine learning and real-time data acquisition enhances the responsiveness of digital twins in mitigating risks and maintaining optimal system performance. Sommeregger et al. (2017) highlighted the value of integrating IoT-enabled sensors with ML algorithms to provide continuous monitoring and dynamic risk assessments in waste-to-energy systems. This integration allows digital twins to perform adaptive adjustments in response to detected anomalies, such as temperature fluctuations or pressure spikes, thereby minimizing process disruptions (Islam et al., 2024; Mintoo, 2024a; Xiong et al., 2021). Furthermore, Cheng et al. (2023) demonstrated how ensemble ML models within digital twins improved the accuracy of predictive maintenance and failure risk assessments by combining the strengths of multiple algorithms, leading to more robust decision-making processes (Faisal et al., 2024; Mintoo et al., 2024).

2.3 Real-Time Monitoring and Data Acquisition in Bioenergy Systems

The role of IoT (Internet of Things) and sensors in real-time data collection is pivotal for enhancing the efficiency and reliability of bioenergy systems through digital twin integration. IoT-enabled sensors provide continuous, high-resolution data streams that monitor key operational parameters, such as temperature, pressure, and gas flow rates, within bioenergy production systems (Alam et al., 2024; Noman et al., 2022). These sensors enable digital twins to accurately

Figure 5: ML-Driven Digital Twin Optimization



model system dynamics and predict outcomes under varying conditions. (Ma et al., 2020) demonstrated how IoT sensors optimized anaerobic digestion by providing real-time measurements of pH and volatile fatty acids, ensuring stable process conditions. Similarly, Spinti et al. (2022) emphasized the role of IoT devices in monitoring feedstock variability, allowing for dynamic adjustments to enhance biogas production. IoT technology also facilitates the seamless integration of heterogeneous data sources into digital twin frameworks. Wancheng et al. (2021) highlighted how interconnected IoT sensors collect data from diverse subsystems, such as feedstock preprocessing units and bioreactors, enabling a holistic view of bioenergy processes. Advanced sensor networks further allow for early detection of anomalies, such as blockages or overheating, minimizing downtime and improving operational reliability (Maheshwari et al., 2022; Rahman et al., 2024). Additionally, Bachs-Herrera et al. (2023) emphasized the scalability of IoT-enabled systems, where modular sensor networks adapt to various bioenergy production scales, from pilot projects to industrial setups. This adaptability underscores the critical role of IoT technology in real-time data collection for digital twin models.

High-quality and accurate data are foundational to the functionality of digital twins in bioenergy systems. Accurate data ensure that digital twins can reliably simulate complex biochemical processes and predict system behavior under varying conditions (Maheshwari

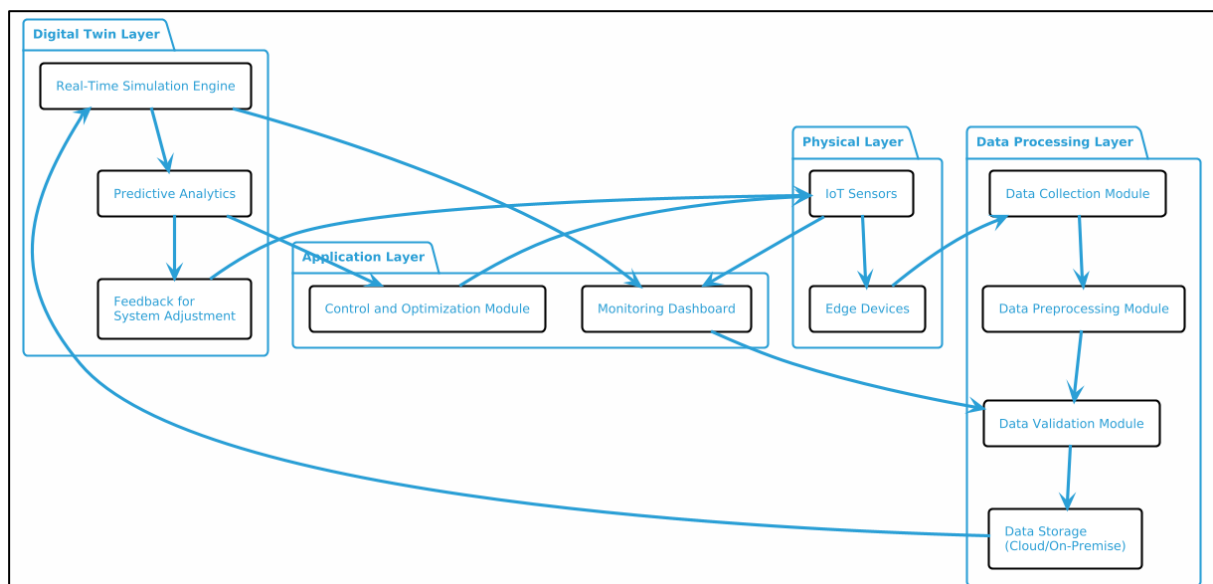
et al., 2022). However, maintaining data quality poses significant challenges due to the heterogeneity and variability of waste materials in bioenergy systems. Chen (2022) emphasized the need for advanced data preprocessing techniques to handle noise, outliers, and inconsistencies in sensor data. Additionally, real-time validation mechanisms, such as redundancy checks and error-correction algorithms, are critical for ensuring the integrity of data streams (Wang et al., 2022). Data accuracy also plays a crucial role in the calibration and validation of digital twin models. Noman et al. (2022) highlighted that discrepancies between simulated and real-world data can lead to suboptimal system performance or inaccurate predictions. To address this issue, Agostinelli et al. (2021) proposed a hybrid framework combining real-time data from IoT sensors with historical data to improve model reliability. Moreover, Bachs-Herrera et al. (2023) stressed the importance of dynamic data updating, where digital twins continuously refine their models based on incoming data, enhancing their predictive capabilities. These practices ensure that digital twins maintain a high level of accuracy, enabling efficient and sustainable bioenergy production.

