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Style Name [ABC2- Office use only, Aptos, 7, Italics]

Review Article

Harnessing Artificial and Digital Twins in Building Information Modelling for Wildfire-Resilient WUI Communities: A Systematic Review

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Abstract

Communities within the wildland–urban interface (WUI) are increasingly exposed to severe and frequent wildfire threats driven by climate change, land-use change, and expanding urban development. Traditional fire management approaches have proven inadequate to address the complex interactions of fire behavior, human exposure, and infrastructure vulnerability. Emerging digital technologies, particularly Building Information Modeling (BIM) and digital twins, offer opportunities to enhance WUI resilience by enabling data-rich, predictive, and adaptive strategies for preparedness and response. This review synthesizes research on integrating BIM, digital twins, and artificial intelligence (AI) to support wildfire modeling, risk assessment, situational awareness, and recovery. A systematic review of 71 peer-reviewed studies revealed a geographically diverse but uneven landscape, concentrated in North America. Most studies addressed mitigation, with limited attention to evacuation/response or recovery. Four thematic applications emerged: predictive wildfire modelling, sensor-based environmental monitoring, structural vulnerability assessment, and evacuation planning. Predictive modelling dominated, while BIM and digital twin applications remained sparse and poorly integrated. Key enablers included advances in AI/ML algorithms, cloud/edge computing, and visualization platforms. Persistent barriers involved interoperability gaps, computational demands, dependence on historical datasets, and limited attention to governance, equity, and trust. In response, this study proposes a layered conceptual framework positioning BIM as a digital foundation, digital twins as adaptive mirrors, AI/ML as predictive engines, and visualization interfaces as decision-support tools, embedded within interoperability, security, and governance mechanisms. These insights provide pathways for advancing digital transformation to strengthen the safety, adaptability, and sustainability of WUI communities facing escalating wildfire risks.

Keywords: Wildland–Urban Interface; Building Information Modeling; Digital twins; Artificial intelligence; Data-driven risk management.

Highlights

- AI leads wildfire resilience research, but BIM and digital twin integration is limited.
- Most studies focus on prediction, with recovery and adaptation largely overlooked.
- Interoperability and governance are key to effective wildfire digital twin systems in WUI.

1 Introduction

Communities located within the wildland–urban interface (WUI) are increasingly exposed to severe and frequent wildfire events, driven by the combined effects of climate change, urban expansion, and land-use transformations (Radeloff et al., 2018). These fire-prone zones, where natural vegetation intermingles with human development, present highly complex fire behavior patterns, putting lives, critical infrastructure, and ecological systems at elevated risk. Traditional approaches to wildfire prevention and response, centered on suppression and hazard mitigation, have proven inadequate in the face of rapidly evolving climate conditions and intensified WUI development pressures (Moritz et al., 2014). As catastrophic fire events in California, Australia, and southern Europe demonstrate, the limitations of conventional strategies demand new, adaptive approaches.

Advances in digital technologies offer a potential paradigm shift for addressing wildfire threats in WUI communities. Building Information Modeling (BIM), originally developed to improve collaboration and information flow across the design and construction lifecycle, provides rich digital representations of the built environment that can be extended for resilience applications (Succar & Kassem, 2015). Digital twins expand upon BIM by dynamically connecting these models to real-time data streams from sensors, IoT devices, and remote sensing platforms, thereby enabling continuous monitoring, prediction, and adaptive management of both individual structures and community systems (Fuller, Fan, Day, & Barlow, 2020). Artificial intelligence (AI) techniques, including machine learning, computer vision, and natural language processing, further enhance this potential by delivering predictive analytics, pattern recognition, and scenario-based reasoning to support timely and effective wildfire risk decision-making (Reichstein et al., 2019).

