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Review

Intelligent Construction Risk Management Through Transfer Learning: Trends, Challenges and Future Strategies

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Abstract: Construction risk management has evolved significantly by integrating artificial intelligence (AI) technologies, particularly machine learning (ML), to enhance predictive capabilities. Transfer learning (TL), a promising subfield of ML, has the potential to further revolutionize construction safety by enabling models trained in one domain to be adapted for related tasks in construction risk scenarios. This systematic review explores the current trends in applying TL to construction risk management, identifies key challenges, and highlights future opportunities for advancement. The review first assesses TL's ability to mitigate common issues such as data scarcity, overfitting, and lengthy model training times, which often hinder traditional ML approaches. Key challenges include the complexity of domain adaptation, the lack of standardized datasets, and the need for robust validation methods. Despite these barriers, the potential for TL to improve predictive accuracy, efficiency, and cross-project learning makes it a transformative tool. Finally, future research directions are proposed to optimize TL techniques for real-time, intelligent construction risk management systems.

***Keywords*:** artificial intelligence (AI), risk management, transfer learning (TL), intelligent construction, literature review

1. Introduction

In construction projects' complex and hazardous environments, effective risk management is critical to safeguarding workers, minimizing financial losses, and ensuring projects are completed on time [1]. Traditional construction risk management methods have evolved significantly with the advent of artificial intelligence (AI) technologies, particularly machine learning (ML), providing advanced capabilities for identifying, assessing, and mitigating risks [2]. However, one of the main limitations of traditional ML models is their reliance on large datasets specific to their application domain [3]. In the construction industry, collecting enough data to train robust models can be challenging due to the fragmented nature of the industry, the variability of projects, and the unique risk factors that can arise at different sites [4]. As a result, machine learning models often encounter problems such as overfitting, poor cross-project generalization, and long training times [5]. In response to these limitations, transfer learning (TL) has emerged as a powerful tool to improve the performance of machine learning models in construction risk management by transferring knowledge gained from one domain to another [6]. As shown in Figure 1, it is a subfield of machine learning that focuses on exploiting pre-trained models from one task or domain and applying them to related tasks,

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usually with less training data. The main advantage of TL is that it reduces the need for large domain-specific datasets, which are often difficult to obtain in the construction field. By leveraging relevant domain knowledge, TL can speed up the development of predictive models while improving their accuracy and robustness across different projects [7]. Applying knowledge already available in related domains (e.g., civil engineering, safety engineering, or even industrial processes in general) is significant in construction risk management [8]. Construction projects are highly variable, with different risks associated with location, project type, and level of stakeholder involvement [9]. Traditional ML models often require significant retraining or customization to accommodate these differences, leading to inefficiency and reduced applicability [10].

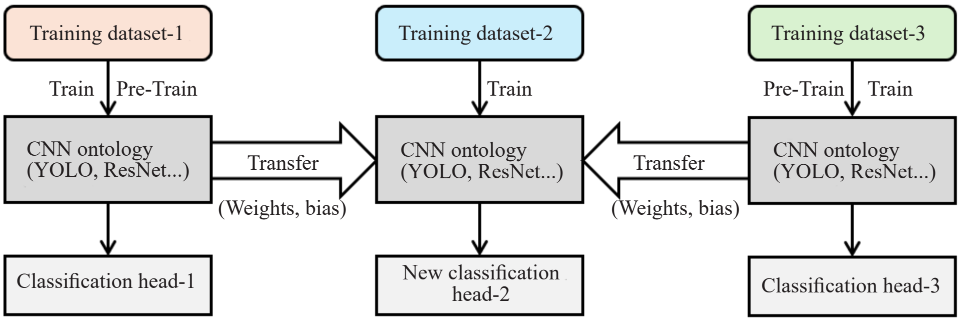

Figure 1. The principle of transfer learning

Increasing attention has been paid to TL's ability to utilize knowledge already available in related fields. For example, Choi et al. [11] used a migration learning-based object detection model, where the model's performance was improved by data augmentation and migration learning despite the limited training data available. Zhao et al. [12] trained a special dataset by labelling helmets and colored vests to detect these two features among construction workers. Specifically, Kalman filtering and Hungarian matching algorithms track pedestrian trajectories. The test experiments were run on an NVIDIA GeForce GTX 1080Ti with a detection rate of 18 frames/second. When the parallel set intersection is set to 0.5, an average accuracy of 0.89 can be achieved. However, it has not been fully explored for specific applications in the construction industry. Therefore, we provide a systematic review of the application of TL in construction risk management, identifying the trends, challenges, and future potential of this emerging approach. Previous reviews of AI and machine learning integration in the construction industry have focused on broader applications such as automation, process optimization, and general safety enhancements [13]. While these studies have provided valuable insights into the potential of AI technologies in the construction industry, they have typically viewed risk management as one component among many [14]. In addition, most reviews center on traditional ML techniques, where each model is trained from scratch using project-specific data [15, 16]. While effective in controlled environments, this approach does not fully address the unique challenges of the construction industry, where data availability, inter-project variability, and the need for real-time risk assessment pose significant barriers. This review differs in focusing specifically on transfer learning and its potential to address these challenges in construction risk management. The paper synthesizes the latest research on TL in construction risk management, provides a more focused discussion of the strengths and limitations of transfer learning, and offers practical insights on how to implement it effectively. In addition, this review critically analyzed the most prominent challenges faced in applying TL in the construction domain, such as the need for domain adaptation, the lack of standardized datasets, and the complexity of validating migration models. This depth and specificity are lacking in previous AI-based reviews, making this paper a new contribution to the field.

