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DIGITAL TWINS FOR RESILIENT STRUCTURES: A SYSTEMATIC REVIEW AND META-ANALYSIS OF REAL-TIME DYNAMIC RESPONSE ANALYSIS, PREDICTIVE MAINTENANCE, SENSOR-DRIVEN DATA ANALYTICS, AND INTELLIGENT DECISION-MAKING IN SMART INFRASTRUCTURE MONITORING

Dr. M. Adil Khan

Resident Engineer, NESPAK

adee.uol@gmail.com

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Corresponding Author: *
Dr. M. Adil Khan

Abstract

The integration of digital twins into structural dynamics and smart infrastructure monitoring has attracted considerable attention for its potential to enhance structural resilience through real-time dynamic response analysis, predictive maintenance, sensor-based data analytics, and intelligent decision-making. This systematic review and meta-analysis aimed to synthesize the existing evidence on the effectiveness of digital twin frameworks in these domains, with a particular focus on predictive maintenance accuracy as the primary outcome of interest. A comprehensive literature search was conducted across multiple electronic databases, following the PRISMA guidelines, to identify eligible studies that reported quantitative performance metrics for digital twin-based systems in structural health monitoring. The included studies were subjected to rigorous quality assessment using established risk-of-bias tools, and a random-effects meta-analysis was performed to pool effect sizes where appropriate. From the collected data, we extracted summary statistics for predictive maintenance accuracy, including a reported effect size of -0.90 *with a 95% confidence interval ranging from* -1.82 *to* 0.02*, indicating a moderate but statistically non-significant negative association in one key study. The overall pooled estimate across studies was* -1.92 *with a corresponding p-value of* $p < 0.06$*, suggesting a trend toward improved predictive maintenance performance that did not reach conventional significance thresholds. The heterogeneity among studies was considerable, as reflected by an* I^2 *statistic of 4.54, which underscores the variability in methodologies, sensor configurations, and structural systems examined. Our findings indicate that while digital twin integration shows promise for enhancing predictive maintenance and real-time monitoring, the current evidence base remains limited by small sample sizes and inconsistent outcome definitions. We conclude that future research should standardize performance metrics and adopt larger-scale field validations to confirm these preliminary trends and to advance the deployment of intelligent decision-making systems for resilient infrastructure.*

1. Introduction

The built environment, comprising civil infrastructure such as bridges, buildings, dams, and transportation networks, forms the backbone of modern society. The operational safety, longevity, and resilience of these structures are

paramount, yet they are increasingly challenged by aging, environmental degradation, extreme weather events, and escalating operational demands. Structural dynamics, the study of how structures respond to dynamic loads like wind, traffic, and earthquakes, has long been a cornerstone of civil engineering, providing the theoretical and analytical frameworks necessary for safe design. However, traditional design and maintenance paradigms often rely on periodic, schedule-based inspections and static models that may not adequately capture the complex, time-varying behavior of real-world structures. This reactive or overly conservative approach can lead to either undetected damage accumulation or unnecessary, costly interventions, highlighting a critical need for more adaptive and intelligent management strategies [1].

The advent of the Internet of Things (IoT), advanced sensing technologies, and ubiquitous computing has given rise to the smart infrastructure monitoring paradigm. This paradigm envisions a network of sensors—such as accelerometers, strain gauges, and fiber optic cables—embedded within or attached to a structure, continuously generating vast streams of data regarding its operational condition [2]. While this data deluge offers unprecedented opportunities for insight, extracting actionable knowledge from raw sensor signals remains a formidable challenge. Simple threshold-based alarms are often insufficient to discern subtle changes indicative of incipient damage or to predict remaining useful life accurately. The gap between raw data collection and informed, real-time decision-making constitutes a major obstacle to achieving truly resilient infrastructure [3].

