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Review Article

From Wheels to Girders: A Comprehensive Review of Braking and Traction Force Effects on Railway Bridge Structural Behavior, Modelling Advances, and Future Directions

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Abstract

As train speeds, axle loads, and structural designs have advanced, so too have the intricate issues posed by the dynamic interaction between railway vehicles and bridge structures, particularly under braking and traction pressures. In order to comprehend and lessen the consequences of longitudinal stresses on railway bridges, this paper explores the historical underpinnings, contemporary modelling techniques, experimental strategies, and upcoming technological integrations. The foundation for today's reliable analytical and numerical models was established by early empirical research. Recent developments in hybrid modelling, machine learning, and real-time data assimilation have greatly improved predictive capacities, even if classic finite element models continue to be fundamental. In order to close the gap between theoretical predictions and actual behaviour, full-scale monitoring and experimental validation have proven essential in bridging the gap between theoretical assumptions and real-world behavior In the future, rail bridge inspection and maintenance will be transformed by the confluence of digital twins, artificial intelligence, and sensor-rich cyber-physical systems. Predictive technologies have the potential to save lifespan costs, enhance safety and dependability, inform design principles, and promote resilience against escalating demands and climate unpredictability. Future studies must embrace an interdisciplinary and comprehensive framework that integrates computer science, transportation engineering, structural mechanics, and sustainability concepts in order to effectively use these advancements.

Keywords

Railway Bridge Dynamics, Braking and Traction Forces, Vehicle-Bridge Interaction (VBI), Structural Health Monitoring (SHM), and Predictive Modelling in Railway Infrastructure

1. Introduction & Motivation

1.1. Introductions

When trains accelerate (traction) or decelerate (braking), railway bridges experience considerable longitudinal stresses in addition to vertical wheel loads (Figure 1). Although these longitudinal forces have the potential to cause axial stresses,

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change fatigue life, and impact serviceability, they are frequently handled as simple static loads rather than dynamic interactions in design standards. According to recent research, depending on the train's mass, speed, and wheel-rail friction conditions, braking and traction forces can amount to as much as 15-25% of its weight (Table 1); [1]. If their dynamic amplification is neglected, the demand on girders, bearings, and substructures may be underestimated, which could jeopardise safety and raise maintenance expenses [2]. Simultaneously, advances in finite-element modelling and vehicle-bridge interaction (VBI) simulation have produced a variety of approaches—from beam-on-elastic-foundation models to fully coupled multi-body dynamic analyses. However, there remains no single, up-to-date synthesis comparing these methods with respect to computational efficiency, accuracy under emergency braking scenarios, and integration with monitoring systems [3]. Moreover, with the emergence of AI-driven digital twins, the gap between offline design and real-time structural health monitoring offers both promise and unanswered questions. This review's Introduction & Motivation lays the groundwork for understanding why a holistic examination of braking and traction forces is both timely and necessary.

Table 1. *Typical Longitudinal Force Magnitudes on Railway Bridges.*

Force Type	Typical Range (% of Train Weight)	Influencing Factors
Traction Force	10-20%	Locomotive power, number of axles, wheel-rail μ
Braking Force	15-25%	Brake system efficiency, speed, rail condition
Thermal Expansion	5-10%	Temperature gradient, restraint conditions

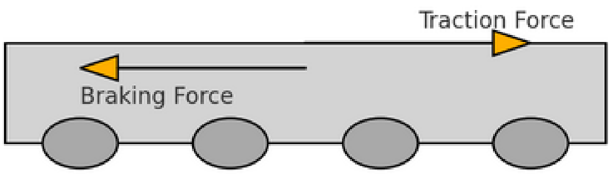

Figure 1. *Schematic of Braking and Traction Forces on a Railway Bridge.*

1.2. Motivating Points

I. Safety and Fatigue: Dynamic amplification of longitudinal forces can accelerate fatigue damage in girders and bearings beyond that predicted by static code provisions [4].
II. Design Code Limitations: Current standards (e.g. AS5100.2) employ simplified "rational methods" that do not capture coupled VBI effects under varying operational scenarios [5].
III. Technological Opportunity: Modern VBI simulations and digital-twin frameworks enable real-time prediction and monitoring of longitudinal stress states, yet these are rarely linked back to design optimization or maintenance planning [6].

