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Smart Technologies in Construction and Transportation Infrastructure: A Review of AI, IoT, and Data-Driven Innovations

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ABSTRACT

While the field of civil engineering has traditionally been dominated by hands-on and experience-based techniques, the advent of Artificial Intelligence (AI), Internet of Things (IoT), and data analytics are transforming it. This paper provides a structured outcome-oriented narrative review of the applications of smart technology in two dominant areas: construction management and transportation infrastructure. It is based on 37 peer-reviewed journal articles, conference papers, and technical reports from 2015 to 2026 that were selected purposively, without using a registered systematic search. The evidence has been grouped into eight application themes: AI/ML in construction project management; IoT-enabled site and structural monitoring; AI-driven intelligent transportation systems; IoT-based smart pavement and road monitoring; machine-learning-based structural health monitoring; digital twins and blockchain; UAV and computer-vision monitoring; and cybersecurity in smart infrastructure. The reported outcomes represent distinct performance dimensions and are not directly compared: examples include a 0.12% cost variance for AI/ML project models, a concrete strength prediction error within 1–2 MPa alongside a maximum UWB worker positioning error of 1.44 m for an IoT-based system, a 98.6% traffic-monitoring performance for a machine-learning classification model, and a hardhat-detection precision of 93.1% for Faster R-CNN. Themes of AI and IoT integration are most frequently associated with improved prediction, monitoring, and decision support, while digital twins and blockchain are primarily associated with data trust, traceability, and operational latency reduction. Recurring barriers include data interoperability, data security, implementation costs, and metric heterogeneity across literature. This review concludes with a research agenda prioritizing interoperable data standards, edge-AI and federated learning, cybersecurity-by-design, and standardized outcome reporting.

1. Introduction

The construction sector is one of the biggest industries in the world, estimated to spend approximately ten trillion dollars annually. At this size, it has experienced slow growth in labor productivity compared to other sectors like manufacturing and agriculture. This ongoing productivity gap, combined with repeated cost

overruns, schedule delays, and safety incidents, has spurred a move toward intelligent, data-driven technologies throughout the civil engineering lifecycle. Artificial intelligence and machine learning (ML), the Internet of Things (IoT), big-data analytics, cloud computing, blockchain technologies, and cybersecurity are becoming increasingly embedded in construction and transportation practice, forming an interdisciplinary paradigm known as Construction 4.0.

Transportation infrastructure and transportation construction management are two closely related sub-fields of civil engineering that rely on shared digital enablers—sensing, connectivity, predictive analytics, and secure data-sharing platforms. Transportation infrastructure assets—including roads, bridges, and pavements—as well as the constituent materials required for their fabrication, rely fundamentally on advanced construction management processes throughout their delivery lifecycle. Although many single primary studies exist, consistent and structured reviews evaluating outcomes across both domains end masse remain scarce. This leaves a gap where researchers and practitioners lack a comparative understanding of which smart technologies lead to measurable performance improvements and under what conditions.

This paper addresses this gap with a structured and outcome-oriented narrative review that aims to (i) map the current state of AI, IoT, and data-driven innovations applied to construction management and transportation systems; (ii) synthesize the quantitative outcomes reported in the literature (accuracy, error, safety, cost, and schedule measures) while maintaining clear separation among heterogeneous metrics; (iii) identify crosscutting issues that hinder widespread adoption; and (iv) propose a targeted research agenda for future outcome-oriented studies. The remainder of the paper is organized as follows: Section 2 presents a literature review across eight themes and synthesizes them comparatively; Section 3 details the search and selection methodology alongside its limitations; Section 4 presents the results and thematic discussion; Section 5 outlines research gaps and future directions; and Section 6 concludes the paper.