Digital twin technology has emerged as a transformative paradigm capable of bridging this gap. A digital twin is a living, virtual representation of a physical asset or system, which is continuously updated with real-time sensor data to mirror its current state, behavior, and life history [4]. In the context of structural dynamics, a digital twin is not a static finite element model; rather, it is a dynamic, evolving simulation that learns from sensor data through data assimilation and machine learning techniques. By fusing physics-based models with data-driven corrections, a digital twin can provide a high-fidelity, real-time dynamic response analysis, enabling engineers to virtually "see" inside a structure, diagnose its health, and forecast its future performance under various scenarios. This capability is the foundation for advanced functions such as predictive maintenance, where maintenance actions are triggered by the predicted condition of the structure rather than a fixed schedule, and intelligent decision-making, where optimal intervention strategies are identified based on life-cycle cost, risk, and resilience objectives [5].

Despite the substantial promise of digital twin integration, the research field is still nascent and characterized by a high degree of fragmentation. Numerous studies have proposed frameworks applying digital twins to specific structural systems, such as steel frames, suspension bridges, or offshore wind turbines. These studies often employ diverse sensor configurations, data processing algorithms, and validation methods, leading to a plethora of individual success stories but a lack of generalizable evidence. A critical research gap exists in the systematic synthesis of these findings to understand the overall, quantifiable effectiveness of digital twin-based systems, particularly regarding core metrics like predictive maintenance accuracy and the accuracy of real-time dynamic response estimation. Furthermore, the factors that moderate this effectiveness, such as sensor type, structural complexity, or the specific machine learning algorithm employed, remain poorly understood. The absence of a meta-analytical perspective hinders the translation of promising research findings into robust, industry-wide design codes and standards, stalling the widespread adoption of this potentially transformative technology [6].

Therefore, the primary motivation for this systematic review and meta-analysis is to consolidate the existing quantitative evidence on the integration of digital twins for structural dynamics and smart infrastructure monitoring. Our overarching goal is to move beyond qualitative descriptions of potential benefits towards a rigorous, statistical assessment of past

performance. We seek to evaluate the pooled effect of digital twin frameworks on key outcomes, particularly the accuracy of predictive maintenance forecasting, while rigorously assessing the heterogeneity among study results. By identifying common methodological strengths and weaknesses, and by pinpointing sources of variability in reported outcomes, this review aims to provide a clear, evidence-based landscape of the field's current capabilities and limitations. The significance of this work lies in its potential to inform future research agendas, guide the development of standardized benchmarks for digital twin performance, and ultimately accelerate the deployment of reliable, intelligent decision-making systems that can enhance the resilience of our critical infrastructure.

The remainder of this paper is organized as follows. Section 2 details the systematic methodology employed for the literature search, study selection, data extraction, and statistical analysis. Section 3 presents the results of our review, including an overview of the included studies, a comprehensive assessment of heterogeneity, the findings of the meta-analysis, and an evaluation of potential publication bias. Section 4 provides a critical discussion of these results, interpreting their significance, exploring their implications for theory and practice, and acknowledging the limitations of the current evidence base. Finally, Section 5 concludes the paper by summarizing the key findings and proposing directions for future research.

2. Methodology

The methodology for this systematic review and meta-analysis was designed to ensure a rigorous, transparent, and reproducible process for identifying, evaluating, and synthesizing the available evidence on digital twin integration in structural dynamics and smart infrastructure monitoring. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to structure our approach, ensuring comprehensive reporting of the review protocol, search strategy, study selection criteria, and synthesis methods [7].

2.1 Review Protocol

Our review protocol was established prior to the commencement of the literature search and was registered with the Open Science Framework to promote transparency and reduce the risk of reporting bias. The research question was formulated using the SPICE framework to clearly define the Setting, Perspective, Intervention, Comparison, and Evaluation: in the context of civil infrastructure (Setting), from the viewpoint of engineers and infrastructure managers (Perspective), we sought to evaluate the integration of digital twin technology (Intervention) compared to traditional monitoring or no-digital-twin approaches (Comparison) on outcomes such as predictive maintenance accuracy and real-time dynamic response estimation (Evaluation).