Despite these opportunities, the integration of AI, BIM, and digital twins for wildfire resilience in WUI communities remains fragmented and underdeveloped. Current research is dispersed across domains such as forestry, civil engineering, and computer science, with limited synthesis of their combined potential, current progress, and implementation challenges. There is a pressing need to examine how these technologies can converge to improve wildfire preparedness, emergency response, and post-event recovery within vulnerable WUI communities. To address this gap, this paper is guided by three research questions:

- RQ1: How have BIM, digital twins, and AI been applied individually or in combination to support wildfire resilience in WUI contexts?
- RQ2: What barriers and enablers affect the integration of BIM, digital twins, and AI into wildfire preparedness, response, and recovery?
- RQ3: What conceptual framework or pathway can advance the deployment of AI-enabled digital twins in BIM for proactive, adaptive WUI fire management?

The contributions of this review are threefold. First, it synthesizes the fragmented body of knowledge on BIM, digital twins, and AI applications for wildfire resilience, bridging insights across disciplines. Second, it identifies key technical enablers and barriers, including interoperability challenges, real-time integration constraints, and the lack of standardized protocols for linking AI models with BIM-based systems. Third, it develops a conceptual framework to guide future research and practice, offering directions for how these technologies can transform WUI communities into data-driven, adaptive, and fire-resilient systems.

2 Methodology

This study employed a systematic literature review to investigate the intersection of AI, BIM, and digital twin technologies in the context of wildfire resilience, particularly within WUI communities. The review design was explicitly structured to address the research questions introduced in Section 1.

2.1 Review Protocol

The review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009). A PRISMA flow diagram was constructed to ensure transparency in documenting the identification, screening, eligibility, and inclusion stages of the review process (Figure 1). The review was structured around five distinct phases of fire management: prevention, mitigation, preparedness, response (suppression), and recovery (learning and adaptation). This phase-based framework, informed by Arango, Nogal, Sousa, Matos, and Stewart (2024), was used solely for categorization during analysis. The protocol also emphasized interdisciplinary coverage by including studies from fire science, civil engineering, computer science,

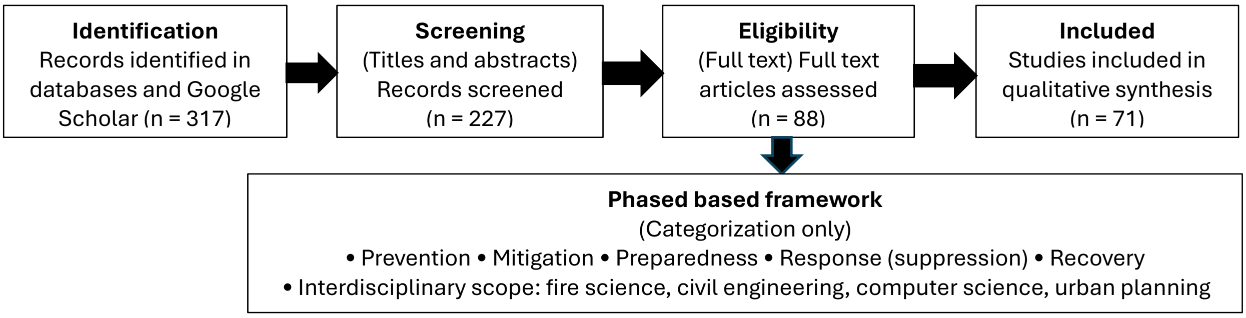

Figure 1. PRISMA Flow Diagram — Systematic review of AI, BIM, and Digital Twin for Wildfire/WUI Resilience.

and urban planning.

2.2 Data Sources and Search Strategy

The literature search was conducted across multiple academic databases, including Scopus, Web of Science and IEEE Xplore, supplemented by Google Scholar for cross-validation of gray and emerging literature. The search terms were carefully constructed to reflect the intersection of wildfire resilience and emerging technologies. Boolean operators and wildcard variations were used to expand coverage. The search string was: ("wildfire" OR "wildland–urban interface" OR "WUI") AND ("resilien" OR "fire management") AND ("building information modeling" OR "BIM") AND ("digital twin*" OR "virtual model*") AND ("artificial intelligence" OR "machine learning" OR "deep learning"). The scope of the search spanned from 2010 to 2024, a period marked by the rapid evolution of digital twin technologies and the widespread adoption of AI in environmental modeling. Only peer-reviewed journal articles, conference proceedings, and high-quality technical reports published in English were retained to ensure the rigor and comparability of evidence.