The remaining sections of this study are as follows: Section 2 describes the research framework and methodology, Section 3 describes the results, Section 4 discusses future directions for improvement, and Section 5 concludes the research and points out the study's limitations.

2. Method

This systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to ensure a transparent and comprehensive approach [17]. Adherence to the PRISMA protocol ensures a transparent and reproducible systematic review process, making research results more reliable and scientific. It helps standardize the process of screening, evaluating, and reporting literature, reducing bias and improving the quality of research [18]. The review begins with a structured literature search across multiple academic databases, including Web of Science, Scopus, and IEEE Xplore, to identify relevant studies published between 2015 and 2024. Search keywords "Transfer Learning" and "Construction Risk" were used to retrieve pertinent studies.

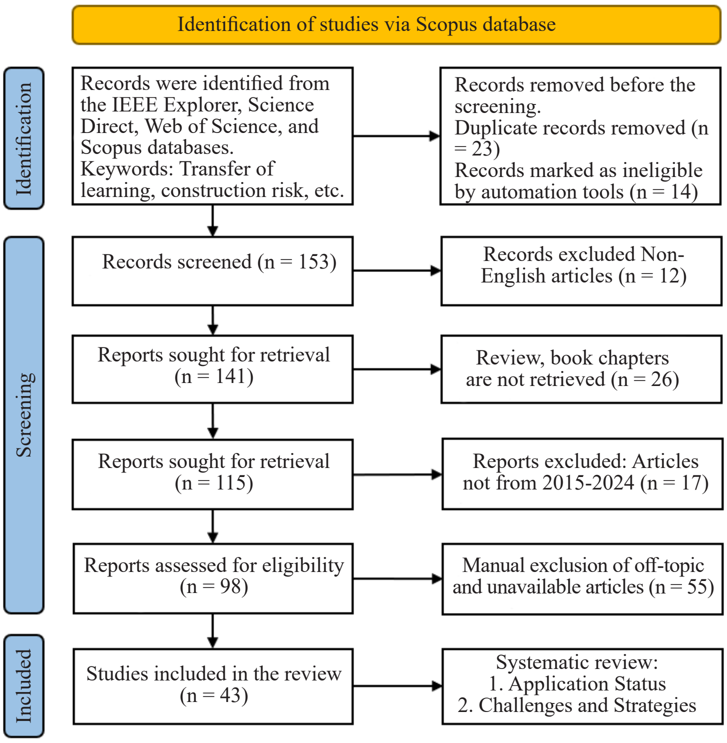

Figure 2. Research flowchart

In line with the PRISMA framework, the search process was documented and visualized in a flow diagram (Figure 2), highlighting the identification, screening, eligibility, and inclusion stages. After removing duplicates, articles were screened based on title and abstract and assessed in full-text form against predefined inclusion criteria. These criteria included relevance to the construction risk domain, the use of transfer learning methodologies, and empirical evidence of practical applications. Studies that lacked sufficient methodological detail or focused solely on theoretical aspects without application were excluded. A final pool of papers (n = 43) was selected for systematic review and qualitative analysis.

3. Results

3.1 *Overview of transfer learning*

The techniques used in transfer learning can be categorized into the following four classes: instance-based transfer learning, mapping-based transfer learning, network-based transfer learning, and adversarial-based transfer learning. Table 1 summarizes the main methods of deep transfer learning in terms of instances, mapping, network structure, and adversarial learning according to the different transfer learning techniques. Each type of method has a different focus and is suitable for various application scenarios.

Table 1. Classification of transfer learning

Types	Description.	Technical methods	Application scenarios
Example-based transfer learning	Adjusting the weights or selective use of source domain samples to fit the target domain by weighing or selecting source domain instances and using them directly for target domain learning.	Sample reweighting, important sampling, and other methods.	Applicable to cases where the data distribution of the source and target domains are different, but the tasks are similar, such as text categorization, image recognition, and so on [19].
Mapping-based transfer learning	Mapping data from source and target domains to a shared feature space reduces their distributional differences and facilitates knowledge migration.	Adversarial feature learning, maximum mean difference (MMD) optimization, principal component analysis (PCA), etc.	Applicable to cases where the feature spaces of the source and target domains are different, but a common feature space can be found, such as image classification, sentiment analysis, etc [20].
Network-based transfer learning	Applying pre-trained neural network models (e.g., conv olutional neural networks) to the target task and migrating some or all network parameters to accelerate target task learning.	Fine-tuning (Fine-tuning), freezing layer weights, cross-layer weight sharing, etc.	Applicable to scenarios where the source and target domain tasks are similar, but the data are different, such as image recognition, natural language processing, and other tasks [21].
Adversarial-based transfer learning	Introduce an adversarial loss function to enhance the model's generalization ability. This will enable the model to learn the target task while counteracting the difference in data distribution between the source and target domains.	Adversarial Generative Networks (GAN), Domain Adversarial Neural Networks (DANN), Adversarial Loss Optimization, etc.	Applicable to scenarios where the source and target domains have significant distributional differences but want to maintain high robustness and generalization ability, such as cross-domain image recognition and style migration [22].

3.1.1 *Example-based transfer learning*

Example-based transfer learning refers to selecting some instances from the source domain by using a specific weight-tuning strategy and assigning appropriate weight values as a complement to the training set of the target domain [23]. The method assumes that "although there are differences between the two domains, some of the instances in the source domain can be utilized by the target domain using appropriate weights." A schematic of example-based transfer learning is shown in Figure 3.