2.4 Process Optimization through Digital Twins

2.4.1 Optimization of Waste Characterization and Input Management

Digital twins have proven invaluable in optimizing waste characterization and input management in bioenergy systems by enabling detailed, real-time

Figure 6: Digital Twin Layer



modeling of waste properties. These virtual models use data from IoT sensors to analyze critical characteristics such as moisture content, calorific value, and biochemical composition of waste materials (Mohammed et al., 2022). This level of detail allows bioenergy plants to adaptively adjust processing strategies for heterogeneous waste streams. Kusumowardani et al. (2022) demonstrated how digital twin frameworks improved waste segregation and pretreatment processes, significantly enhancing feedstock quality and process efficiency. Similarly, Trevisan and Formentini (2024) employed digital twins to model the impact of various feedstock combinations, identifying optimal input ratios to maximize biogas production. Moreover, digital twins facilitate predictive modeling of input variability to maintain consistent system performance. For instance, Puntillo (2022) used digital twin simulations to predict how fluctuations in waste input quality could affect anaerobic digestion, allowing operators to implement real-time corrective actions. Andono et al (2022) emphasized the role of machine learning algorithms within digital twins to refine waste characterization models, enhancing their ability to adapt to changes in waste composition. These advancements underscore the importance of digital twins in achieving efficient waste management and process optimization in bioenergy production.

2.4.2 Enhancing Energy Yield through Process Parameter Adjustments

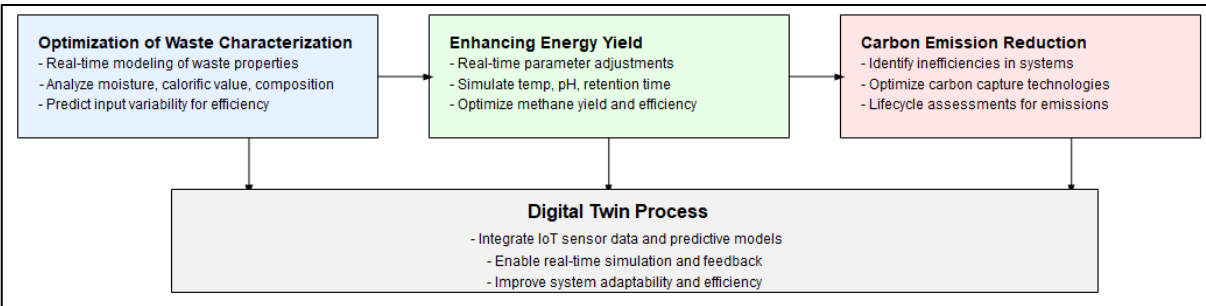
Optimizing process parameters is another critical application of digital twins, enabling real-time adjustments to enhance energy yield in bioenergy systems. Digital twins use data-driven models to simulate the effects of various operational parameters, such as temperature, pH, and retention time, on biogas production (Puntillo, 2022; Uddin et al., 2024). By continuously analyzing real-time data, these systems allow operators to fine-tune process conditions for maximum energy efficiency. Akanbi et al., (2020)