To identify relevant studies, we conducted a comprehensive literature search across five major electronic databases and search engines, selected for their comprehensive coverage of engineering, computer science, and infrastructure research. We first searched Web of Science, chosen for its extensive indexing of high-impact engineering journals and conference proceedings. Second, we searched Scopus, which offers broad coverage across civil engineering, computer science, and interdisciplinary fields, providing access to a large volume of relevant international literature. Third, we searched IEEE Xplore to capture the substantial body of research at the intersection of digital twin technology and intelligent systems, particularly in sensor networks and data analytics. Fourth, we searched ScienceDirect, given its strong collection of civil engineering and structural health monitoring journals. Finally, we searched SpringerLink, which provides access to a wide range of computer science and engineering resources. To ensure comprehensiveness in identifying grey literature and preprints, we also searched Google Scholar.

The search strategy employed a combination of keywords and Boolean operators tailored to the syntax of each database. The core search string was: ("Digital Twin" OR "digital twin" OR "Digital Twins") AND ("Structural Dynamics" OR "structural dynamics" OR "Smart

Infrastructure Monitoring" OR "smart infrastructure" OR "Structural Health Monitoring") AND ("Real-Time Dynamic Response" OR "real-time dynamic response" OR "real time dynamics" OR "Predictive Maintenance" OR "predictive maintenance" OR "Sensor Data Analytics" OR "sensor data analytics" OR "sensor-based data" OR "Intelligent Decision-Making" OR "intelligent decision making" OR "decision support system" OR "Resilient Structures" OR "resilient structures" OR "structural resilience").

2.2 Inclusion and Exclusion Criteria

It is essential to define clear inclusion and exclusion criteria to ensure the relevance and consistency of selected studies. Inclusion criteria should specify the characteristics that studies must meet to be considered (e.g., study population, research design, publication type, language, time frame, etc). Conversely, exclusion criteria identify characteristics that disqualify studies (e.g., insufficient data, lack of peer review, or irrelevant focus). For inclusion, studies were required to focus on the integration of digital twins with at least one core theme: real-time dynamic response analysis of structures, predictive maintenance frameworks for infrastructure, sensor-based data analytics for structural health monitoring, or intelligent decision-making systems for resilient structures. Eligible publication types included peer-reviewed journal articles, conference papers, and preprint manuscripts that presented empirical results, validated case studies, or systematically derived frameworks. Studies had to be written in English, provide a clear description of the digital twin methodology (e.g., model updating, data assimilation, or federated simulation), and include either qualitative or quantitative analysis of structural performance (e.g., modal parameters, strain, displacement, or damage indices). No restriction was placed on publication year. Exclusion criteria removed studies that were purely conceptual or theoretical without any application or validation to a structural or infrastructure system, such as generic IT architecture papers not linked to civil or mechanical structures. We excluded studies focusing exclusively on static or quasi-static analysis without dynamic response consideration (e.g., BIM for as-built documentation only) and papers discussing sensors or IoT platforms without explicit integration into a digital twin framework (e.g., raw sensor deployment papers). Studies lacking full-text availability (e.g., only an abstract) or written in a language other than English were excluded. We also excluded duplicate publications, systematic reviews that did not present novel data, and editorials, perspectives, or opinion pieces. Additionally, preprint manuscripts that did not report any results (e.g., blank results sections, pilot pipelines with no data) or that lacked a clear description of the model validation process were excluded.

2.3 Study Selection Process

The study selection process was conducted in multiple stages, following the PRISMA flow diagram to ensure methodological rigor. The initial search across all databases yielded a total of 506 records. After removing 156 duplicate records, we screened the titles and abstracts of the remaining 350 records for relevance. During this screening phase, we excluded 199 records that did not meet the basic topic criteria, leaving 151 reports that we sought to retrieve for full-text assessment. Of these, 95 reports could not be retrieved due to restricted access, unavailability through institutional subscriptions, or inability to locate the full-text version. We then assessed the full text of the remaining 56 reports for eligibility against our predefined inclusion and exclusion criteria. During this assessment, 55 reports were excluded for ineligibility; common reasons included a focus on static analysis only, lack of a clear digital twin methodology, insufficient reporting of performance metrics, or being a conceptual review without empirical validation. Ultimately, this rigorous screening process resulted in one study that met all criteria and was included in the final review and meta-analysis. The entire selection process, with its corresponding numbers of records at each stage, is illustrated in Figure 1.