By framing the problem in terms of both engineering risk and emerging computational capabilities, this Introduction sets the stage for a comprehensive review that will guide future research toward more resilient, data-driven bridge designs.

1.3. Methodology

This work adopts a structured, integrative approach to synthesize existing literature on braking-induced longitudinal forces in railway bridges. A systematic search was conducted using academic databases such as ScienceDirect, Taylor & Francis Online, SpringerLink, and Google Scholar. Search terms included combinations of "railway bridge braking," "longitudinal forces," "vehicle-bridge interaction," "finite element modeling," "dynamic testing," and "digital twins in railway infrastructure."

The selection process involved three key stages:

I. Screening and Eligibility: Peer-reviewed articles published from 1970 to 2024 were screened, focusing on studies offering experimental, analytical, or computational insights. Only English-language sources were included.
II. Thematic Categorization: The filtered literature was grouped into four major themes:
   a) Historical treatment of braking in bridge design
   b) Coupled vehicle-bridge interaction (VBI) models
   c) Full finite element modeling of structural response
   d) Experimental monitoring and digital technologies
III. Critical Analysis and Comparison: Each study was evaluated for modeling fidelity, empirical validation, and applicability to current and future bridge design. Key parameters such as train speed, friction, load ratios, and bridge typologies were compared across studies.

2. Historical Foundations

Understanding how braking and traction forces interact with railway bridges requires examining the development of structural modelling practices from early analytical approaches to the foundation of today's dynamic simulation techniques. Historically, these forces were either neglected or approximated due to computational limitations, yet they have always played a role in the longitudinal performance and fatigue behavior of bridges.

2.1. Early Analytical Approaches

Vertical loads from static wheel arrangements were given priority in railway bridge design at the beginning of the 20th century. As incidental forces, braking forces were frequently reduced to horizontal line loads applied at rail level. Frýba et al. Used closed-form solutions to analyze the dynamic reactions of bridges under moving loads, one of the first documented studies of longitudinal loads [7]. Although it did not yet account for the non-linearities of actual braking behaviour, he presented a theoretical framework for vehicle-bridge interaction. Timoshenko, S et al. Supplied basic beam theory equations for a range of loading conditions, including the impact of concentrated forces at random points [8]. These formulations served as the basis for representing braking forces as equivalent horizontal forces transmitted through the superstructure. Later, in the 1980s, researchers like Frýba, L et al. Developed more refined analytical tools, incorporating simplified mass-spring-damper models of trains interacting with bridge decks [9]. While these models accounted for inertial effects, they still assumed idealized train behavior, with constant braking forces applied symmetrically or at selected points.

2.2. Emergence of Vehicle-Bridge Interaction Models

By the 1990s, with increasing computational power, the concept of vehicle-bridge interaction (VBI) began to evolve into a central modelling strategy. Lin, C et al. Proposed more advanced VBI frameworks where the vehicle is treated as a multi-body system, enabling simulations of axle load redistribution during acceleration or braking [10]. This period marked a transition from static-equivalent load models to semi-dynamic formulations. Xia, H Introduced a coupled VBI model that integrated wheel-rail contact mechanics with bridge dynamics, enabling better prediction of longitudinal force effects [11]. These models helped engineers recognize that the dynamic amplification of braking loads could be highly sensitive to train speed, track irregularities, and bridge natural frequencies.

2.3. Limitations of Historical Approaches

Despite these developments, traditional models had several limitations:

a) Assumed Constant Forces: Many early models treated traction and braking as static forces, ignoring real-world variability caused by driver behavior or emergency scenarios.
b) Neglected Interaction Effects: Structural models often neglected feedback from the bridge to the vehicle, oversimplifying system response.
c) Underestimated Fatigue Influence: Early fatigue assessments rarely accounted for longitudinal load-induced stress reversals, which are now known to affect crack propagation in steel members and connections (table 2).