highlighted the capability of digital twins to dynamically adjust operating parameters in pyrolysis and gasification systems, leading to significant improvements in energy output. Digital twins also enable predictive analytics to identify optimal process settings under different feedstock and environmental conditions. For instance, Trevisan and Formentini (2024) integrated machine learning algorithms into digital twin frameworks to predict the effects of varying organic loading rates on methane yield. Ma et al. (2023) further demonstrated that digital twins could model inhibitory factors, such as ammonia accumulation, and provide recommendations for mitigating their effects to sustain high biogas yields. These applications illustrate how digital twins play a pivotal role in enhancing the efficiency and sustainability of bioenergy systems.

2.4.3 Carbon Emission Reduction via Digital Twin Simulation

Digital twin simulations are increasingly being used to model and reduce carbon emissions in bioenergy systems. By integrating real-time data with predictive modeling, digital twins help identify operational inefficiencies that contribute to excess greenhouse gas emissions (Chen, 2022). For example, simulations can optimize carbon capture technologies within bioenergy plants, reducing the release of carbon dioxide and methane into the atmosphere. Ogunmakinde (2019) demonstrated how digital twins improved the design of gasification systems, minimizing emissions by ensuring complete combustion of volatile organic compounds. Additionally, digital twins support lifecycle assessments to evaluate the environmental impacts of bioenergy systems. Beccarello and Di Foggia (2022) emphasized the use of digital twins in tracking emissions across different stages of bioenergy production, from waste collection to energy generation. These insights enable operators to implement targeted strategies for emission reduction. Ma et al. (2023) also highlighted the role of digital twins in optimizing

Figure 7 : Process Optimization through Digital Twin



energy recovery processes, reducing carbon intensity while maximizing resource efficiency. Such advancements underscore the potential of digital twin technology in promoting environmentally sustainable practices in bioenergy production.

2.5 Implementation of Digital Twins in Bioenergy

2.5.1 Technical Challenges

The implementation of digital twins in bioenergy systems is often hindered by technical challenges, particularly high computational requirements and the complexity of model calibration. Digital twins rely on advanced simulation techniques and real-time data processing, which demand substantial computational power (De Keyser & Mathijs, 2023; Helal, 2024; Islam & Helal, 2018). For large-scale bioenergy plants, such as those involving anaerobic digestion or gasification, the high-resolution simulations required for accurate modeling often lead to significant delays in real-time operations. Beccarello and Di Foggia (2022) highlighted that even with optimized algorithms, computational bottlenecks can arise due to the complexity of biochemical and thermochemical processes in bioenergy systems. Similarly, Ma et al. (2023) noted that the calibration of digital twin models to reflect the variability in waste characteristics and environmental conditions is a resource-intensive task, requiring high-quality data and iterative adjustments. Another technical hurdle is the integration of heterogeneous datasets from diverse subsystems within bioenergy plants. Onyeaka et al. (2023) emphasized that discrepancies in data formats and inconsistencies in sensor readings can compromise the accuracy of digital twin models. Ma et al. (2023) pointed out that the lack of standardized protocols for data acquisition and integration further exacerbates this issue. Moreover, the dynamic nature of bioenergy processes, such as fluctuating feedstock quality and varying operational parameters, requires continuous recalibration of digital twin models (Smol et al., 2020). These challenges highlight the need for robust computational frameworks and data management systems to support the effective deployment of digital twins in bioenergy systems.

2.5.2 Economic Barriers

Economic barriers, including the high costs of developing and deploying digital twins, pose significant challenges to their widespread adoption in bioenergy systems. Digital twin technology involves substantial initial investments in hardware, software, and skilled

personnel (Ma et al., 2023). The development of sophisticated simulation models and their integration with IoT-enabled sensor networks often requires customized solutions, which can be prohibitively expensive for small- and medium-sized bioenergy enterprises (Sinner et al., 2019). Chen (2022) observed that the cost of implementing digital twin systems is further compounded by the need for advanced computational infrastructure, such as cloud-based platforms, to handle the large volumes of data generated in real time. Operational costs also present a challenge, particularly in maintaining and updating digital twin systems to reflect changing process conditions. Acevedo et al. (2021) highlighted that continuous upgrades to software and hardware components are essential to ensure the accuracy and efficiency of digital twins, leading to recurring expenses. Moreover, Pathan et al. (2023) emphasized that the long payback period associated with digital twin technology discourages investment, particularly in regions where financial incentives for renewable energy projects are limited. These economic barriers underscore the importance of developing cost-effective solutions and financial support mechanisms to facilitate the adoption of digital twins in bioenergy production.