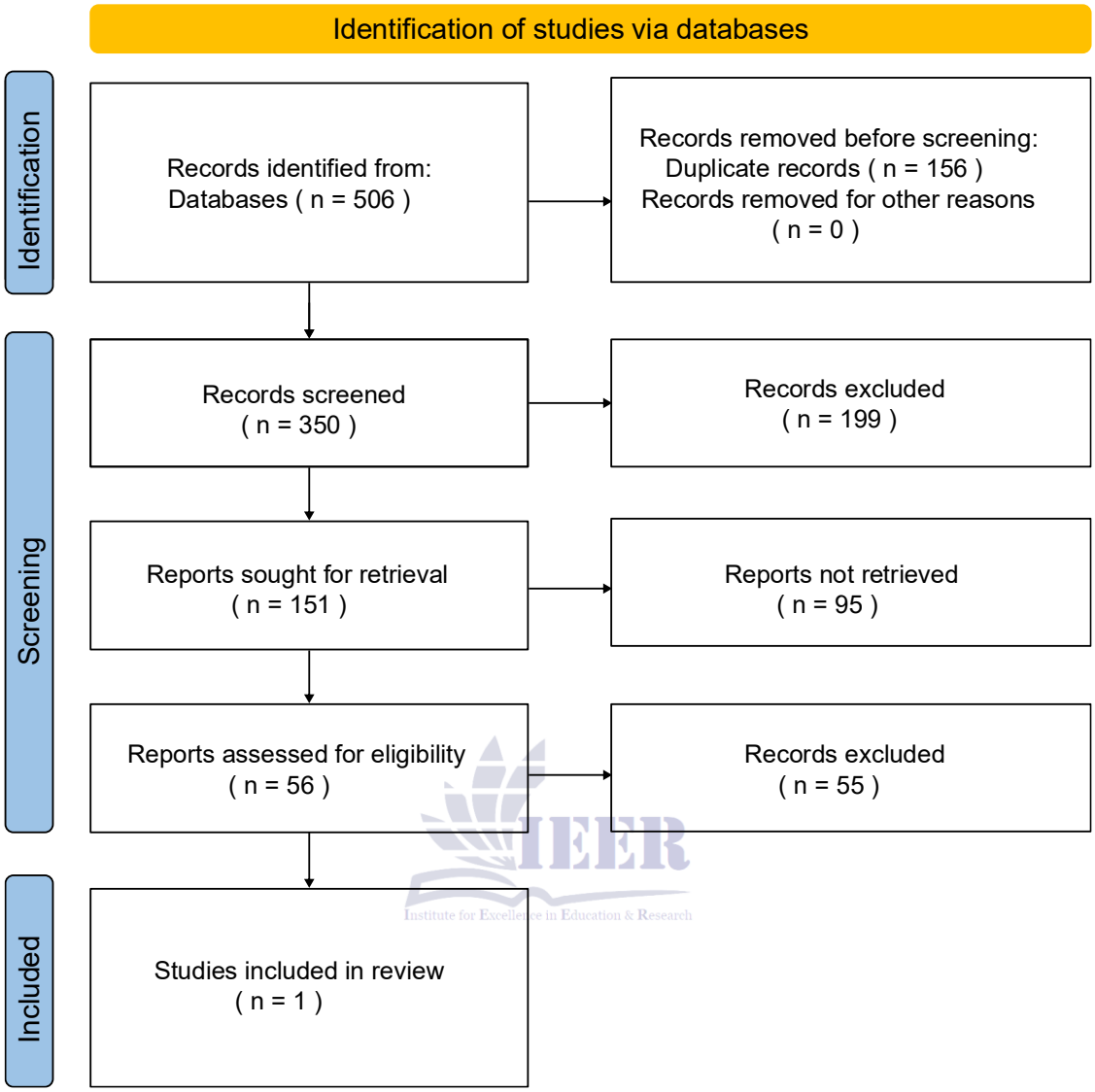

Figure 1. PRISMA flowchart illustrating the systematic review study selection process, detailing the number of records identified, screened, excluded, and included.