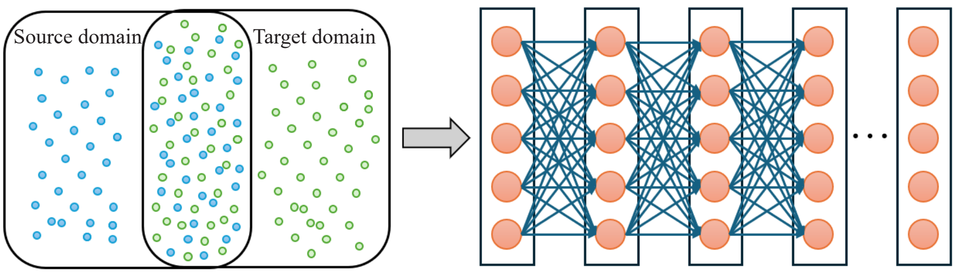

Figure 3. Schematic of example-based transfer learning

Instances with light blue meanings in the source domain that differ from the target domain are excluded from the training dataset; instances with dark blue colors in the source domain that have similar meanings to the target domain are included in the training dataset with appropriate weights. It migrates instances from the source domain directly to the target domain for training, usually requiring rebellion or filtering techniques to select cases like the target domain [24]. This type of transfer learning is one of the most intuitive and widely used methods. Instance, selection transfer learning, selects instances like the target domain for migration by selecting cases from the source domain to avoid migrating unwanted instances. This approach reduces data overfitting and increases the model's generalization ability. Adaptive transfer learning selects the most appropriate migration instances by adaptively selecting source and target domain data to improve migration effectiveness [25]. This approach is typically used with other migration learning methods, such as feature extraction or mapping construction.

3.1.2 *Mapping-based transfer learning*

Mapping-based transfer learning refers to mapping instances in the source and target domains into a new data space [26]. In this latest data space, instances from both domains are similar and fit into a joint neural network. The underlying assumption is that "although there are differences between the original two domains, they can be more similar in a well-designed new data space". A schematic of mapping-based transfer learning is shown in Figure 4.

Concurrently, the mapping of instances from the source and target domains to the new data space exhibits a greater degree of similarity. The most recent data space is employed as the training set for the neural network, comprising all instances within that space. Migration learning establishes a mapping between the source and target domains by reconstructing the source and target domains' feature representations, thereby facilitating the training of the target domain's model [27]. The mapping thus enables a more nuanced comprehension of the similarities and differences between the source and target domains by the target domain model. Maximum Likelihood Estimation-based Mapping Migration Learning employs a maximum likelihood estimation method to estimate the mapping between the distributions of the source and target domains, thereby assisting the training of a target domain model [28]. This approach is predicated on assuming that the data distributions between the source and target domains exhibit some similar or probabilistic relationship. Adaptive Mapping Migration Learning is a method that establishes the most appropriate mapping by adaptively selecting the data in the source and target domains to improve migration. This approach is typically employed with other migration learning methods, such as neural networks or adversarial generative networks.

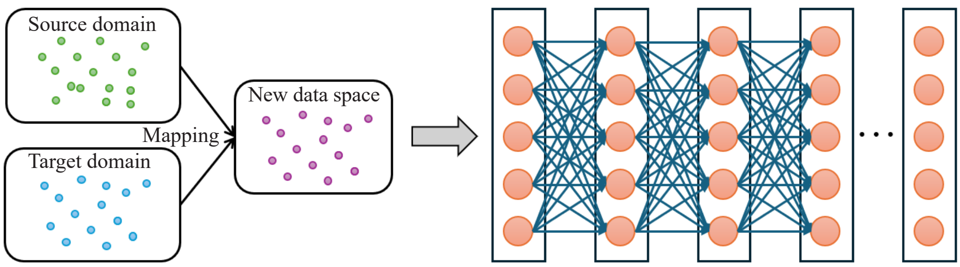

Figure 4. Schematic of mapping-based transfer learning

3.1.3 *Network-based transfer learning*

Network-based transfer learning refers to reusing part of a network that has been pre-trained in the source domain, including its network structure and connection parameters, and migrating it as part of a deep neural network used in the target domain [29]. It assumes that "neural networks are like the processing mechanism of the human brain, which is an iterative and continuous abstraction process. The network's front layer can be considered a feature extractor, and the extracted features are generalizable". A schematic of network-based transfer learning can be seen in Figure 5.

A comprehensive training data set initially facilitates the network's development within the source domain. Secondly, a proportion of the network pre-trained for the source domain is transferred to a proportion of a new network designed for the target domain. Subsequently, the transferred sub-networks may be updated by implementing a fine-tuning strategy. Neural network-based mapping and migration learning: the utilization of neural networks enables the creation of a mapping between the source and target domains, thereby facilitating the training of a model for the target domain [30]. This approach typically employs a pre-trained neural network as a feature extractor or encoder to map data from the source domain to the data space of the target domain. Feature extraction-based mapping migration learning establishes a mapping between the source and target domains by using a neural network to extract feature representations of the source and target domains, thereby aiding the training of models in the target domain [31]. This approach typically employs a pre-trained neural network as a feature extractor, whereby high-level feature representations are extracted from instances of the source domain and subsequently applied to model training in the target domain. Adaptive Neural Network Migration Learning is a method that builds the most appropriate neural network by adaptively selecting source and target domain data to improve the migration effect. This approach is frequently employed with other migration learning techniques, such as Adversarial Generative Networks or Minimizing Reconstruction Error.