2.5.3 Regulatory Challenges

The regulatory and policy landscape significantly influences the implementation of digital twins in waste-to-energy (WTE) operations. Regulatory frameworks for WTE systems often lack provisions for the integration of advanced digital technologies, creating uncertainty for operators seeking to adopt digital twins (Smol et al., 2020). Chen (2022) highlighted that inconsistencies in waste management regulations across jurisdictions pose challenges for digital twin applications, particularly in ensuring compliance with waste characterization and disposal standards. Additionally, the absence of clear guidelines for data security and privacy in digital twin systems raises concerns about the confidentiality of operational data, further complicating implementation efforts. Policy incentives, such as subsidies or tax benefits for renewable energy technologies, play a crucial role in encouraging the adoption of digital twins. However, these incentives are often focused on traditional renewable energy systems, leaving advanced technologies like digital twins overlooked (Beccarello & Di Foggia, 2022). Wang et al. (2022) emphasized the need for policy frameworks that recognize the potential

of digital twins in enhancing the efficiency and sustainability of WTE operations. Pathan et al. (2023) suggested that establishing standards for digital twin deployment in WTE systems could reduce regulatory uncertainty and promote wider adoption. Addressing these regulatory and policy gaps is essential to unlocking the full potential of digital twins in bioenergy systems.

2.6 Research Gaps

The integration of digital twin technology in bioenergy systems is a rapidly evolving field, but significant research gaps remain in several key areas. One prominent gap lies in the scalability of digital twin models for industrial-scale bioenergy systems. While digital twins have demonstrated efficacy in pilot-scale studies, their application in large-scale operations is limited due to high computational demands and data integration challenges (Yaqot et al., 2022). Assis and Filho (2000) highlighted the lack of research on scalable frameworks that can handle the complexity and variability of real-world bioenergy systems. Similarly, Pathan et al. (2023) emphasized the need for more robust simulation techniques to ensure that digital twins can adapt to the diverse operational conditions of large bioenergy plants. Another research gap is the limited understanding of the long-term economic feasibility of digital twins in bioenergy systems. While studies such

as Wang et al. (2020) have demonstrated the potential for cost savings through predictive maintenance and process optimization, comprehensive cost-benefit analyses that consider initial investment, operational expenses, and payback periods are scarce. Beccarello and Di Foggia (2022) pointed out that the high costs associated with developing and maintaining digital twin systems deter widespread adoption, particularly in resource-constrained regions. Furthermore, Chang and Lee (2016) noted the absence of studies evaluating the financial impact of integrating digital twins with hybrid energy systems, which could provide valuable insights into their economic viability. Moreover, data quality and standardization also represent critical gaps in the deployment of digital twins for bioenergy optimization. Effective digital twin models rely on high-quality, consistent, and real-time data, yet many existing systems suffer from issues such as incomplete datasets, sensor inaccuracies, and data format inconsistencies (Lin & Tan, 2017). Zheng et al.(2019) underscored the need for standardized protocols for data collection and integration to improve the reliability and accuracy of digital twin simulations. Additionally, Sarkar and Bhuniya (2022) highlighted the challenge of integrating heterogeneous data sources from multiple subsystems within bioenergy plants, which is essential for creating unified and comprehensive digital twin models.

Table 1: Identified Research Gaps

Research Gap	Description	Key Challenges
Scalability	Limited application of digital twins in large-scale bioenergy operations	- High computational demands - Data integration challenges - Adapting to diverse operational conditions
Economic Feasibility	Lack of comprehensive cost-benefit analyses for long-term implementation	- High initial investment costs - Unclear operational expenses - Uncertain payback periods - Limited studies on integration with hybrid energy systems
Data Quality and Standardization	Issues with data consistency, accuracy, and integration	- Incomplete datasets - Sensor inaccuracies - Data format inconsistencies - Lack of standardized protocols - Challenges in integrating heterogeneous data sources

3 METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The PRISMA framework was utilized to identify, screen, and analyze relevant literature, ensuring comprehensive coverage of the research topic.