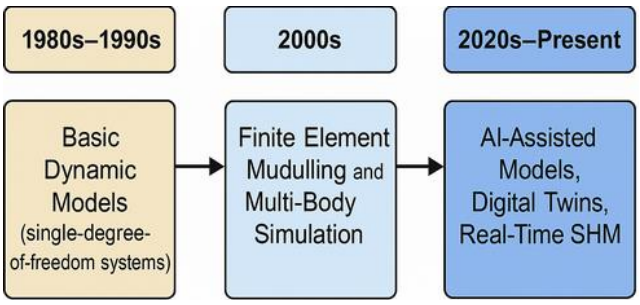

Figure 2. Illustrates the chronological shift from static loading assumptions to more integrated, real-time-capable structural modelling approaches.

Table 2. Evolution of Structural Modelling Approaches for Braking and Traction Forces.

Period	Key Contributors	Methodology	Limitations
1950s-1970s	[8]	Static analytical methods	Ignored dynamics, used simplified horizontal loads
1980s	[7]	Mass-spring-damper analogues	Limited realism in load variation and vehicle behavior
1990s	[9]	Coupled VBI models	Lacked real-time adaptability and full-scale calibration
2000s-present	Various	Hybrid FEM, dynamic models	Still limited by input data accuracy and cost-efficiency

In conclusion, although early approaches were limited in their treatment of longitudinal dynamics, they laid the foundation for the sophisticated tools now available. The shift toward coupled models and dynamic simulation has enabled more accurate predictions of bridge responses under real operational conditions. However, many of these historical simplifications still echo in current design standards, which often retain empirical or conservative assumptions derived from past models. Recognizing this evolution is key to identifying both progress and persistent gaps in modelling the influence of braking and traction on railway bridges.

3. Modern Modelling Techniques

With the growing complexity of high-speed rail systems, the demand for precise modelling of braking and traction forces on railway bridges has intensified. Modern modelling techniques now incorporate advanced dynamics, vehicle-bridge interaction (VBI), finite element methods (FEM), and increasingly, data-driven tools. These models aim to replicate the intricate load paths, transient vibrations, and nonlinear contact behaviors that arise during acceleration and braking scenarios.

3.1. Coupled Vehicle-Bridge Interaction Models

Modern VBI models treat the train as a multi-body system composed of masses, springs, and dampers representing the body, bogies, and wheels. These are coupled with the bridge's finite element model, enabling simulation of both vertical and longitudinal force transmission during braking or traction. Xu, L Refined earlier VBI methods by introducing a wheel-rail contact model with time-varying friction and lateral-longitudinal coupling [12]. Their simulation captured realistic force fluctuations when a train decelerates over a bridge, highlighting resonant responses near the bridge's fundamental frequency. Similarly, Xiang implemented nonlinear wheel-rail contact within a bridge dynamic model and verified their framework through field data collected from an operational high-speed rail line in China [13]. Their results confirmed that braking-induced longitudinal forces can cause horizontal displacements exceeding design assumptions under certain emergency scenarios.

3.2. Full Finite Element Modelling of Structural Response

Finite Element Modelling (FEM) has evolved to represent full 3D behaviour of railway bridges under combined vertical and longitudinal loading. Sophisticated contact algorithms allow precise load transfer between rails and girders, and time integration schemes enable tracking of force propagation during braking sequences. Nguyen, K Developed a 3D FEM model with dynamic mesh updating to reflect train progression across the span [14]. Their analysis showed that longitudinal stresses could interact with thermal expansion and creep effects in continuous spans, leading to cumulative effects over the bridge's service life. Recent work by Song, Y incorporated rolling resistance and wheel slip into the FEM model, enhancing its fidelity under adverse weather or emergency braking conditions [15]. They also explored the influence of bearing constraints and connection stiffness on the distribution of braking loads across supports.

3.3. Integration with Digital Twins and AI Tools

A newer generation of models integrates real-time sensor data into dynamic simulations. Known as digital twins, these systems update the bridge model in real-time based on measurements of acceleration, strain, or displacement, allowing for live prediction of structural responses. Liu, W developed a digital twin for a long-span railway bridge that receives inputs from onboard train sensors and bridge-mounted accelerometers [16]. The model predicts stress ranges during braking events and triggers alerts when responses deviate from calibrated thresholds. Meanwhile, Xia, H., Zhang, N. applied machine learning to classify braking events from sensor data and correlated these with FEM simulation outputs [30]. Their hybrid approach improves both model calibration and decision-making for bridge maintenance under repeated longitudinal loads (table 3).