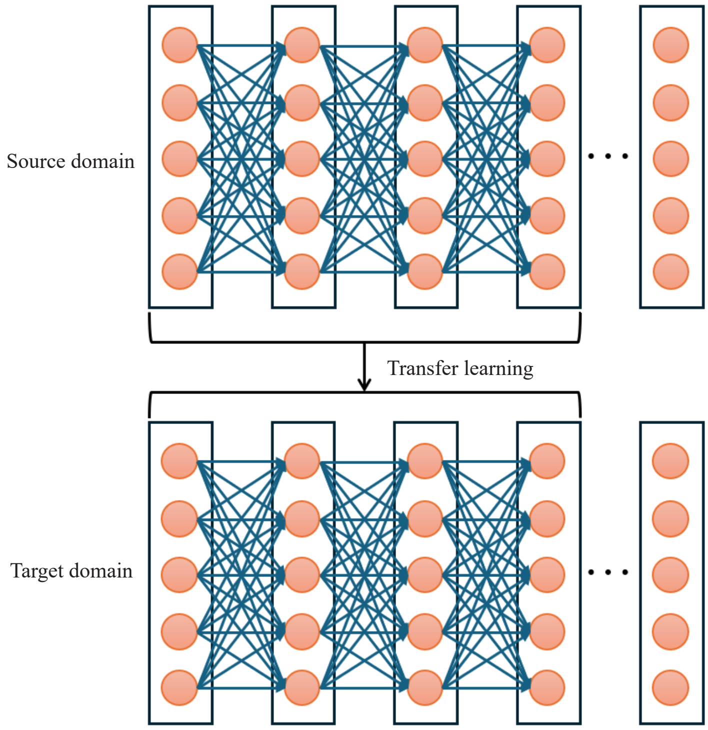

Figure 5. Schematic diagram of web-based transfer learning

3.1.4 *Adversarial-based transfer learning*

Adversarial-based transfer learning refers to the introduction of Generative Adversarial Network (GAN)-inspired adversarial techniques to find transferable representations that apply to both the source and target domains [32]. This assumes that "for effective transfer, a good representation should be discriminative for the main learning task and not differentiated between the source and target domains". A schematic of adversarial-based transfer learning is shown in Figure 6.

In the context of training large-scale datasets in the source domain, the initial layers of the network are employed as feature extractors to extract features from both domains and subsequently feed them into the adversarial layer [33]. The adversarial layer is tasked with distinguishing between the sources of the features. A decline in the performance of the adversarial network indicates a reduction in the distinction between the two types of features, which suggests enhanced migration potential [34]. Conversely, improving the adversarial network's performance implies a more significant divergence between the feature types, thereby indicating superior migration ability. Subsequently, the adversarial layer's performance will be considered to prompt the migration network to identify more generic migratory features.

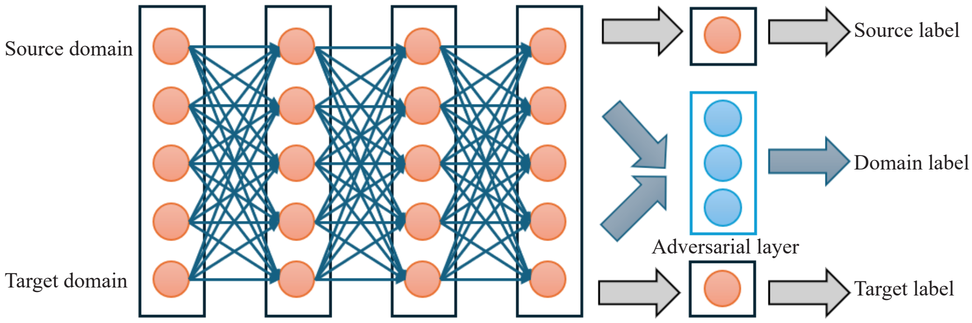

Figure 6. Schematic diagram of adversarial-based transfer learning

3.2 *Application of transfer learning*

Transfer learning in construction risk management covers various areas, including computer vision, natural language processing, speech recognition, recommender systems, and drone/robot navigation [35]. By migrating knowledge from historical projects, these techniques can improve the efficiency of construction risk identification and management, helping engineering teams better cope with risks such as safety hazards, quality issues, cost overruns, etc., and providing vital support for successful project implementation [36]. Table 2 summarizes 12 studies typical of the last five years.

Table 2. Status of the application of transfer learning in intelligent construction risk