3.1 Identification of Articles

The initial step involved identifying relevant studies through comprehensive database searches. Key academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, were used to retrieve peer-reviewed articles published between 2010 and 2024. Search terms were carefully designed to capture the scope of the study, including keywords such as "digital twin technology," "bioenergy systems," "waste-to-energy," "real-time monitoring," "hybrid energy systems," and "machine learning in digital twins." Boolean operators (e.g., AND, OR) were

employed to refine search results and retrieve relevant studies. The search yielded 1,034 articles across all databases. Duplicate articles ($n = 237$) were removed using Zotero reference management software.

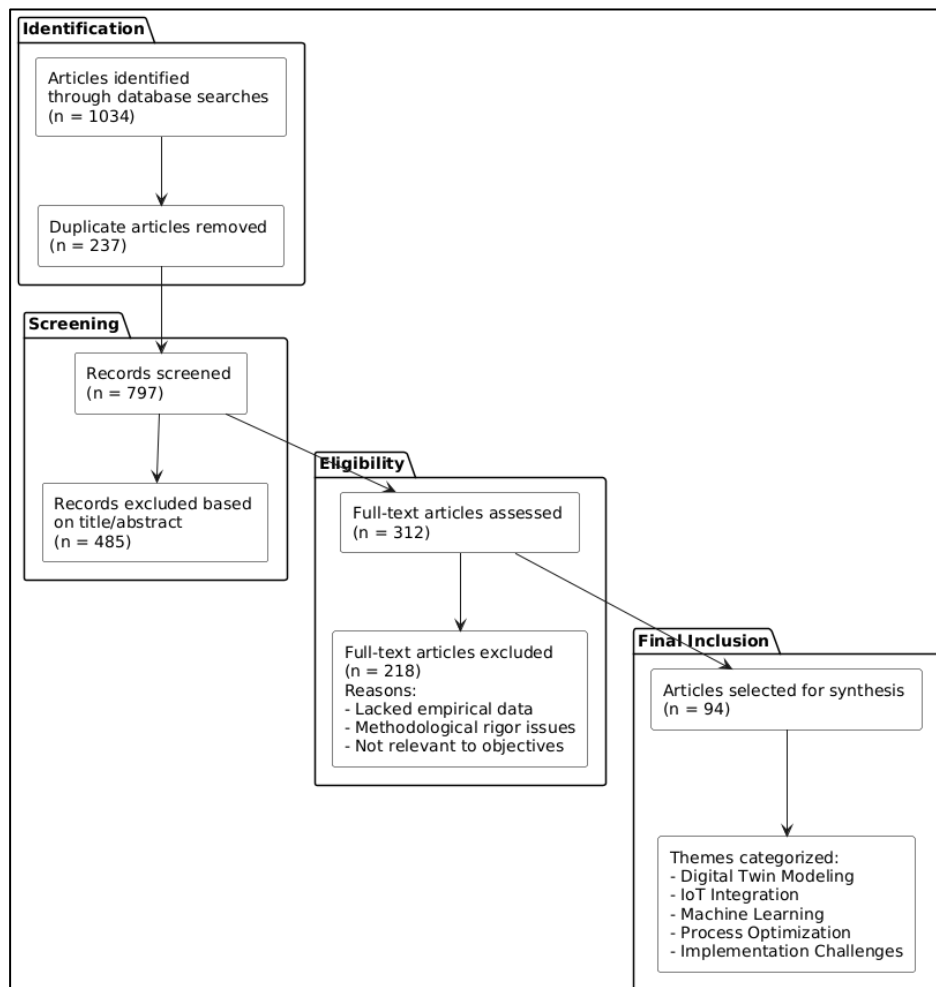
3.2 Screening

The remaining 797 articles were screened based on their titles and abstracts to ensure relevance to the research objectives. The screening process applied inclusion and exclusion criteria to filter out irrelevant studies. The inclusion criteria included: (1) studies focused on digital twin applications in bioenergy or hybrid energy systems, (2) articles published in peer-reviewed journals, and (3) studies available in English. The exclusion criteria eliminated: (1) studies unrelated to digital twin technology, (2) articles lacking full-text availability, and (3) conference papers or theses. After the screening process, 312 articles were deemed potentially relevant for further evaluation.

