A Socio-Technical Framework for AI-Driven Digital Integration in Sustainable Construction

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Abstract

The digital transformation of construction increasingly depends on the ability to integrate artificial intelligence (AI), data-driven analytics, and interconnected digital systems into operational environments characterized by heterogeneous data, distributed stakeholders, and complex information flows. However, technological integration alone does not guarantee effective digital transformation because organizational processes, human decision-making, information governance, and system interoperability influence how computational capabilities are translated into practical outcomes. This research develops a conceptual socio-technical framework for AI-driven digital integration in sustainable construction by synthesizing the methodological and technical insights contained in seven provided studies concerning encrypted traffic classification, deep learning, convolutional neural networks, representation learning, and anonymous traffic identification. Although the source literature is primarily situated in network-security contexts, its underlying principles concerning data characterization, deep feature extraction, end-to-end learning, and traffic identification provide transferable foundations for understanding secure and intelligent information infrastructures. The proposed framework integrates five layers: data acquisition and characterization, AI-based representation and classification, secure digital integration, socio-technical decision coordination, and sustainability-oriented operational application. The analysis indicates that AI-driven construction integration should be treated as an adaptive information system rather than as an isolated algorithmic deployment. The framework emphasizes the importance of reliable data representation, contextual classification, secure information exchange, human oversight, and continuous learning. The study contributes a conceptual bridge between AI-enabled information processing and socio-technical digital integration while identifying limitations arising from the indirect transfer of findings from cybersecurity research to construction management.

Keywords: Artificial Intelligence; Digital Integration; Sustainable Construction; Socio-Technical Systems; Deep Learning; Data Classification; Digital Transformation; Secure Information Systems; Construction Management; Intelligent Decision-Making.

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1. Introduction

Construction is an information-intensive domain in which decisions depend on the continuous exchange of heterogeneous information among project participants, digital platforms, physical assets, and operational systems. The increasing adoption of digital technologies creates opportunities for more intelligent coordination, automated information processing, and evidence-based decision-making. Nevertheless, digitalization can also produce fragmented information environments when systems generate incompatible data structures or when decision-makers cannot reliably interpret the information produced by computational tools. Consequently, the central challenge is not simply the introduction of AI but the integration of AI into a socio-technical environment in which technological capabilities and human-organizational processes remain interdependent.

The provided literature offers an important technical foundation for this problem. Rezaei and Liu (2019) examine deep learning for encrypted traffic classification and emphasize the growing relevance of learning-based approaches to complex information environments. Len (2021) similarly surveys encrypted traffic classification based on deep learning, demonstrating the importance of automated feature extraction and classification in situations where conventional information-processing techniques may be inadequate. Wang et al. (2017a) demonstrate the use of convolutional neural networks (CNNs) for representation learning in traffic classification, while Wang et al. (2017b) investigate end-to-end encrypted traffic classification through one-dimensional convolutional neural networks. Together, these studies indicate that AI systems can transform complex raw information into representations suitable for classification and decision support.

The relevance of these findings to construction is conceptual rather than domain-specific. The studies do not directly investigate sustainable construction, construction project management, or environmental performance. Therefore, this article does not claim empirical evidence that the reported cybersecurity models directly improve construction outcomes. Instead, it extracts transferable architectural principles: data characterization, automated representation learning, classification, secure information processing, and continuous analytical adaptation.

The objective of this research is therefore to construct a socio-technical framework explaining how these principles can support AI-driven digital integration in sustainable construction. The framework considers AI not as an independent technological component but as a layer embedded within data infrastructures, organizational processes, human decision-making, and sustainability-oriented operational objectives. The study is particularly significant because it identifies a pathway through which technical advances in intelligent information classification can inform broader digital integration strategies.

2. Literature Review

2.1 Deep Learning and Intelligent Information Classification

The literature supplied for this study predominantly addresses the classification of network traffic under increasingly complex and partially concealed information conditions. Rezaei and Liu (2019) position deep learning as an important approach for encrypted traffic classification, reflecting the difficulty of extracting meaningful patterns when conventional observable information is restricted. This principle is relevant to digital integration because construction platforms likewise generate heterogeneous and sometimes incomplete information streams.

Len (2021) provides a survey-oriented perspective on encrypted traffic classification using deep learning. The significance of this work lies in its recognition that modern classification systems require automated learning mechanisms capable of identifying patterns without relying exclusively on manually engineered representations. From a socio-technical perspective, this suggests that intelligent digital systems should be designed to convert complex information into interpretable classifications that can subsequently support human decisions.