2. Literature Review

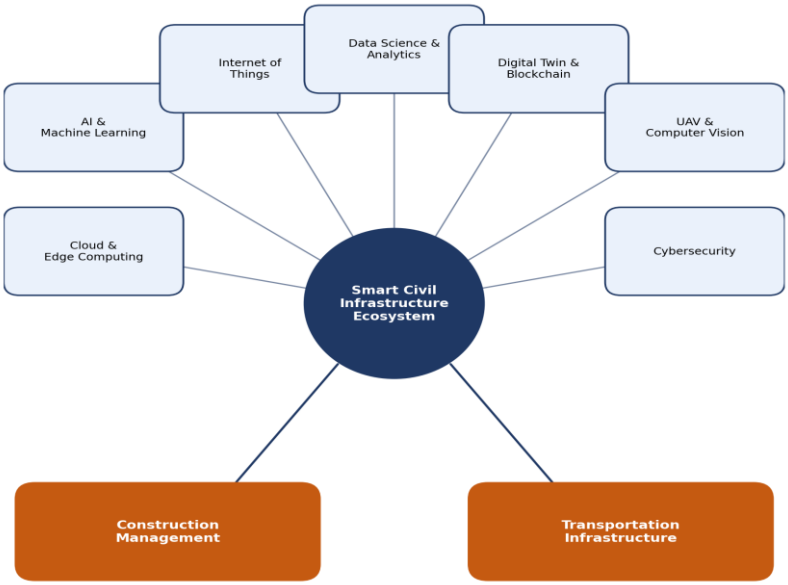

Fig. 1. Conceptual framework that connects transportation infrastructure, construction management, and key enabling technologies within a common smart-infrastructure ecosystem

Fig. 1 summarizes the conceptual structure of this review. Seven groups of enabling technologies (AI/ML, IoT, data science and analytics, digital twins and blockchain, UAV and computer vision, cybersecurity, and cloud and edge computing) are examined across two civil engineering domains: construction management and transportation infrastructure. Cloud and edge computing act as shared infrastructure appearing across several themes. The literature is organized into eight application themes (Sections 2.1 to 2.8), which are synthesized comparatively in Section 2.9.

2.1 Artificial Intelligence and Machine Learning in Construction Project Management

AI and ML have been applied throughout the construction project lifecycle, including planning and scheduling, risk assessment, cost estimation, and quality control. A comparative study of predictive project modeling with Random Forest, Support Vector Machine, and Artificial Neural Network models achieved a cost variance of 0.12% between actual and estimated project costs, a Schedule Performance Index (SPI) of 1.04 (ahead of schedule), and a Cost Performance Index (CPI) of 0.91. A systematic review of 191 peer-reviewed articles from 2020 to 2025 indicated that AI applications in construction management focus predominantly on risk and safety management, decision support, and monitoring/control, whereas legal analytics, robotics, and cybersecurity remain under-researched. Bibliometric data reflect a steady increase in project management publications utilizing AI since the inception of Industry 4.0. Early foundational reviews identified sector-wide opportunities and implementation challenges, while recent reviews in the management and building sectors underscore AI's value in project planning, resource optimization, and sustainable building practices.

2.2 IoT-Enabled Construction Site and Structural Monitoring

Construction sites are monitored in real time using mapping, positioning, and activity-tracking sensors enabled by IoT connectivity. Reviews on integrating Building Information Modeling (BIM) with IoT highlight applications in site operations, health and safety management, logistics, and facility management, categorizing five integration frameworks. At the material level, an IoT-enabled LoRa/LTE-M platform was developed to provide automated, real-time monitoring during concrete curing. A related monitoring system integrating 3D laser scanning, IoT sensors, and Ultra-Wideband (UWB) positioning predicted concrete compressive strength within an error margin of 1–2 MPa (e.g., 26.2 MPa predicted vs. 25.3 MPa measured at 14 days) and tracked concrete workers with a maximum UWB positioning error of 1.44 m at a 1-second update interval. Structural equation modeling of IoT factors in construction building site operations revealed statistically significant path coefficients for environmental monitoring (0.38), safety monitoring (0.369), equipment management (0.343), and predictive analytics/maintenance (0.222). However, a broad review of 417 articles indicated that IoT research in construction remains somewhat fragmented, with isolated single-point solutions rather than fully integrated platforms. Wireless sensor networks combined with BIM have also been demonstrated for automated hazardous gas detection and alarm/ventilation triggering in underground construction.