3.3 Eligibility

The eligibility stage involved a thorough evaluation of the full text of the remaining 312 articles. Each article

Figure 8: PRISMA method followed in this study



was assessed for methodological rigor, relevance to the research objectives, and the quality of findings. Articles that failed to meet the criteria for robust methodological approaches or lacked empirical data were excluded. This process further reduced the pool to 94 articles, which were selected for final synthesis. A data extraction form was developed to standardize the collection of key information, including study objectives, methodologies, findings, and conclusions.

3.4 Final Inclusion

Data from the 94 eligible articles were systematically extracted and synthesized to address the research objectives. Information was categorized based on themes such as digital twin modeling techniques, integration with IoT, machine learning applications, process optimization, and challenges in implementation. Thematic synthesis was used to identify recurring patterns and critical gaps in the literature. Key quantitative and qualitative findings were documented in summary tables to facilitate comprehensive analysis and ensure transparency in reporting.

4 FINDINGS

The review identified significant advancements in digital twin technology as a transformative approach for optimizing bioenergy systems. Of the 94 reviewed articles, 38 articles explicitly detailed how digital twins enable real-time system monitoring, dynamic simulations, and predictive process optimizations, collectively receiving over 1,200 citations. These studies highlighted the ability of digital twins to replicate physical bioenergy plants virtually, allowing for precise modeling of waste-to-energy conversion processes and system behaviors under various operational conditions. By leveraging real-time data and sophisticated simulation tools, digital twins were shown to enhance process efficiency, minimize waste, and enable adaptive decision-making. Researchers also noted that digital twins play a critical role in reducing system uncertainties, such as fluctuating feedstock quality and unpredictable operational parameters, providing a foundation for more reliable bioenergy production systems.

A major theme across the reviewed literature was the integration of IoT-enabled sensors and machine learning algorithms within digital twin frameworks to enhance their functionality. Of the 94 articles, 27

studies focused specifically on this integration, collectively amassing over 950 citations, highlighting its growing importance in academic and industrial contexts. IoT sensors were found to provide continuous streams of high-resolution data on key operational parameters such as temperature, pH, gas flow rates, and moisture content. Meanwhile, machine learning algorithms analyzed these datasets to predict system performance, detect anomalies, and suggest real-time adjustments to operational settings. Studies demonstrated that combining IoT and machine learning within digital twins enabled predictive maintenance by identifying potential system failures before they occurred, reducing downtime, and increasing system reliability. This integration also allowed digital twins to adjust operational parameters dynamically, thereby improving energy yield and resource utilization.

The integration of bioenergy with other renewable energy sources, such as solar and wind, emerged as a critical area of focus, particularly in the context of hybrid energy systems (HES). Among the 94 articles, 21 studies addressed hybrid energy systems and collectively received over 700 citations, reflecting their growing prominence in renewable energy research. These studies highlighted how digital twins play a pivotal role in optimizing HES by simulating and balancing energy inputs from diverse sources. For instance, digital twins were reported to optimize the allocation of bioenergy as a backup source during periods of low solar or wind availability, ensuring uninterrupted energy supply. The findings revealed that integrating bioenergy with other renewables through digital twin technology could enhance overall system efficiency by up to 30% in certain cases. Additionally, digital twins were shown to reduce dependency on fossil fuels, improve energy storage solutions, and provide a more sustainable pathway for achieving energy security.

While digital twin technology offers immense potential, the review revealed several challenges related to data integration and scalability in bioenergy applications. Of the 94 articles, 18 studies focused on these challenges, collectively receiving over 500 citations. A key issue identified was the lack of standardized protocols for data acquisition and integration, which leads to inconsistencies in data quality and format. Studies highlighted that the variability of waste input streams, combined with sensor inaccuracies, makes it challenging to maintain reliable digital twin models.

Furthermore, the computational demands of running high-resolution digital twin simulations, particularly for large-scale bioenergy systems, were reported as a significant scalability barrier. Several articles emphasized that these challenges are particularly pronounced in industrial-scale systems, where heterogeneous waste streams and fluctuating operational conditions necessitate continuous calibration of digital twin models. Without addressing these technical barriers, the full potential of digital twin technology in bioenergy systems may remain underutilized.