The relationship between deep learning and representation is further illustrated by Wang et al. (2017a), who employ CNNs for representation learning in malware traffic classification. Their approach demonstrates the value of learning representations directly from input data rather than depending entirely on predefined features. This principle can be conceptually transferred to construction information systems in which data may originate from multiple digital sources and possess different structural characteristics.

2.2 End-to-End Learning and Digital Integration

Wang et al. (2017b) investigate end-to-end encrypted traffic classification using one-dimensional CNNs. The importance of this study for the present framework is architectural: an end-to-end approach attempts to reduce unnecessary separation between raw information processing and classification. In an integrated construction environment, analogous principles could support pipelines in which data acquisition, feature representation, classification, and decision-support functions are connected within a coherent digital architecture.

Xu et al. (2016) similarly focus on a deep learning network traffic classification method, reinforcing the broader trajectory toward automated learning-based classification. Zhang (2017), meanwhile, addresses anonymous traffic identification using website fingerprints, demonstrating the importance of identifying behavioral or structural patterns even when direct identification is difficult. DraperGil et al. (2016) examine encrypted and VPN traffic using time-related characteristics, illustrating another important principle: useful information may be extracted from indirect characteristics rather than from direct content.

Collectively, these studies indicate that intelligent information systems can operate through multiple analytical representations, including temporal characteristics, learned representations, and traffic patterns. The theoretical implication for construction is that digital integration should not depend exclusively on explicit or manually structured project information. AI systems may also derive useful patterns from indirect relationships among digital events, provided that the resulting classifications are sufficiently reliable and interpretable.

2.3 Research Gap

A clear gap emerges from the supplied literature. The references provide substantial conceptual material concerning AI-based classification and intelligent information processing, but they do not explicitly address the socio-technical requirements of sustainable construction. There is consequently a missing bridge between technical AI architectures and the organizational, operational, and sustainability dimensions of construction.

This gap motivates the framework developed in this study. The framework does not reinterpret cybersecurity studies as construction evidence; rather, it identifies their underlying computational principles and integrates those principles into a conceptual construction-management architecture.

3. Methodology

3.1 Research Design

This study adopts a conceptual research and structured literature-synthesis methodology. The seven supplied references constitute the exclusive evidence base. Because the literature focuses primarily on encrypted traffic, malware traffic, network classification, and anonymous traffic identification, the analysis identifies transferable technical mechanisms rather than claiming direct empirical applicability to construction.

The analytical process consists of four stages. First, the technical mechanisms reported across the references are identified. Second, these mechanisms are grouped into common functional capabilities, including data characterization, representation learning, classification, and identification. Third, these capabilities are interpreted through a socio-technical perspective involving human users, organizational procedures, and digital infrastructure. Fourth, the resulting components are organized into a construction-oriented conceptual framework.

3.2 Proposed Socio-Technical Framework

The proposed framework contains five interconnected layers.

Layer 1: Data Acquisition and Characterization.

The first layer collects and characterizes information generated by digital construction environments. The conceptual basis derives partly from DraperGil et al. (2016), where temporal characteristics are used to identify encrypted and VPN traffic. The transferable insight is that useful classification does not necessarily require complete access to the semantic content of a data stream. In a construction context, analogous indirect characteristics could include event sequences, system interactions, equipment-status patterns, or temporal changes in project information.

Layer 2: AI-Based Representation Learning.

The second layer transforms raw or heterogeneous information into machine-learned representations. Wang et al. (2017a) provide the primary conceptual foundation through CNN-based representation learning. Rather than requiring all relevant features to be explicitly designed in advance, an AI system can learn representations from structured input. For construction, this could support the analysis of heterogeneous digital records where relationships are difficult to encode manually.

Layer 3: Classification and Intelligent Interpretation.

The third layer applies learned representations to classification and identification. Rezaei and Liu (2019), Len (2021), and Xu et al. (2016) collectively support the proposition that deep learning can be employed to classify complex information patterns. Within construction, the framework conceptualizes classification as a decision-support mechanism rather than an autonomous authority. For example, an AI platform could classify project information into operational categories, identify unusual data patterns, or prioritize information requiring managerial review.

Layer 4: Secure Digital Integration and Socio-Technical Coordination.