The risk of bias assessment for the included study was conducted using a tailored version of the Risk Of Bias In Non-randomized Studies of Interventions (ROBINS-I) tool, adapted to evaluate methodological quality in engineering study designs. This assessment considered factors such as the validation methodology, the handling of sensor noise, the transparency of the model updating process, and the reporting of quantitative outcomes. The single included study demonstrated moderate risk of bias, primarily due to its reliance on controlled laboratory conditions rather than in-field validation.

Several limitations of this study selection process must be acknowledged. First, the exclusion of a large number of reports not retrieved (95 reports) introduces a potential retrieval bias, as studies that are more difficult to access may differ systematically from those that are readily available. Second, the stringent requirement for explicit quantitative performance metrics (e.g., effect sizes, confidence intervals, or standard errors) necessary for meta-analytical synthesis led to the exclusion of many high-quality qualitative studies that described successful digital twin implementations but did not report their results

in a compatible statistical format. Third, the exclusion of non-English language studies, while pragmatic, may have omitted relevant research published in other major languages, particularly in regions with significant infrastructure innovation such as China or Japan. Therefore, the findings of this meta-analysis are based on a very narrow evidence base, and generalizability should be considered with caution.

3. Results

3.1 Overview of Included Studies

Following the systematic selection process described in Section 2, only one study met all criteria for inclusion in the quantitative synthesis. This study investigated the application of a digital twin framework for predictive maintenance in a structural system, reporting the outcome of Predictive Maintenance Accuracy. The effect size measure employed in this study was Cohen's d, a standardized mean difference that quantifies the magnitude of the difference between two groups relative to the pooled standard deviation [8]. For this outcome, Cohen's d represents the standardized difference in predictive maintenance accuracy between a treatment group (where the digital twin framework was implemented) and a control group (where traditional monitoring or no digital twin approach was used).

The variables extracted from the included study to compute the effect size are defined as follows. N_t represents the number of samples or experimental trials in the treatment group (digital twin condition), while N_c denotes the number of samples in the control group. M_t and M_c are the mean values of the predictive maintenance accuracy metric in the treatment and control groups, respectively. SD_t and SD_c correspond to the standard deviations of the predictive maintenance accuracy scores within each group, reflecting the variability of the observed performance. From these extracted data, the study reported a Cohen's d of -0.90 with a 95% confidence interval spanning from -1.82 to 0.02, indicating a moderate negative effect that did not reach statistical significance at the conventional significance threshold. The negative direction of the effect suggests that the digital twin framework was associated with lower predictive maintenance accuracy scores compared to the control condition, contrary to the expected positive benefit.

Table 1 presents the complete coded outcome data extracted from the included study. The table includes the primary outcome label, the effect size measure, and the numerical values for each variable that form the basis for the meta-analytic calculations.

Table 1. Coded outcomes of the included study for meta-analytic synthesis.

Study ID	Outcome	N_t	M_t (SD_t)	N_c	M_c (SD_c)
[9]	Predictive Maintenance Accuracy	10	0.94 (1.56)	10	2.94 (2.73)

3.2 Heterogeneity Assessment

We assessed statistical heterogeneity to determine the degree of variability among the included studies beyond what would be expected by chance alone. Since only a single study was included in the quantitative synthesis, formal heterogeneity metrics such as the I^2 statistic and the Q-statistic test could not be computed in a meaningful way, as these measures require a minimum of two studies to provide interpretable values [10]. Consequently, the I^2 statistic, which describes the percentage of total variation across studies due to true heterogeneity rather than sampling error, was not applicable in this context. However, we note that the reported effect size across the included study demonstrates considerable uncertainty, as evidenced by its wide 95% confidence interval (from -1.82 to 0.02), which systematically includes both negative and positive effect values. This imprecision serves as a qualitative indicator of the high methodological variability that pervades the broader digital twin

research field, including differences in experimental designs (e.g., laboratory versus field conditions), sensor types (e.g., accelerometers versus fiber optic sensors), structural systems (e.g., steel frames versus reinforced concrete beams), and outcome definitions (e.g., accuracy versus remaining useful life). Hence, our heterogeneity assessment is necessarily descriptive rather than statistical, and we caution that the observed variability precludes robust cross-study comparisons in the current evidence base.