Ref.	Type	Model	Contribution	Limitation
[6]	Mapping-based transfer learning	Hybrid deep neural networks (MTCNN, MobileNet, LSTM)	Save personal image information of construction workers.	1. Failure to integrate positional data, biosignals, and motion data. 2. Insufficient data set size.
[37]	Example-based transfer learning	Convolutional neural network (CNN)	Safety guardrail detection in 2D images.	1. Unresolved masking issue, assuming that the guardrail is always visible.
[38]	Example-based transfer learning	CNN	Inspection of construction equipment.	1. The baseline data set only includes dump trucks, excavators, loaders, concrete mixers, and road rollers.
[39]	Adversarial-based transfer learning	Generative adversarial network	Identification of unsafe lifting behavior of tower crane.	1. Inability to recognize different tower crane postures, including, for example, flathead tower cranes, jib slewing tower cranes, and attached tower cranes.
[40]	Network-based transfer learning	Apriori algorithm	Safety risk transfer in metro shield construction.	1. The results of the study are only applicable to subway construction.
[41]	Example-based transfer learning	Regionally Fully Convolutional Networks (R-FCN)	Automatic construction helmet detection.	1. Limitations in the structure of the algorithm. 2. Insufficient quality and quantity of learning data.
[42]	Adversarial-based transfer learning	Mask R-CNN	Modular integrated structure module inspection.	1. Focus only on detecting modules from images or videos. 2. Communication strategies between camera networks are not investigated.
[43]	Mapping-based transfer learning	K-BERT	Generate risk response measures for metro construction.	1. The construction of the semantic knowledge base in the field of metro construction is in manual form. 2. Only the extraction of countermeasures in the paragraphs of standard specifications for subway construction was realized.
[44]	Mapping-based transfer learning	CNN	Identifying the process of installing modules in high-rise modular buildings.	1. The module installation process is simply categorized into hooking, lifting, and positioning.
[45]	Network-based transfer learning (LinkNet)	CNN	Pixel-level identification and quantification of underwater cracks in dams.	1. Other types of structural damage such as spalling, exposed aggregate, and holes were not considered. 2. Temporal information between different frames was ignored.
[46]	Network-based transfer learning (DenseNet)	CNN	Detection of helmet wearing on construction sites.	1. The types of helmets considered were limited.
[47]	Example-based transfer learning	FCN	Detecting semantic regions in construction site images.	1. Insufficient accuracy.

3.2.1 *Computer vision*

Computer vision is used in construction site risk management to monitor, detect, and recognize potential hazards. Transfer learning helps to apply pre-trained vision models to construction projects and improve the accuracy of visual recognition by migrating knowledge even if the amount of data in a new project is small. First, the pre-trained behavioral recognition model applies to monitor workers' unsafe behaviors at construction sites, such as failure to wear protective equipment and violating safety norms. For example, Zdenek et al. [37] used migration learning to construct a neural network for essential feature extraction using a 16-layer Visual Geometric Group Architecture (VGG-16) model, obtaining a high accuracy of 96.5%. Second, Transfer learning can be applied to image recognition tasks to learn from equipment failure data from other projects and identify potentially problematic equipment, tools, or structural issues in new construction projects. For example, Hongjo et al. [38] created a benchmark dataset of five categories, dump trucks, excavators, loaders, concrete mixers, and rollers, by migrating knowledge from models trained in other domains with large amounts of training data. This benchmark dataset included a variety of shapes and poses for each category with an average accuracy of 96.33%. Finally, with camera surveillance, Transfer learning can help learn common safety hazard patterns, such as pit collapse and improper material stacking, from other projects and migrate them to real-time monitoring of the current construction site. For example, Weiguang et al. [39] proposed a transfer learning-based recognition framework to identify unsafe lifting behaviors of tower cranes, precisely tilting lifting, sudden braking, and sudden unloading. The model architecture was developed through deep adversarial domain adaptation and achieved an accuracy of 76.74%.

3.2.2 *Natural language processing*

Natural language processing (NLP) techniques are widely used in construction risk management tasks such as document processing, report analysis, and information extraction. Migration learning can be learned from many historical projects and applied to risk identification and assessment of new projects. First, transfer learning can extract key risk factors from annotated construction incident reports and migrate this knowledge to new projects, helping to automatically analyze and generate construction risk reports and identify potential high-risk areas. For example, Transfer learning can analyze complex construction contracts and bidding documents to extract potential project risks and critical conditions, avoiding risks buried in the contract. For example, Wu et al. [40] combined text mining, association rules, and complex networks to investigate underground construction safety incident reports and explore the risk transfer process. Jin et al. [48] designed a new engineering project similarity metric algorithm (PBG-MMD) to guide the selection of knowledge transfer source domains by combining engineering data distance distribution and engineering project knowledge context. Second, learning from construction regulations and safety standards in different countries or regions through migration learning models automatically adapts to new regulatory environments, helping to identify construction practices or potential violations that do not meet local standards. Wang et al. [49] addressed the problem of automatically constructing a knowledge graph (KG) from unstructured documents with the help of transfer learning. Finally, Transfer learning can analyze complex construction contracts and bidding documents to extract potential project risks and critical conditions, avoiding risks buried in the contract.

3.2.3 *Speech recognition*

Speech recognition technology can be used to parse and communicate real-time voice commands at construction sites through migration learning to improve construction efficiency and safety. It is especially suitable for speech recognition tasks in noisy environments. First, workers usually need to communicate commands by voice at construction sites. Through migration learning, pre-trained speech recognition models are applied to construction scenarios to ensure that commands can be accurately recognized and executed under complex environmental noise, thus reducing construction risks caused by communication errors. For example, the model proposed by Xiong et al. [50] combines a convolutional neural network (CNN) to extract features and a recurrent neural network (RNN) to utilize contextual information to deal with construction environments with polyphony and noise. Second, transfer learning can be used to learn emergency response speech patterns in different scenarios from historical projects, helping to quickly recognize speech alarms (e.g., fire, gas leakage, etc.) on the construction site and automatically send out warning signals or activate the emergency response plan. For example, Shin et al. [51] pre-trained with natural images (ImageNet) via self-supervised learning; subsequently, fine-tuning was performed on target audio samples. Pre-training using the self-supervised learning scheme significantly improved sound classification performance after validation on the following benchmarks: ESC-50, UrbanSound8k, and GTZAN.