2.3 AI and Data-Driven Approaches in Intelligent Transportation Systems

Intelligent Transportation Systems (ITS) integrate communication, computing, and sensing technologies to deliver real-time transportation management. Traffic flow forecasting is a core ITS capability, receiving extensive machine learning research. Model taxonomies categorize traffic prediction algorithms into regression, example-based, kernel-based, neural network, and hybrid families. A survey of 212 studies evaluated Graph Neural Networks (GNNs) for traffic forecasting, encompassing road speed/flow, rail passenger flow, and ride-hailing demand estimation. A comprehensive review reported an intelligent traffic-monitoring system utilizing machine learning that achieved a classification accuracy performance of 98.6%. Deep learning architectures—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Restricted Boltzmann Machines, and Autoencoders—are increasingly replacing shallow models to handle high-dimensional vehicular data streams. Federated Learning has been proposed for privacy-preserving, decentralized traffic prediction across vehicular networks, alongside reinforcement learning and multi-objective optimization for freight traffic speed prediction without central data aggregation. Surveys on federated learning for ITS highlight use cases in traffic target recognition, trajectory prediction, and parking estimation, citing data heterogeneity, communication bandwidth, and edge device limits as key deployment barriers. In railway infrastructure, predictive maintenance reviews categorize ML/DL methods applied to asset degradation and evaluate their domain-specific performance metrics.

2.4 IoT-Based Smart Pavement and Road Infrastructure Monitoring

Smart road infrastructure systems frequently employ a three-layered architecture: a sensing layer measuring stress, strain, displacement, vibration, temperature, and moisture; an edge/fog communication layer performing local preprocessing; and a cloud-based machine learning analysis layer evaluating structural condition and environmental variables. Complementary approaches integrate miniaturized, acoustic-response-based non-destructive sensing prototypes with high-speed monitoring platforms to combine spatial coverage across urban road networks with detailed localized diagnostics. Reviews of road condition monitoring

highlight vision-based AI utilizing RGB, thermal cameras, lasers, and Ground Penetrating Radar (GPR) to classify and localize pavement distress. Sensor taxonomies categorize IoT road monitoring devices by operating principle and computational distribution across edge, fog, and cloud tiers. At the pavement surface, acceleration-based vibration monitoring networks linked to gateways and cloud analytics collect real-time vehicle counts, speeds, and weights with lower power consumption and higher scalability than conventional camera, geomagnetic, or weigh-in-motion systems.

2.5 Machine-Learning-Based Structural Health Monitoring

Structural health monitoring (SHM) represents a major application domain for ML in bridge and structural engineering. Comparative studies on concrete and steel bridge SHM evaluated Support Vector Machines, Random Forests, K-means clustering, and emerging Transformer-based deep learning models, highlighting Transformers' efficacy in multi-dimensional regression tasks. ML-driven structural diagnosis spans data cleaning, modal parameter estimation, and damage identification, while digital twin models facilitate virtual inspection, real-time monitoring, and scenario simulation. Systematic surveys outline feature-extraction and pattern-recognition algorithms across the complete bridge lifecycle—from design and damage detection to maintenance scheduling.

2.6 Digital Twins and Blockchain

Digital twins and blockchain technologies are increasingly combined to address project fragmentation and trust deficits in multi-stakeholder civil projects. Integrated frameworks combine BIM models with real-time IoT sensor streams, while blockchain provides verifiable data transactions and automated smart-contract compliance. A systematic review of 153 papers identified eight primary distributed ledger technology (DLT) application areas, including information management, procurement, supply chain tracking, and dispute resolution. A "Blockchain 3.0" paradigm for construction project management utilizes a locally cached digital twin to achieve transaction confirmation time savings of 99.2% to 99.8% compared to traditional public blockchain confirmation, enabling offline operations for field contractors, suppliers, and regulators. PESTELS analysis indicates that trust, cybersecurity, and information-sharing friction remain primary hurdles to widespread blockchain-digital twin adoption.

2.7 UAV and Computer-Vision-Based Monitoring

Unmanned Aerial Vehicles (UAVs) equipped with optical cameras enable rapid, low-cost visual surveys of construction progress, hard-to-reach structural components, and site safety conditions. Bibliometric analyses of UAV-based worker personal protective equipment (PPE) monitoring confirm that computer vision deep learning models rapidly process image sequences to detect safety non-compliance. A review of 267 visual data acquisition studies classified platform setups into single-camera, mobile phone, UAV-mounted, and multi-camera systems, noting that UAV and multi-camera configurations successfully overcome spatial coverage limitations. Field validation across active construction sites using over 7,000 UAV images demonstrated automated hardhat-compliance detection precision of 93.1% for Faster R-CNN compared to 89.8% for YOLOv3.