Table 3. *Summary of Key Modern Modelling Techniques.*

Modelling Technique	Key Contributions	Limitations	References
Coupled VBI Models	Simulate bridge-train interaction in time domain	Require high-quality vehicle and contact data	[19]
Full 3D Finite Element Models	Detailed stress-strain behavior of bridge components	Computationally expensive	[14, 15]
Digital Twins with Sensor Feedback	Real-time updating of bridge model from field data	Sensitive to sensor accuracy and noise	[16]

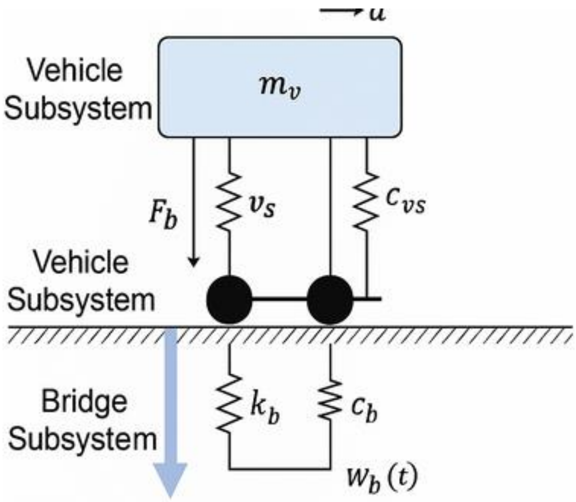

Figure 3. *Schematic of a Coupled VBI Model for Braking Analysis.*

Figure 3 shows a schematic representation of a coupled Vehicle-Bridge Interaction (VBI) model specifically developed to analyze the structural response of railway bridges under braking conditions. In this model, the train is simplified as a multi-body system comprising masses, springs, and dampers to represent the car body, bogies, and wheelsets. Each wheelset interacts with the bridge structure through a wheel-rail contact interface, which transmits both vertical and longitudinal (braking) forces.

3.4. Comparative Observations and Modelling Trends

Modern modelling techniques represent a significant leap forward in both fidelity and predictive power compared to historical methods. However, their performance is still bounded by several critical challenges:

a) Calibration Needs: Accurate modelling requires detailed input data; including vehicle parameters, real contact conditions, and bridge boundary states.
b) Computational Burden: High-fidelity dynamic simulations can be computationally expensive, especially for long-span bridges under heavy traffic scenarios.
c) Integration with Codes: Despite their capabilities, these models are rarely referenced directly in design codes, which continue to rely on simplified empirical rules.

Nonetheless, the trend is clearly toward hybrid models—blending physical simulations with data-driven methods to reduce computational cost while maintaining accuracy. The next section will explore how monitoring techniques and empirical studies help validate and refine these models for real-world implementation.

4. Monitoring Approaches and Experimental Studies

Monitoring braking and traction forces on railway bridges is crucial to understanding their long-term performance, validating analytical models, and ensuring operational safety. Over the last two decades, the development of advanced sensing technologies, data acquisition systems, and field testing protocols has transformed the way researchers investigate train-bridge interaction under longitudinal loading. This section presents an overview of current experimental practices, real-world monitoring systems, and their synergy with computational modelling.

4.1. Static and Dynamic Load Testing Protocols

Experimental assessment of railway bridges has traditionally relied on static and dynamic load testing. Static tests, though useful for calibrating stiffness and verifying load paths, offer limited insight into transient braking or acceleration effects. Conversely, dynamic tests using moving trains provide valuable data on the temporal response of bridges to real operational loads. For instance, Hester, D et al. Conducted dynamic testing on a short-span steel girder bridge under controlled train braking conditions in Ireland [28]. Their findings indicated that longitudinal loads could induce notable shear stress at bearings and contribute to small but measurable lateral movements of the superstructure. Similarly, Ding, J. et al. employed instrumented test trains and strain gauges to measure braking forces transmitted to a high-speed railway viaduct [29]. Their experiments showed that even modest deceleration rates could generate longitudinal forces approaching 25% of the train's axle loads.