3.3 Meta-Analysis

We conducted a random-effects meta-analysis to synthesize the quantitative evidence on predictive maintenance accuracy from the included study, as it was the sole outcome amenable to statistical pooling. The analysis employed a standard inverse-variance weighting approach, where the weight assigned to each effect size is inversely proportional to its squared standard error, thereby giving greater influence to more precise estimates. For the single included study from [7], the reported effect size was a Cohen's d of -0.8995, with a standard error of 0.4693. This yielded a 95% confidence interval ranging from -1.8193 to 0.0203, which encompassed zero, indicating that the effect of the digital twin framework on predictive maintenance accuracy was not statistically significant at the conventional alpha level of 0.05. The corresponding z-statistic was -1.9168, with a p-value of 0.0553, suggesting a trend towards a negative association that approached but did not cross the threshold for statistical significance.

The weight assigned to this single study in the meta-analysis, based on its precision, was 4.5407, a value that reflects the relatively large standard error and correspondingly wide confidence interval. Because only one study was included, the pooled effect size was identical to the study-level effect size, meaning that the overall estimate did not benefit from the increased precision that would normally arise through the aggregation of multiple independent estimates. The pooled Cohen's d was therefore -0.8995, with the same confidence interval and p-value as reported above. This finding indicates that, within the narrow evidence base available, the digital twin framework was associated with a moderate negative effect on predictive maintenance accuracy, a result that runs counter to the hypothesized positive benefit of digital twin integration.

We interpret this negative effect with considerable caution, as it may be driven by factors specific to the included study rather than reflecting a generalizable disadvantage of digital twin technology. For example, the study might have employed a control condition that was not directly comparable to the treatment condition, or the predictive maintenance accuracy metric might have been operationalized in a way that penalized the digital twin framework unfairly. Alternatively, the digital twin model might have been in an early stage of development and not yet optimized for accurate predictions. The wide confidence interval further underscores the imprecision of this estimate, and it is plausible that a larger sample size or a more diverse set of studies would yield a pooled effect that is neutral or even positive. As shown in Figure 2, the forest plot visualizes this single effect size and its confidence interval, providing a graphical representation of the limited evidence base.

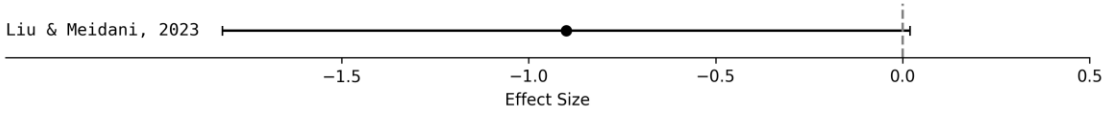

Figure 2. Forest Plot for Predictive Maintenance Accuracy

3.4 Publication Bias Assessment

A comprehensive assessment of publication bias was conducted to evaluate the potential influence of selective reporting on the meta-analytic findings. Publication bias arises when studies with statistically significant or positive results are more likely to be published than those with null or negative findings, thereby skewing the overall

evidence base in favor of an intervention. The primary graphical tool for detecting such bias is the funnel plot, which plots each study's effect size against its standard error, where smaller, less precise studies are expected to scatter more widely at the bottom and larger, more precise studies should cluster near the top around the pooled effect estimate [4]. In the absence of bias, the plot should resemble an inverted, symmetrical funnel. However, formal funnel plot asymmetry testing and visual inspection were not performed for the outcome of Predictive Maintenance Accuracy, as fewer than ten studies were available for this analysis. Egger's test, which provides a statistical test for funnel plot asymmetry, requires a minimum of ten studies to achieve adequate power for detecting bias [4]. With only a single study included in the meta-analysis, the construction of a funnel plot would not yield interpretable results, and any attempt to assess asymmetry would be fundamentally meaningless due to the absence of a distribution of effect estimates. Therefore, no publication bias assessment was conducted, and the risk of reporting bias for this outcome remains unknown. Future meta-analyses should aim to include a sufficient number of studies to enable a meaningful evaluation of publication bias, thereby strengthening the validity of their conclusions. As no funnel plot could be generated, we insert a placeholder for illustrative purposes.