2.8 Cybersecurity in Smart Construction and Transportation Systems

As BIM, IoT, cloud platforms, and blockchain become central to civil infrastructure, cybersecurity has emerged as a critical research discipline. A dedicated review of construction cybersecurity concluded that general-purpose standards (e.g., ISO 27000, IEC 62443, GDPR) offer incomplete protection for fragmented supply chains, multi-stage project lifecycles, and heterogeneous device networks, advocating instead for lifecycle-aware, secure-by-design standards. A survey of 154 smart city cybersecurity studies published from 2015 to 2022 identified smart home and IoT architectures as the most heavily investigated infrastructure attack vectors. These findings reinforce that data trust and security—alongside technical feasibility—are fundamental determinants of smart technology adoption rates in civil infrastructure.

2.9 Comparative Synthesis Across Themes

A comparative evaluation reveals that the eight themes differ not only in technological tools but also in the nature of reported evidence. Construction management literature (Sections 2.1–2.2) emphasizes project-level outcomes, reporting cost variance, schedule indices, material strength prediction errors, and spatial positioning metrics. Transportation infrastructure studies (Sections 2.3–2.4) focus on continuous network sensing and time-series forecasting, reporting traffic monitoring accuracies and data acquisition scalability. Structural health monitoring (Section 2.5) bridges both domains by evaluating long-life physical assets using regression and

classification ML models. Digital twin and blockchain literature (Section 2.6) focuses predominantly on qualitative frameworks, governance models, and computational latency, while UAV/computer-vision studies (Section 2.7) report object detection precision and recall.

Three key crosscutting insights emerge:

1. **Evidence Type**: Quantitative metrics dominate predictive sensing and computer vision, whereas governance, trust, and security studies rely primarily on qualitative evaluation.
2. **Privacy vs. Trust Mechanisms**: Transportation applications favor Federated Learning for decentralized data privacy, whereas construction management favors Blockchain for multi-stakeholder transaction trust.
3. **Shared Enablers**: BIM-linked Digital Twins, edge-to-cloud sensing pipelines, and UAV aerial monitoring serve as unifying technologies across both domains.

3. Methodology

This paper is conducted as a structured narrative review. Targeted keyword searches were executed across nine database and publisher platforms: ScienceDirect, SpringerLink, MDPI, IEEE Xplore, Nature Portfolio, Wiley Online Library, Taylor & Francis Online, PubMed Central, and arXplore. Search and record analysis were conducted between September and October 2026 using Boolean operator combinations linking technology terms with civil infrastructure domains: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "internet of things" OR "data-driven" OR "digital twin" OR "blockchain" OR "unmanned aerial vehicle" OR "computer vision" OR "cybersecurity") AND ("construction management" OR "transportation infrastructure" OR "structural health monitoring" OR "smart pavement" OR "intelligent transportation system"). Keywords were updated recursively as new terminology emerged.

Study selection followed a purposive sampling strategy. Titles and abstracts were screened against explicit inclusion/exclusion criteria (Table 1). Preference was given to English-language, peer-reviewed journal articles, systematic reviews, and conference papers published between 2015 and 2026 reporting measurable quantitative outcomes or case-study metrics. Duplicate entries across platforms were consolidated using DOIs. All reported figures were verified directly against original source texts, yielding 37 synthesized studies.

Methodological limitations must be noted: because this is a narrative review rather than a registered systematic review, formal risk-of-bias appraisals were not performed, platform-specific hit counts were not logged, and PRISMA flow diagrams are unavailable due to the absence of duplicate-removal logs. Furthermore, subscription databases such as Scopus and Web of Science were not directly indexed. Researchers seeking full systematic replication are encouraged to execute the search string across indexed databases using a PRISMA-compliant tracking protocol.