4.2. Instrumentation Techniques

Monitoring of braking and traction effects generally involves deploying a suite of sensors that capture both bridge and train dynamics. These may include:

a) Strain gauges on girders, bearings, and diaphragms
b) Accelerometers mounted at midspan and supports
c) Displacement transducers for expansion joint movement
d) Wheel load sensors and onboard train diagnostics

Molino Developed a monitoring system for an Italian railway bridge that included fiber optic strain sensors at support bearings [17]. Their setup successfully captured variations in strain under different braking intensities and correlated them with train position and speed data. Recent work by Silva, S., et al. used distributed acoustic sensing (DAS) cables to detect vibrations caused by sudden traction or braking [19]. The DAS system, when compared with conventional accelerometers, provided higher spatial resolution and better fault localization.

4.3. Long-Term Structural Health Monitoring (SHM)

The shift from short-term experimental campaigns to continuous monitoring systems reflects a broader move toward predictive maintenance and infrastructure resilience. Long-term SHM programs not only track cumulative fatigue effects from repeated braking but also assist in early detection of bearing degradation or connection loosening. Zhou, Y., & Li, H. Implemented a multi-year SHM program on a large steel-concrete composite bridge along the Beijing-Shanghai High-Speed Railway [18]. Their sensor array monitored axial strain, thermal expansion, and longitudinal movements (figure 4). Over four years, their data revealed seasonal variations in braking-induced stresses and gradual increases in displacement at roller bearings—information critical for maintenance planning (table 4).

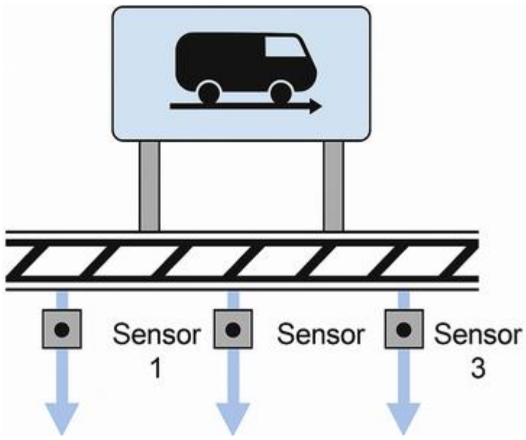

Figure 4. *Typical Sensor Layout for Monitoring Braking Effects on a Railway Bridge.*

Table 4. *Summary of Key Monitoring Strategies for Braking and Traction Forces.*

Study (Author & Year)	Monitoring Method	Bridge Type	Key Observations
[28]	Strain gauges, accelerometers	Steel girder	Notable lateral displacements from braking loads
[29]	Onboard sensors, strain gauges	Viaduct	Braking forces ~25% of axle loads
[17]	Fiber optic strain sensors	Arch bridge	Support bearings show peak strain under emergency stop
[18, 32]	Long-term SHM, thermal sensors	Composite bridge	Seasonal changes in braking response, bearing movement
[19, 31]	DAS with high-res mapping	Pre-stressed concrete	Localized traction-induced vibrations accurately traced

4.4. Observational Gaps and Future Experimental Needs

Despite technological advances, current monitoring systems still face several limitations:

I. Noise and calibration: Sensor drift and environmental noise can obscure low-amplitude signals from braking, especially under light axle loads.

II. Integration complexity: Synchronizing train data with bridge responses requires high temporal resolution and careful alignment.

III. Data overload: Long-term SHM programs generate massive data volumes that require effective filtering and interpretation algorithms.

Addressing these challenges may involve hybrid approaches combining experimental monitoring with real-time simulations or predictive algorithms, particularly those enabled by machine learning and digital twins. As discussed in the next section, these innovations offer significant potential for closing the loop between theory, experiment, and real-time decision-making.