The fourth layer recognizes that intelligent classification must operate within a controlled information environment. Wang et al. (2017b) and Zhang (2017) demonstrate the broader importance of analyzing information under encrypted or anonymous conditions. For construction, this implies that digital integration should account for information security, controlled access, data provenance, and the possibility that information may be incomplete or obscured. Human users remain essential because technical classifications must be interpreted in relation to project objectives, contractual responsibilities, and organizational procedures.

Layer 5: Sustainability-Oriented Decision Support.

The final layer translates AI-generated information into decisions relevant to sustainable construction. Importantly, the supplied references do not empirically establish specific sustainability outcomes. Therefore, the framework treats sustainability as an application objective rather than as a demonstrated result. AI-based digital integration may conceptually support more informed decisions concerning resource coordination, operational efficiency, waste-related processes, or project monitoring, but such applications require independent construction-specific validation.

3.3 Socio-Technical Interaction Mechanism

The framework is based on a feedback mechanism rather than a linear technology pipeline. Data are acquired and characterized, AI models generate representations and classifications, human decision-makers evaluate the resulting information, organizational processes determine actions, and subsequent digital interactions generate new data.

This feedback structure addresses a fundamental limitation of purely technical AI deployment. A classification can be computationally accurate but operationally inappropriate if users misunderstand it, if organizational procedures cannot respond to it, or if the underlying data are inconsistent. Thus, effective digital integration requires alignment among algorithmic performance, information quality, human interpretation, and organizational response.

The end-to-end perspective discussed by Wang et al. (2017b) is particularly relevant here because integration benefits from reducing unnecessary fragmentation between data processing and analytical outcomes. However, an end-to-end computational architecture should not be interpreted as an end-to-end organizational architecture. Human validation and governance remain necessary where decisions have operational or sustainability consequences.

3.4 Hypothetical Construction Application

Consider a digitally integrated construction project in which multiple information systems continuously generate operational data. Instead of treating each system independently, the proposed framework would characterize information streams, use learned representations to identify recurring patterns, classify potentially relevant events, and present those classifications to project personnel.

Suppose the system identifies a recurring temporal pattern associated with a specific operational condition. The AI model would not automatically impose a managerial decision. Instead, the pattern would be presented to an appropriate human decision-maker, who could compare it with project schedules, resource conditions, and organizational procedures. The resulting decision would then become part of the subsequent information cycle.

This example illustrates the central socio-technical principle: AI produces analytical capability, while people and organizational systems provide contextual interpretation and accountability.

4. Results

The synthesis produces five principal findings concerning AI-driven digital integration.First, representation quality is foundational to intelligent integration. Across the literature, classification performance is connected to the ability to derive meaningful representations from complex information. Wang et al. (2017a) demonstrate this through CNN-based representation learning, while Rezaei and Liu (2019) and Len (2021) establish the broader importance of deep learning for encrypted traffic classification. The implication is that construction AI systems should prioritize the transformation of heterogeneous data into analytically meaningful representations before attempting higher-level decision support.

Second, indirect information can possess analytical value. DraperGil et al. (2016) show the relevance of time-related characteristics in traffic characterization, while Zhang (2017) investigates identification based on website fingerprints. These studies suggest that intelligent systems can learn from patterns that do not necessarily constitute explicit semantic content. In construction, this supports a conceptual move toward event-based and behavior-based analytics rather than reliance solely on manually entered project information.

Third, end-to-end computational integration can reduce analytical fragmentation. Wang et al. (2017b) demonstrate an end-to-end classification architecture using one-dimensional CNNs. The framework extends this principle conceptually by connecting data processing, AI interpretation, human validation, and organizational response. However, the findings also indicate that computational integration must be distinguished from socio-organizational integration.

Fourth, classification should function as decision support rather than unrestricted automation. The supplied literature demonstrates increasingly automated identification and classification mechanisms, but it does not establish that such systems should replace human judgment in complex operational environments. Consequently, the proposed construction framework places human interpretation between AI-generated classifications and consequential organizational decisions.

Fifth, security and uncertainty are integral to digital integration. The prominence of encrypted, VPN, and anonymous traffic in the literature demonstrates that information systems frequently operate under restricted observability. Wang et al. (2017b) and Zhang (2017) reinforce this challenge. A sustainable construction information architecture should therefore be designed with the assumption that data may be incomplete, protected, distributed, or difficult to interpret. This creates a requirement for robust AI pipelines and explicit governance mechanisms.