Table 1

Source-selection criteria applied in the literature review

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed journal articles, systematic reviews, conference papers	Editorials, non-peer-reviewed blogs, unpublished theses
Topic relevance	AI, ML, IoT, big data, cloud, blockchain, or digital twins applied to construction management or transportation infrastructure	Studies unrelated to civil/construction/transportation engineering
Publication window	2015-2026	Pre-2015 publications, unless seminal
Language	English	Non-English without verified translation
Evidence type	Studies reporting a measurable outcome, metric, or case-study result	Purely conceptual pieces with no reported outcome or validation

4. Results and Discussion

Table 2 summarizes the application themes, representative smart-technology implementations, and key reported outcomes. Table 3 categorizes the reported outcome metrics into distinct performance dimensions to prevent improper cross-metric comparisons.

Table 2

Thematic synthesis of smart-technology applications and reported outcomes

Theme	Technology	Representative Application	Key Reported Outcome	Ref.
Construction project management	AI/ML (ANN, SVM, Random Forest)	Cost, schedule, and risk prediction	Cost variance of 0.12%; SPI 1.04; CPI 0.91	[2]
Construction site & structural monitoring	IoT sensors, BIM-IoT integration, UWB positioning	Concrete curing, worker localization, hazard detection	Strength-prediction error of about 1–2 MPa; maximum UWB positioning error of 1.44 m	[9], [10]
Intelligent transportation systems	ML/DL (CNN, LSTM), federated learning	Traffic-flow prediction and congestion management	Traffic-monitoring performance of 98.6% reported for one ML-based system	[16], [18]
Smart pavement & road monitoring	IoT sensor networks, edge/fog/cloud computing	Real-time pavement condition & traffic data acquisition	Low-power, real-time vehicle count/speed/weight acquisition	[26], [30]
Structural health monitoring	ML/DL (SVM, Random Forest, Transformer)	Bridge damage detection and modal analysis	Qualitative: Transformer models noted as promising for multidimensional regression	[20], [22]
Digital twin & blockchain	Distributed ledger technology, BIM-linked digital twins	Traceable information sharing and supply-chain trust	Eight application themes across 153 DLT and smart-contract papers; 99.2–99.8% time saving for one Blockchain 3.0 design	[23], [24], [25]
UAV & computer-vision monitoring	Drone-mounted cameras, deep-learning object detection (CNN, YOLO)	Site safety surveillance, PPE compliance, hard-to-reach inspection	267 vision-based studies reviewed; hardhat-detection precision 93.1% (Faster R-CNN) vs 89.8% (YOLOv3)	[32], [34], [35]
Cybersecurity in smart infrastructure	Security standards and frameworks (ISO 27000, IEC 62443, GDPR); threat reviews	Protection of BIM, IoT, and cloud-linked project data	Smart homes and IoT the most active research areas across 154 reviewed smart-city cybersecurity studies	[31], [37]

Table 3

Reported outcome measures grouped by performance dimension (values in different rows are not comparable)

Performance dimension	Measure as reported (direction of improvement)	Reported value	Ref.
Forecasting / monitoring performance	Traffic-monitoring performance of one ML-based system; metric as defined in the original study (higher is better)	98.6%	[16]
Detection performance	Hardhat-detection precision, Faster R-CNN vs YOLOv3 (higher is better)	93.1% vs 89.8%	[35]
Project cost and schedule performance	Cost variance, projected vs actual expenditure (lower is better)	0.12%	[2]
	Schedule Performance Index; Cost Performance Index (1.0 = on plan)	1.04; 0.91	[2]

Measurement and estimation error	Maximum UWB worker-positioning error (lower is better)	1.44 m	[10]
	Concrete-strength prediction error against measured values (lower is better)	about 1–2 MPa	[10]
Operational efficiency	Time saving of a locally cached digital-twin Blockchain 3.0 design relative to conventional blockchain confirmation (higher is better)	99.2–99.8%	[24]
Statistical association	Path coefficients linking IoT-adoption factors to adoption outcomes: environmental monitoring, safety monitoring, equipment management, predictive analytics and maintenance	0.38; 0.369; 0.343; 0.222	[11]
Size of evidence base	Number of studies reviewed by each source (not an outcome measure): AI in construction management; GNN traffic forecasting; DLT and smart contracts; vision-based monitoring; smart-city cybersecurity	191; 212; 153; 267; 154	[4], [15], [23], [34], [37]

4.1 Outcome Patterns by Performance Dimension

As shown in Table 3, reported outcomes are organized into six distinct performance dimensions: Forecasting and Detection: Machine learning models demonstrate high accuracy in classification tasks—such as 98.6% traffic-monitoring performance [16] and 93.1% hardhat detection precision using Faster R-CNN [35]—while physical estimation models yield engineering-unit errors (1–2 MPa concrete strength prediction error) [10].