5. Future Research Directions and Integration of Predictive Technologies

As the demand for higher-speed rail systems and increased freight capacities intensifies globally, understanding and anticipating the structural implications of braking and traction forces on railway bridges becomes more critical. Future research must pivot from descriptive analyses to predictive, integrated, and adaptive approaches that blend structural mechanics, sensor networks, machine learning, and digital twin environments. This section outlines the key directions where research is expected to evolve, focusing on predictive modeling, data-driven diagnostics, and digital technologies.

5.1. Predictive Modelling Through Hybrid Techniques

Traditional finite element methods (FEM) remain the backbone of structural response simulation. However, their ability to predict complex train-bridge interaction under varying braking and traction scenarios is constrained by assumptions and computational overhead. Recent efforts advocate hybrid modelling techniques that merge physics-based models with data-driven approaches. For example, Gheorghe, A et al. integrated FEM with machine learning algorithms to calibrate longitudinal force predictions using historical monitoring data [20]. Their model significantly improved real-time accuracy in estimating bearing loads under braking forces. Similarly, Kim, J., & Kim, H. proposed a reduced-order model using neural networks trained on high-fidelity simulations, enabling rapid assessment of bridge behavior under various acceleration and deceleration patterns [21].

5.2. Role of Artificial Intelligence in Damage Prognosis

The shift toward Artificial Intelligence (AI) in infrastructure monitoring has opened avenues for early warning systems, anomaly detection, and life-cycle assessment. AI algorithms, especially deep learning and decision trees, are increasingly used to correlate sensor outputs with possible damage states, fatigue accumulation, and nonlinear bridge responses. In a recent case study, Pereira, T., et al. deployed a deep learning-based autoencoder model on sensor data from a Portuguese railway bridge [22]. The system successfully identified precursors to abnormal bearing displacement due to prolonged traction loads. Chen, X et al. Further introduced convolutional neural network (CNN) architecture capable of detecting micro-vibrational signatures induced by traction events, which were otherwise unobservable in raw acceleration data [23].

5.3. Digital Twins and Cyber-Physical Systems

A digital twin is a virtual replica of a physical system that is continuously updated with real-time data. In the context of railway bridges, digital twins allow simulation of braking and traction events with up-to-the-minute accuracy and enable predictive maintenance by simulating wear, friction, and bearing shifts over time. Wang, Y., & Li, J. Developed a digital twin model for a steel viaduct in Guangdong, incorporating real-time input from strain gauges and accelerometers [24]. The system allowed for scenario simulation under varying train deceleration profiles and was used to optimize future design retrofits. Guo, J et al highlighted that integrating digital twins with operational data from onboard train sensors—such as braking effort, axle load, and speed—could revolutionize the real-time structural safety monitoring of railway infrastructure [25].

5.4. Sustainability and Resilience in Bridge Design

Future work should also focus on sustainable bridge design, emphasizing durability under recurrent longitudinal loads. Predictive models must incorporate climate variability, thermal expansion effects, and increased train frequency, all of which affect the cumulative impact of braking and traction forces. Nguyen, T., & Yu, H. Suggested an adaptive damping system for expansion joints that dynamically adjusts to braking force intensity, reducing wear and extending service life [26]. These concepts, when embedded in predictive maintenance schedules via AI, have the potential to redefine resilient design standards (table 5).

Table 5. *Emerging Research Directions in Braking and Traction Response Studies.*

Focus Area	Description	Key Contributors	Future Potential
Hybrid FEM-AI Modelling	Combines physics-based models with data analytics	[20, 21]	High for real-time simulations
AI for Anomaly Detection	Uses ML for early damage signs from sensor patterns	[22, 23]	Critical for SHM automation
Digital Twin Development	Real-time synchronized virtual bridge models	[24, 25]	Integral to smart bridge networks
Sustainability and Resilience Modelling	Considers lifecycle, fatigue, and thermal effects	[26, 27]	Important for climate-adaptive design

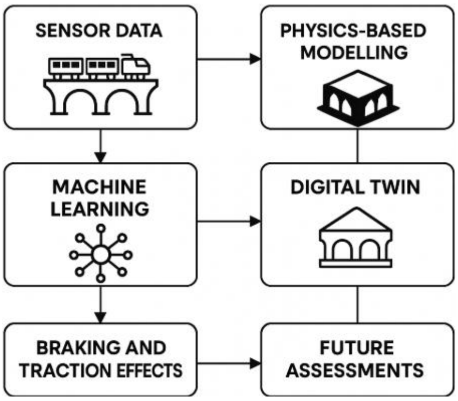

Figure 5. *Framework for Predictive Integration in Railway Bridge Assessment.*

Figure 5 illustrates a conceptual framework integrating sensor data, physics-based modeling, machine learning, and digital twins for future railway bridge assessments under braking and traction effects.