3.2.4 *Expert system*

Transfer learning helps expert systems learn the best practices from historical projects to provide project managers with decision support and risk alerts. First, based on the risk control measures implemented in historical projects, the transfer learning recommender system can recommend suitable safety management measures or risk prevention and control strategies for current projects. For example, Peng et al. [52] proposed a multi-source transfer learning guided integrated LSTM method (MTE-LSTM) for building multi-load prediction, obtaining highly accurate load prediction results. Secondly, migration learning can analyze the use of equipment and processes in different projects to recommend the most suitable equipment, materials, and construction processes for the current project, optimizing construction efficiency and reducing risks. For example, Anam et al. [53] used transfer learning to learn mappings from atypical to typical texture scales, and the gap between the transfer and pure learning approaches narrowed as the size of the training increased. Finally, based on project types and historical accident data, the recommendation system of migration learning can recommend personalized safety training content for different workers, ensuring that all personnel know about risk prevention and control related to their positions. For example, Sousa et al. [54] proposed a transfer learning approach incorporating data augmentation techniques tested under a tenfold cross-validation scheme. The proposed framework can utilize images from more than 35 actual fire events, providing higher variability and allowing the method to be evaluated in many real scenarios.

3.2.5 *Other areas*

In addition to the mainstream techniques described above, transfer learning is used in many other regions to support construction risk management. Firstly, transfer learning can be used for autonomous navigation and environment awareness for drones and robots, helping them to identify obstacles, risky areas, etc., in construction sites to ensure efficient and safe site inspections and monitoring. Yuvaraj et al. [55] used EfficientNet (TL-EN) architecture with transfer learning support to develop an effective crack classification model. A vision-enabled Unmanned Aerial Vehicle (UAV) was used to study the surface of a high-rise building, and 99% accuracy was obtained. Second, transfer learning allows migrating weather or geologic hazard prediction models from other regions to new projects for real-time risk warnings. For example, Cai et al. [56] proposed a migration learning-based early warning method for wind farm loss rate prediction. The neighboring wind farms are migrated to the target wind farm as the source domain to compensate for the lack of sample size due to extreme weather. The theoretical value calculation model and the actual value prediction model of wind power are given, respectively, to calculate the loss rate of wind farms under extreme weather. Finally, migration learning can extract valuable design and construction information from historical project BIM data and apply it to the current project to optimize the BIM model and help identify design flaws, construction conflicts, and possible risk points. For example, Wang et al. [57] applied artificial neural networks and transfer learning techniques to accelerate the dataset creation process and automate procedures for energy analysis in a BIM environment.

4. Discussion

4.1 *The challenges of transfer learning*

As indicated in Table 3, the application of transfer learning in the construction risk domain faces challenges such as differences in data distribution, task inconsistency, scarcity of labels, and environment complexity, which leads to insufficient generalization of the model to new projects. In addition, real-time requirements, data privacy and security issues, lack of model interpretability, and excessive consumption of computational resources limit its wide application. Difficulties in cross-domain knowledge transfer and insufficient data on target projects exacerbate these issues, making it difficult to fully utilize the effectiveness of transfer learning in construction risk management.

Table 3. The challenges of transfer learning

ID	Challenges	Description	Ref.
1	Label scarcity	Data in the construction risk domain usually lacks precise labeling, especially in new projects, and it is difficult to obtain enough labeled data for migration learning.	[58]
2	Task inconsistency	Tasks vary significantly from one construction project to another, e.g., materials, equipment, and processes differ, resulting in migration learning that does not apply to new tasks.	[59]
3	High real-time requirements	Real-time detection and feedback are required in construction risk management, and updating and adjusting the migration learning model may not meet the real-time requirements.	[60]
4	Environmental complexity	Factors in the construction environment, such as weather, geology, equipment, etc., are complex and changing, and these dynamic changes can affect the migration learning model's generalization ability.	[61]
5	Data privacy and security	Construction project data (e.g., personnel and equipment information) involves privacy and security issues, which may limit cross-project data sharing and affect the migration effectiveness of the model.	[62]
6	Insufficient model interpretability	The "black box" problem of migration learning models is serious, especially in construction risk management. It is difficult to explain the decision basis of the model, which affects the trust level.	[63]
7	Insufficient data volume	When the amount of data from the target project is insufficient, the migration learning model may rely too much on the source project data, resulting in overfitting or poor model performance.	[64]
8	High consumption of computing resources	Migration learning requires a lot of computational resources and time, especially during the training and fine-tuning of deep learning models, and may not be suitable for real-time applications.	[65]
9	Difficulty in cross-domain knowledge migration	Knowledge migration between different types of construction projects (e.g., homes, bridges, tunnels, etc.) may be ineffective and lead to model failure due to domain differences.	[66]

4.2 *Strategies to address the challenges*

(1) Hybrid modeling strategy

Combine traditional domain knowledge-driven and migration learning-based intelligent models to create a hybrid model system. Risk analysis models based on engineering practices tend to have good interpretability in construction risk management, while migration learning models can handle large amounts of complex data. Combining the two can make up for the shortcomings of migration learning in terms of interpretability and generalizability while enhancing the predictive accuracy of the models. For example, the study by Abdolmajid et al. [67] introduces a data-driven risk identification framework that uses historical data and artificial intelligence techniques, precisely word embedding models. The model matches various risky items from past projects by considering the semantics of words, with an input dataset drawn from the risk registers of more than 70 major US transport projects. The model has been tested and has a recall rate of over 66% for risk detection on new projects, with an F1 score of 0.59. Xu et al. [68] fused concept drift algorithms and constructed knowledge source discrimination rules to automate knowledge source selection and schedule updating for dynamic knowledge transfer in construction projects. It is important to try the integration and comparison of different models with TL. A study [69] used 12 deep learning models trained on 192 crack images and found that the EfficientNetB0 model outperformed other models in classifying cracked surface bricks and normal (undamaged) surface bricks of drilled concrete with an accuracy of 91%.