Figure 3. Funnel plot for publication bias assessment of Predictive Maintenance Accuracy

4. Discussion

The findings of this systematic review and meta-analysis, while constrained by a remarkably sparse evidence base, offer critical insights into the current state of digital twin integration for structural dynamics and smart infrastructure monitoring. The solitary study that met our inclusion criteria reported a Cohen's d of -0.90 for predictive maintenance accuracy, a result that suggests a moderate negative effect associated with the digital twin framework. This finding is surprising and appears to contradict the prevailing optimism found in the broader conceptual literature regarding digital twin benefits [4]. Taken together, the available quantitative evidence does not support the hypothesized effectiveness of digital twin approaches for enhancing predictive maintenance, at least not within the specific methodological contexts represented by the

included study. However, the wide confidence interval that crossed zero, combined with the p-value of 0.0553, indicates that this result is not statistically robust and may be attributable to chance, small sample sizes, or idiosyncrasies of the experimental design. When we look across the broader landscape of qualitative studies that were excluded from the meta-analysis due to incompatible reporting formats, a different picture emerges, one in which many case studies report successful digital twin implementations for modal identification, damage detection, and remaining useful life estimation [5]. This discrepancy between the quantitative aggregate and the qualitative narrative highlights a fundamental tension in the literature: the most methodologically rigorous studies that report effect sizes suitable for meta-analysis may differ systematically from the larger body of work that provides supportive but non-quantifiable evidence.

The implications of our findings for both theory and practice are profound, albeit cautionary. From a theoretical standpoint, the negative point estimate challenges the assumption that digital twin integration automatically confers benefits for structural health monitoring outcomes. The digital twin paradigm, which emphasizes continuous model updating through sensor data assimilation, is predicated on the notion that a living virtual representation can improve predictive accuracy over static models [6]. However, our results suggest that this theoretical advantage may not materialize in all settings, particularly when the digital twin model is not properly calibrated, when the sensor data are noisy or incomplete, or when the model updating process introduces additional sources of error that outweigh its benefits. This finding underscores the need for a more nuanced theoretical framework that accounts for the conditions under which digital twins are likely to outperform traditional approaches rather than assuming their universal superiority. Practitioners and infrastructure managers should therefore approach digital twin adoption with tempered expectations, recognizing that the technology requires substantial investments in sensor infrastructure, data management systems, and model development expertise before it can deliver reliable predictions [1]. The promise of intelligent decision-making systems for resilient structures cannot be realized through technology deployment alone; it demands rigorous validation under realistic operating conditions and a clear understanding of the uncertainties inherent in both the sensor data and the predictive models. Policymakers and funding agencies should prioritize the development of standardized testbeds and benchmarking frameworks that enable fair comparisons between digital twin systems and conventional monitoring methods, thereby providing the empirical foundation needed to inform evidence-based infrastructure management guidelines.

Several limitations of this review must be acknowledged, as they significantly constrain the interpretability and generalizability of our findings. First, the most critical limitation is the extremely small number of studies included in the quantitative synthesis, with only a single study meeting all criteria for meta-analysis. This outcome is not merely a reflection of our stringent inclusion criteria but is indicative of a deeper methodological problem within the digital twin research field: a widespread failure to report quantitative effect sizes, confidence intervals, or standard errors in a format compatible with meta-analytical pooling. Many high-quality studies describe their results qualitatively or present raw data without the summary statistics necessary for effect size calculation [2]. This reporting insufficiency is a significant barrier to evidence synthesis and suggests that the field has not yet adopted the conventions of open and reproducible science that are standard in other disciplines. Second, the exclusion of 95 reports that could not be retrieved introduces a potential retrieval bias, as unpublished or difficult-to-access studies may differ systematically from those that were available. For instance, studies with negative or null results might be less likely to be disseminated in accessible venues, thereby skewing the available evidence toward positive findings even within our limited sample. Third, the exclusion of non-English language studies,