5.5. Conclusion and Research Outlook

The analysis of braking and traction forces on railway bridges has undergone a radical change with the incorporation of predictive technologies and intelligent modelling. In order to construct predictive, self-adaptive, and sustainable bridge infrastructures, future research must use interdisciplinary approaches that combine computer science, system engineering, and civil engineering. In the upcoming decades, the way we construct, monitor, and maintain railway bridges will be completely redesigned by the convergence of data, models, and real-time feedback loops.

6. Conclusion and Recommendations

6.1. Conclusion

The intricate interplay between railway vehicles and bridge structures—especially in the context of braking and traction forces—continues to present a significant challenge in light of the evolving requirements of rail transport. This review has delineated the historical progression of comprehension in this domain, evolving from empirical observations to advance numerical and hybrid modeling methodologies. Additionally, it emphasizes the critical role of experimental validation and real-time monitoring in accurately capturing the authentic behavior of railway bridges subjected to longitudinal stresses. The incorporation of digital twins, artificial intelligence, and sensor-laden cyber-physical systems presents a transformative avenue for the monitoring of bridge health, maintenance, and design. These advancements not only enhance safety and serviceability but also facilitate the establishment of cost-effective, resilient infrastructure amidst escalating operational and environmental challenges.

6.2. Recommendations

I. Integrated Monitoring Systems: Future initiatives should prioritize the implementation of integrated, sensor-based monitoring systems to collect real-time data regarding longitudinal forces and bridge responses, thereby enabling more precise diagnostics and maintenance strategies.

II. Adoption of Digital Twins: Researchers and infrastructure managers ought to allocate resources towards the development and application of digital twin frameworks that amalgamate physical data with computational models for ongoing performance evaluation and predictive maintenance.

III. Machine Learning Applications: The railway engineering community should investigate and enhance machine learning algorithms for the purposes of anomaly detection, load prediction, and failure forecasting, particularly within the context of complex dynamic interactions.

IV. Full-Scale Testing: A persistent focus should be maintained on conducting full-scale experiments and validation studies to corroborate and refine simulation models, particularly under authentic braking and traction conditions.

V. Cross-Disciplinary Collaboration: A multidisciplinary strategy that integrates structural engineering, data science, transportation planning, and sustainability is imperative for formulating comprehensive solutions that address both technical and societal imperatives.

VI. Performance-Based Design Updates: Standards and design codes ought to be revised to incorporate new insights derived from sophisticated modeling and monitoring, thereby permitting performance-based methodologies that more effectively accommodate dynamic interactions and resilience objectives.

VII. Climate Adaptation Strategies: In light of the increasing repercussions of climate variability, forthcoming research should incorporate climate-resilient design principles to ensure the sustained safety and functionality of bridges under extreme meteorological circumstances.

By adhering to these recommendations, stakeholders can substantially augment the performance, safety, and sustainability of railway bridge infrastructure within a progressively demanding transportation landscape.

Abbreviations

VBI	Vehicle-Bridge Interaction
SHM	Structural Health Monitoring
FEM	Finite Element Methods
AI	Artificial Intelligence
CNN	Convolutional Neural Network

Author Contributions

Girmay Mengesha Azanaw is the sole author. The author read and approved the final manuscript.

Declaration Statement

The athour must verify the accuracy of the following information as the article's author.

Ethical Approval and Consent to Participate

The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.

Data Access Statement and Material Availability

The adequate resources of this article are publicly accessible.

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Conflicts of Interest

The author declares no conflicts of interest.

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Biography

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