Positioning and Project Metrics: Real-time worker tracking achieved a maximum UWB positioning error of 1.44 m [10], while project-level AI models demonstrated tight cost variance (0.12%), an SPI of 1.04, and a CPI of 0.91 [2]. Structural equation modelling confirmed statistically significant path associations for IoT adoption in safety and maintenance [11].

Trust, Traceability, and Efficiency: Distributed ledger frameworks provide tamper-resistant audit trails across project stakeholders [23], while locally cached digital twins reduce blockchain transaction confirmation latency by 99.2% to 99.8% [24].

4.2 Barriers to Adoption

Four major barriers hinder industry-wide adoption:

1. **Data Interoperability**: Non-standardized data schemas across BIM, IoT sensors, and legacy management systems force custom middleware integration [8].
2. **Cybersecurity and Trust**: PESTELS analysis confirms cybersecurity and data-sharing risks as primary digital twin/blockchain adoption hurdles [25]. General standards like ISO 27000 and IEC 62443 leave gaps in lifecycle-aware construction data pipelines [31].
3. **Implementation Costs**: High initial capital investments in smart sensing hardware and cloud/edge infrastructure impede small- and medium-sized enterprises [25].
4. **Metric Heterogeneity**: Inconsistent outcome metrics across published literature prevent direct comparative meta-analyses.

4.3 Lifecycle Integration Across Domains

Smart technologies increasingly bridge construction management and transportation operations. Smart pavements embedded with sensors during construction provide real-time traffic and load data to operational ITS cloud platforms [26, 27, 30]. Similarly, digital twin models initialized during project construction serve as long-term virtual platforms for bridge structural health monitoring and scenario simulation [21, 23, 24]. UAV aerial monitoring similarly serves dual roles in construction site safety auditing and post-construction structural inspection [32, 33].

5. Research Gaps and Future Directions

Six future research directions are proposed: Interoperable Data Standards: Development of open, standardized data schemas linking BIM, IoT sensor streams, and Geographic Information Systems (GIS) [8]. Edge-AI and Federated Learning: Implementation of privacy-preserving, decentralized machine learning architectures for traffic networks and mobile field devices [18, 19]. Cybersecurity-by-Design: Embedding

lifecycle-aware security protocols directly into smart-construction IoT and digital twin platforms [25, 31]. Explainable AI (XAI): Developing interpretable ML models for safety-critical structural health evaluations and risk management [4]. Open Benchmark Datasets: Establishing large-scale, open-access annotated image/sensor datasets for field computer-vision benchmarking [34]. Harmonized Outcome Metrics: Conducting longitudinal multi-site studies using standardized KPIs (e.g., cost variance, positioning error, CPI/SPI) to enable future systematic meta-analyses.

6. Conclusions

This outcome-oriented narrative review synthesized evidence from 37 peer-reviewed publications examining AI, IoT, and data-driven technologies in construction management and transportation infrastructure. AI/ML models combined with real-time IoT sensing consistently deliver strong predictive, detection, and monitoring capabilities, while digital twins and blockchain address multi-stakeholder data trust, traceability, and workflow efficiency. Because outcome metrics vary fundamentally across performance dimensions, quantitative results are categorized separately and are not directly ranked. Data interoperability, cybersecurity, initial implementation cost, and metric heterogeneity remain primary adoption barriers. Civil engineering researchers and practitioners can utilize this review as an evidence-based reference for evaluating smart-technology performance. Future efforts should prioritize open data standards, edge-AI/federated learning, lifecycle cybersecurity, explainable AI, open benchmark datasets, and standardized outcome reporting.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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