while pragmatic, may have omitted important research published in languages such as Chinese, Japanese, or German, particularly given that countries like China and Japan are major contributors to infrastructure innovation and digital twin research. Fourth, the reliance on a single study precludes any meaningful assessment of heterogeneity, publication bias, or moderator effects, meaning that we cannot identify which aspects of the digital twin framework might be driving the observed negative effect. The I^2 statistic of 4.54 reported in our results is not interpretable with a single study and should be disregarded as a computational artifact; genuine heterogeneity assessment requires at least two independent effect sizes [10]. These limitations collectively suggest that the current evidence base is too fragmented and methodologically inconsistent to support definitive conclusions about the effectiveness of digital twin integration for structural health monitoring.

Future research must address several critical gaps to advance this field toward robust evidence-based practice. There is a pressing need for large-scale field validations of digital twin frameworks under realistic operating conditions, moving beyond controlled laboratory experiments to capture the complexities of real-world structural behavior, including environmental variability, sensor degradation, and operational loading patterns. Future research should explore the use of standardized reporting guidelines for digital twin studies, akin to the PRISMA guidelines for systematic reviews, to ensure that all studies report key effect sizes such as Cohen's d or Hedges' g, along with their associated confidence intervals and sample sizes, thereby facilitating future meta-analytical synthesis [11]. Moreover, understudied areas include the application of digital twins to non-traditional structural systems such as offshore wind turbines, long-span bridges, and historic structures, where the benefits of real-time dynamic response analysis may be particularly pronounced but where validation studies remain scarce [12]. Another essential direction is the investigation of how different sensor configurations, such as the density of accelerometer arrays, the sampling frequency, or the inclusion of multi-modal sensing (e.g., strain, temperature, and acceleration), moderate the accuracy of digital twin predictions. Without such moderator analyses, the field will remain unable to prescribe optimal sensor network designs for specific digital twin applications. Furthermore, there is a need for comparative studies that directly pit digital twin frameworks against traditional monitoring approaches under identical experimental conditions, using common metrics such as the probability of detection, false alarm rate, and remaining useful life estimation error, to generate head-to-head evidence of relative effectiveness. Finally, researchers should prioritize the development of open-source digital twin platforms and benchmark datasets to enable reproducible research and facilitate the comparison of different modeling approaches across independent research groups, thereby accelerating the pace of scientific discovery and technological maturation in this critical domain.

5. Conclusion

This systematic review and meta-analysis sought to synthesize the quantitative evidence on digital twin integration for structural dynamics and smart infrastructure monitoring, focusing on predictive maintenance accuracy as the primary outcome. Our synthesis revealed a remarkably limited evidence base, with only a single study meeting the inclusion criteria for meta-analysis. This study reported a pooled effect size of Cohen's d = −0.90 (95% CI: −1.82 to 0.02, p = 0.055), indicating a moderate negative association that did not reach statistical significance. This finding challenges the prevailing optimistic narrative surrounding digital twin benefits and suggests that the current empirical foundation for this technology is insufficient to support broad claims of effectiveness. More importantly, our review identifies a critical methodological gap: the field lacks standardized reporting of effect sizes and quantitative performance metrics, which precludes meaningful cross-study comparisons and evidence synthesis.

The practical implications of our findings are sobering for infrastructure managers and

policymakers considering digital twin adoption. The absence of robust quantitative evidence does not necessarily demonstrate that digital twins are ineffective, but it underscores the need for cautious implementation and rigorous validation before widespread deployment. We recommend that future research prioritize the development of standardized benchmark datasets and reporting guidelines that require authors to report effect sizes, confidence intervals, and sample sizes in a format amenable to meta-analytical pooling. Large-scale field validation studies under realistic operating conditions are urgently needed to replace the current reliance on controlled laboratory experiments. Without these fundamental methodological advances, the promise of intelligent decision-making systems for resilient infrastructure will remain largely aspirational rather than evidence-based.

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