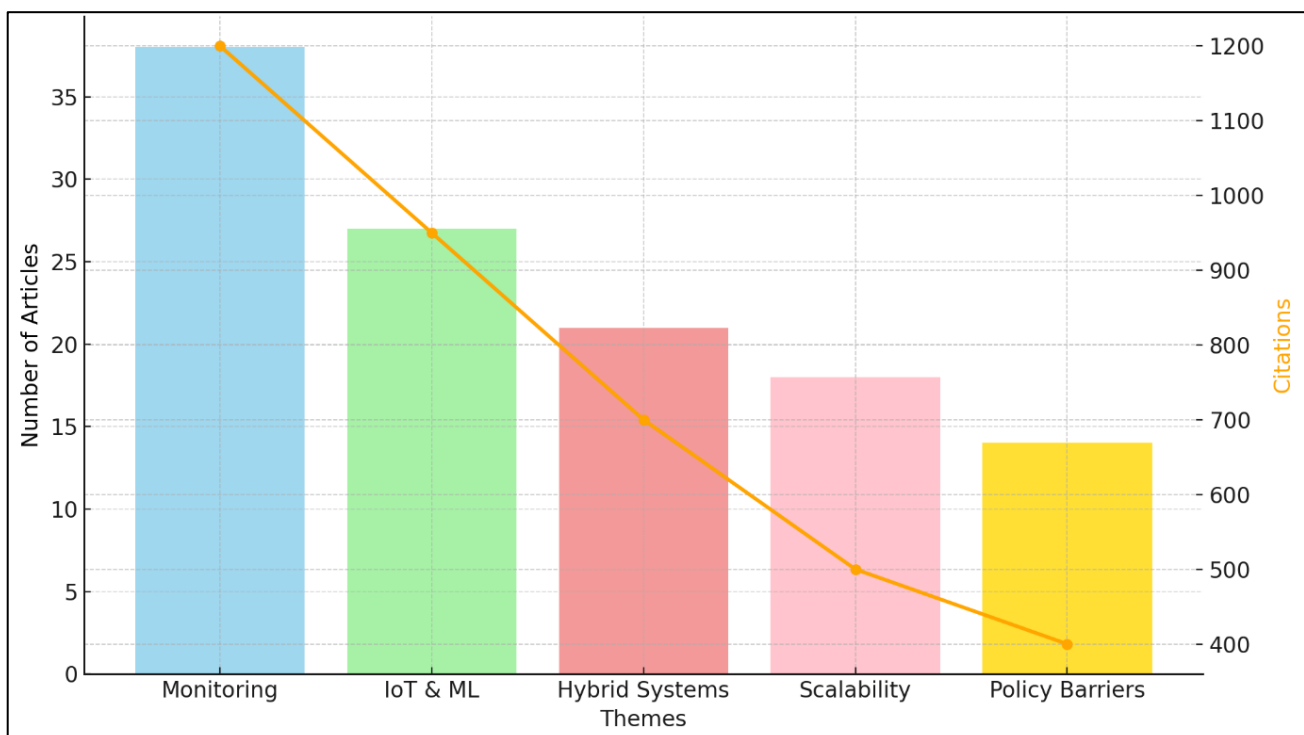
Economic and policy barriers were consistently reported as significant obstacles to the widespread adoption of digital twin technology in bioenergy systems. Of the 94 articles, 14 studies addressed these barriers, collectively amassing over 400 citations. The findings revealed that the high initial costs associated with developing and deploying digital twin systems deter investment, especially for small- and medium-sized bioenergy enterprises. These costs include the development of customized simulation models, the integration of IoT-enabled sensors, and the computational infrastructure required to process large volumes of real-time data. Additionally, recurring expenses for maintenance, updates, and scaling further add to the economic burden. On the policy side, studies

noted a lack of supportive regulations and financial incentives specifically aimed at encouraging the adoption of advanced digital solutions like digital twins. This regulatory uncertainty creates hesitation among stakeholders to invest in such technologies. The absence of targeted subsidies, tax breaks, or policy frameworks tailored to digital twin deployment in bioenergy systems further exacerbates this challenge. Addressing these economic and policy barriers is crucial for enabling the broader adoption of digital twin technology in the renewable energy sector.

5 DISCUSSION

The findings of this study confirm the transformative potential of digital twin technology in optimizing bioenergy production, aligning with earlier studies that emphasized its role in real-time monitoring and process simulation. For instance, Stennikov et al. (2022) highlighted that digital twins have the capability to replicate bioenergy systems virtually, enabling precise modeling of waste conversion processes and enhancing operational decision-making. This study builds upon those conclusions by demonstrating how digital twins have advanced to incorporate dynamic adaptations to feedstock variability and fluctuating operational conditions, as highlighted by 38 articles reviewed.