(2) Domain adaptive mechanism

Adopt more advanced domain adaptive algorithms so that the model can be adjusted according to the differences in data distribution in different construction projects. As depicted in Figure 7, facade spraying robots need to work in a variety of construction environments, such as complex exterior surfaces, different weather conditions, material properties, and different building structure types. The model can automatically detect the differences between the source and target projects through adaptive technology and learn the features with the most migration value. For example, Lu et al. [70] proposed a novel multi-source migratory learning energy prediction model based on Long Short-Term Memory (LSTM) and Multi-Kernel Maximum Mean Difference (MK-MMD) domain adaptation using Dynamic Temporal Warping (DTW) to select the source domain. Guo et al. [71] proposed a reconstruction domain adaptation transfer network (RDATN) in the industrial application of mechanical fault diagnosis. RDATN mainly consists of health condition identification and domain adaptation. The former is used for health condition identification, while the other is used to extract domain invariant features.

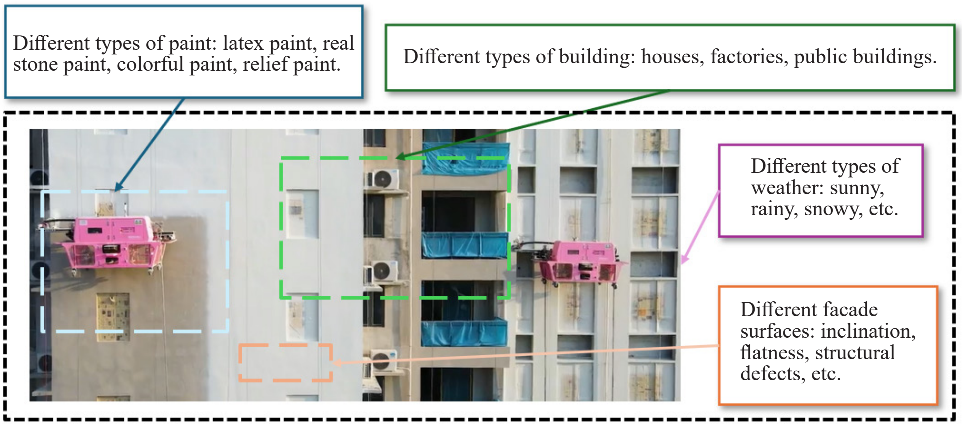

Figure 7. Adaptive mechanism for façade robot construction scenarios

(3) Less sample learning and meta-learning

Introduce less-sample learning and meta-learning techniques to improve the learning ability of models in data-poor situations. These methods allow models to quickly adapt to new environments and make accurate risk predictions using only a tiny amount of new project data. For example, in construction risk management, applying a few-sample learning to a target project migrates limited high-quality data by pre-training the model, allowing the model to quickly adapt to the unique characteristics of the new project through meta-learning. Xu et al. [72] built an external few-sample meta-learning module based on different classification tasks (called meta-batches) to produce robust classifiers for new damage types, in which a subset of supports and queries, including some of the damage types and a small number of samples were randomly drawn from the original image dataset. Tamascelli et al. [73] trained classification algorithms on an extensive, generalized accident database to learn the relationship between accident characteristics and the severity of consequences from various examples. Subsequently, the knowledge gained is transferred to another domain to predict the number of fatalities and injuries in new accidents.

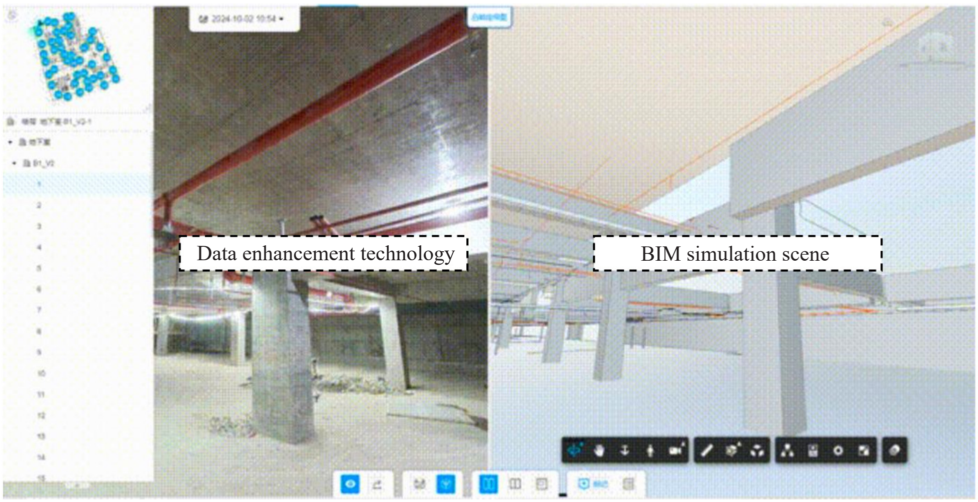

Figure 8. BIM simulation platform based on data enhancement technology

(4) Data enhancement and simulation

More high-quality data are generated through data enhancement and simulation techniques to address the problem of scarce labels and insufficient data in the construction domain. For example, Matrone et al. [74] used the increasing availability of three-dimensional (3D) data such as Light Detection and Ranging (LiDAR), Mobile Mapping Systems (MMS), or point clouds from Unmanned Aerial Vehicles (UAVs), which provide an opportunity for the rapid generation of 3D models to support cultural heritage (CH) restoration, preservation and maintenance activities. As indicated in Figure 8, using data enhancement techniques (e.g., image flipping, rotating, cropping, etc.) to extend the training data of the visual detection model or generating virtual data of environments and risk scenarios based on simulation platforms (e.g., BIM simulation) to supplement the insufficient data of the actual project. Gugssa et al. [75] performed PPE glove detection based on transfer learning to improve construction safety.