Overall, the findings support a layered socio-technical architecture in which AI capabilities are embedded within secure information infrastructures and mediated through human and organizational processes. The evidence does not establish direct sustainability improvements, but it provides a defensible conceptual basis for investigating how intelligent digital integration could be developed and evaluated in construction.

5. Discussion

The proposed framework contributes theoretically by repositioning AI-driven construction digitalization from a technology-centric problem to a socio-technical integration problem. The literature demonstrates that deep learning can classify complex information, learn representations, and identify patterns under conditions in which direct information may be unavailable. Rezaei and Liu (2019) and Len (2021) establish the broader importance of deep learning for difficult classification environments, while Wang et al. (2017a) and Wang et al. (2017b) demonstrate representation-learning and end-to-end architectural approaches. The present framework extends these principles by arguing that computational intelligence becomes organizationally valuable only when it is connected to users, procedures, and decision processes.

A major theoretical implication is the distinction between technical intelligence and organizational intelligence. A CNN or other deep-learning model can discover statistical regularities, but statistical recognition does not itself establish contextual meaning. In construction, the same digital pattern may have different implications depending on project stage, operational conditions, contractual requirements, or resource constraints. Consequently, human interpretation should not be considered an external addition to an AI system; it is a functional component of the overall socio-technical architecture.

The literature also exposes an important trade-off between automation and transparency. Automated representation learning can reduce dependence on manually engineered features, as indicated by Wang et al. (2017a). However, greater automation can make it more difficult for users to understand why a system generated a particular classification. This problem becomes particularly important when AI outputs influence resource allocation or sustainability-related decisions. The framework therefore favors human-in-the-loop decision processes rather than unrestricted algorithmic autonomy.

Security constitutes a second major trade-off. The references focus heavily on encrypted and anonymous traffic, indicating that useful classification can be performed even when direct information is constrained. DraperGil et al. (2016) and Zhang (2017) demonstrate the analytical value of indirect characteristics. Nevertheless, construction systems must balance analytical capability with privacy, access control, and information governance. Greater observability may improve analytics but can simultaneously increase organizational and security risks.

The framework also has significant limitations. Most importantly, the evidence base is not construction-specific. None of the supplied studies directly validates AI-driven digital integration in sustainable construction. Therefore, the framework should be treated as a conceptual transfer of computational principles rather than as empirical proof. Furthermore, the references focus primarily on classification problems, whereas sustainable construction involves broader decision dimensions that cannot be reduced to classification alone.

A further limitation concerns model generalization. AI systems trained on one information environment may perform differently when transferred to another environment. Construction projects vary substantially in data quality, technological maturity, organizational structure, and operational context. Consequently, future empirical research should test the framework using real construction datasets and compare different AI architectures under controlled conditions.

Despite these limitations, the framework provides a useful research direction. It connects representation learning, classification, secure information processing, human decision-making, and sustainability-oriented application within a single conceptual architecture. Its central proposition is that successful digital integration depends not on AI capability alone but on the alignment of AI with the broader socio-technical system.

6. Conclusion

This study developed a socio-technical framework for AI-driven digital integration in sustainable construction using exclusively the seven supplied references. Although the source literature primarily addresses encrypted traffic, malware traffic, network classification, deep learning, and anonymous traffic identification, its technical principles provide useful foundations for conceptualizing intelligent digital infrastructures.

The framework consists of five interconnected layers: data acquisition and characterization, AI-based representation learning, classification and interpretation, secure digital integration with socio-technical coordination, and sustainability-oriented decision support. Its central contribution is the integration of these technical capabilities with human judgment and organizational processes rather than treating AI as an isolated computational tool.

The synthesis indicates that representation learning, indirect pattern recognition, end-to-end processing, and automated classification can inform the architecture of intelligent construction information systems. However, the study does not claim that the supplied cybersecurity research directly proves sustainability improvements in construction. Such conclusions require construction-specific empirical investigation.

Future research should therefore validate the proposed framework through real project datasets, longitudinal implementation studies, comparative AI experiments, and assessments of human-AI collaboration. Particular attention should be given to data quality, model generalization, interpretability, cybersecurity, organizational adoption, and measurable sustainability outcomes. The resulting research agenda can move the field from conceptual transfer toward empirically validated AI-enabled sustainable construction systems.

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