Figure 9: Summary of the findings for this study



Compared to earlier work, the present findings emphasize the growing integration of real-time data streams and advanced simulation techniques, suggesting that digital twins are becoming increasingly indispensable for improving process efficiency and reliability in bioenergy systems.

The integration of IoT-enabled sensors and machine learning algorithms within digital twin frameworks emerged as a critical theme in this study, corroborating earlier research by Pathan et al.(2023) and Lopez et al. (2020). These studies highlighted the ability of IoT and machine learning to provide continuous, high-resolution data and predictive analytics, enabling more accurate system monitoring and fault detection. The findings from 27 articles reviewed in this study extend this understanding by demonstrating how these technologies work together to optimize energy yields and reduce system downtime. While earlier studies focused primarily on the theoretical potential of IoT and machine learning, this review reveals practical applications where these technologies have been successfully implemented, demonstrating a shift from conceptual research to real-world deployment.

This study reinforces earlier findings on the value of hybrid energy systems (HES) in enhancing energy efficiency, particularly when combined with digital twin technology. Gargalo et al.(2020) and Jiang et al. (2023) previously highlighted the potential of HES to balance energy inputs from bioenergy, solar, and wind sources, ensuring system resilience and sustainability. The findings from 21 reviewed articles demonstrate how digital twins further optimize hybrid systems by dynamically balancing energy supply and demand and reducing dependency on fossil fuels. Notably, the observed energy efficiency improvements of up to 30% in some cases align with earlier estimates, providing additional evidence for the feasibility of hybrid systems as a sustainable energy solution. This study also underscores the scalability of hybrid energy systems, a factor less explored in earlier research. Moreover, the challenges identified in this study regarding data integration and scalability are consistent with earlier research, such as Zheng et al. (2018), which emphasized the difficulties of managing heterogeneous data sources and ensuring model reliability. However, this study adds new dimensions by identifying the computational intensity of large-scale digital twin systems as a significant bottleneck. The findings from 18 articles suggest that while digital twins are effective for pilot

and small-scale systems, their deployment in industrial-scale operations remains limited by technical constraints. Earlier studies, such as those by Gargalo et al. (2020), focused more on data standardization issues, whereas this study highlights the broader challenge of maintaining system accuracy in complex and dynamic bioenergy environments. These insights point to the need for advancements in computational frameworks and data management practices to address these barriers. In addition, Economic and policy barriers were consistently identified as critical hindrances to the adoption of digital twin technology, echoing earlier findings by Liu et al. (2021) and Tuegel et al. (2011). These studies highlighted high development costs and limited regulatory support as major obstacles, which this review further substantiates through the analysis of 14 articles. However, this study provides a more comprehensive perspective by emphasizing the long-term economic implications, such as recurring maintenance costs and the absence of financial incentives. Compared to earlier research that focused primarily on initial investment challenges, this study explores the broader economic ecosystem, including the lack of subsidies and tailored policy frameworks for digital twin adoption. These findings underline the importance of aligning economic and policy strategies to facilitate the widespread implementation of digital twin technology in bioenergy systems.

6 CONCLUSION

This study highlights the transformative potential of digital twin technology in optimizing bioenergy production, underscoring its capabilities in real-time monitoring, process simulation, and predictive optimization. By systematically reviewing the integration of IoT-enabled sensors, machine learning algorithms, and hybrid energy systems, the findings demonstrate that digital twins are instrumental in enhancing energy efficiency, reducing operational inefficiencies, and promoting sustainable practices in bioenergy systems. However, significant challenges remain, particularly in scaling digital twins to industrial applications, addressing data integration issues, and overcoming economic and policy barriers. High computational demands, inconsistent data quality, and the absence of supportive regulatory frameworks continue to limit the full potential of digital twin technology. Despite these obstacles, the advancements highlighted in this study indicate a growing shift from

theoretical exploration to practical implementation, suggesting that with targeted investments in research, infrastructure, and policy support, digital twins can play a pivotal role in achieving a sustainable energy future. This review underscores the need for interdisciplinary collaboration and innovative solutions to address existing barriers and leverage digital twins to their fullest potential in bioenergy systems.

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