(5) Multi-task migratory learning

Multi-task migration learning is used in the construction risk domain to allow the model to learn multiple related construction tasks (e.g., quality control, schedule management, and safety monitoring) at the same time. By sharing knowledge between different tasks, the model can utilize the information in the source project more effectively and improve the migration effect. For example, a joint learning framework is designed to combine other tasks closely related to construction risk (e.g., schedule delay prediction, equipment failure detection, etc.) with the risk prediction task, and the multi-task learning model is utilized to enhance the accuracy of risk assessment [76]. An online learning strategy allows the model to update itself in a real-time data stream during construction by continuously learning from new data. The model can quickly adapt to dynamic changes on the construction site and improve its ability to cope with real-time risks. For example, in a construction risk monitoring system, an online learning module is deployed to collect data from sensors, monitoring equipment, etc., in real time and dynamically update the risk model to cope with real-time environmental changes (e.g., weather, equipment status, personnel behavior, etc.) [77].

(6) Model explanatory enhancement

Enhance the explanatory nature of the transfer learning model so that its prediction results can accurately identify risks and provide reasonable explanations that are easy for construction managers to understand and apply. By integrating explanatory models such as Local Interpretable Model-agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP), the transfer learning model can output explainable risk factors in decision-making, helping managers understand potential risk sources [78]. For example, by incorporating explainable AI (XAI) technology, an explanatory module can be added to the output of a construction risk transfer learning model to explicitly show the features and data on which the model is based, helping the construction team understand the basis of the model's predictions. Build a secure data-sharing mechanism to promote data interoperability between different construction projects, and at the same time, introduce technologies such as federated learning to ensure data privacy and security [79]. In construction, data between different projects often cannot be shared openly [80]. Federated Learning enables models to share knowledge across projects without directly exchanging data. For example, introducing a federated learning framework allows construction companies to share knowledge of risk management models without exchanging sensitive data, improving the performance of models on different projects while protecting data privacy [81, 82]. In addition, visualization techniques and knowledge-driven methods can be combined. On the one hand, techniques such as heat map and feature importance analysis are used to visualize the input feature regions that the model focuses on; on the other hand, domain knowledge is incorporated to combine the model outputs with the actual logics and rules in the construction project to ensure that the model's inference process is in line with the engineering practice. In addition, the attention mechanism or generative adversarial network is introduced to further reveal the key features and potential causal relationships behind the model decisions.

5. Conclusion

Applying transfer learning in construction risk has significant potential to effectively utilize data and knowledge from historical projects to support risk assessment and management of new projects. Through migration learning, models can learn key features from source projects and quickly adapt to new environments, improving the efficiency and accuracy of risk identification during construction. However, due to the complexity, variability, and data scarcity of construction projects, migration learning faces challenges such as difficulties in transferring cross-domain knowledge, insufficient labeling, and differences in data distribution. To better apply migration learning, techniques such as domain adaptation, multi-task learning, and online learning need to be adopted, combined with explanatory models and privacy protection mechanisms, to improve the generalization ability, real-time performance, and reliability of the models.

This study combines the actual needs of the construction field and the technological advantages of transfer learning to promote the development of construction intelligence and data-driven management. It suggests that future research can focus on the following five directions:

(1) Construction safety prediction and management: To improve safety management on construction sites, reduce accident rates, and achieve real-time monitoring and decision support through cross-project safety risk prediction and less sample learning.

(2) Construction quality monitoring and assessment: Applying transfer learning for heterogeneous data fusion and cross-domain defect detection to help improve the accuracy and efficiency of quality monitoring in different projects and reduce project training costs.

(3) Intelligent construction equipment optimization: Using transfer learning to optimize equipment scheduling and fault prediction, transferring the experience of equipment performance under different working conditions to new projects, improving equipment utilization efficiency, and reducing maintenance costs.

(4) Construction schedule management and forecasting: The multi-project schedule forecasting model and dynamic adjustment mechanism allow for cross-project construction schedule optimization, reducing schedule deviation and improving the project's overall schedule control capability.

(5) Construction cost control and optimization: Migrate cost forecasting experience from previous projects to new projects, especially in data-poor environments, to improve cost control accuracy and optimize construction companies' cost management.

It is worth noting that the effect of transfer learning is affected by various factors. To improve the effectiveness of transfer learning, it is necessary to consider these factors comprehensively and make appropriate adjustments and optimizations. For example, the effect of transfer learning can be improved by using public and industry features for finer differentiation, adopting complex feature engineering techniques, optimizing the neural network architecture and training hyperparameters to improve the generalization ability of the model, performing unsupervised and semi-supervised training, and choosing appropriate loss functions and metrics to optimize the model and tuning.

Conflict of interest

The authors declare that they have no conflict of interest.

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