2.3 Inclusion and Exclusion Criteria

Studies were included if they addressed: (a) the use of BIM or digital twins for wildfire or WUI resilience; (b) applications of AI to wildfire risk management; (c) integration of infrastructure modeling with fire behavior prediction; or (d) frameworks or prototypes relevant to proactive wildfire management. Unlike many prior reviews that focused exclusively on fire ecology or computational fire science, this review required explicit attention to the built environment and the socio-technical dimensions of fire resilience.

Studies were excluded if they considered wildfire ecology in isolation, presented AI algorithms without hazard application, or examined BIM solely in non-risk management contexts.

2.4 Screening and Selection

The initial search yielded 315 publications. After removing duplicates and conducting a screening of titles and abstracts, 88 articles were selected for full-text review. Of these, 71 were retained for analysis after meeting all inclusion criteria. Each article was coded for bibliographic details, research objectives, methods, technologies used, level of integration, resilience phase addressed, data types used, and study limitations.

2.5 Data Analysis and Synthesis

The selected studies were analyzed using thematic analysis (Braun & Clarke, 2006). Coding employed a combined inductive–deductive approach: deductive codes were derived from the research questions and the phase-based framework to ensure alignment with the study aims, while inductive coding allowed themes to emerge organically from the data. Codes were grouped into higher-order categories aligned with the research questions mentioned in Section 1.

3 Results

The systematic review identified 71 peer-reviewed studies that met the inclusion criteria. These studies collectively span multiple countries, with the majority concentrated in North America, followed by Australia, Canada, Spain, Chile, and parts of Asia. They represent a diverse range of technological applications, geographical contexts, and resilience phases, offering a rich but uneven landscape of innovation at the intersection of AI, BIM, and digital twin technologies for wildfire resilience in WUI communities. The phase distribution was highly skewed: 60 studies (≈85%) addressed mitigation, six focused on reactiveness (evacuation and response), and only five targeted recovery (post-fire assessment and adaptation). In line with the research questions in Section 1, the results are organized into the following sections.

3.1 Applications of AI, BIM, and Digital Twins for Wildfire Resilience

To address RQ 1, the review examined current applications across resilience phases. Four thematic areas emerged: predictive wildfire modelling (prevention/mitigation), sensor-based environmental monitoring (detection), structural vulnerability assessment (preparedness), and evacuation planning (response).

3.1.1 Predictive Wildfire Modelling

Predictive modelling was the dominant theme, with 51 studies (≈72%) focused on fire spreading and its impact on built environments. These studies employed a variety of AI enablers, such as convolutional neural networks (CNNs), ensemble learning, and graph neural networks (GNNs), to forecast wildfire spread, ignition probability, and severity. Machine learning (ML) was the most prevalent technology category (33 ML-only studies), followed by ML+GIS integrations (22 studies), while only a handful incorporated digital twins (5) or BIM (2). For instance, Shahriar, Choi, and Islam (2025) developed a hybrid GNN-LSTM framework to forecast the Fire Weather Index across CONUS, achieving high spatial accuracy but at significant computational cost. Similarly, Gu, Csiszar, Tsidulko, and Guo (2025) used satellite data and machine learning to estimate fire radiative power, enhancing understanding of fire intensity. Other notable approaches include ensemble-based ignition prediction (Tong & Gernay, 2023), hybrid ML for large-fire projection (Li et al., 2024), and deep learning for ember hotspot prediction on gable roofs (Al-Bashiti, Nguyen, Naser, & Kaye, 2024). However, most models relied heavily on historical data, which introduces limitations when fire behavior shifts due to climate change or land-use alterations. Integration with BIM was minimal. Only two studies (Sun & Turkan, 2020; F. Wang, Xu, Chen, Nzige, & Chong, 2021) explored BIM for fire safety or evacuation modelling, and none linked regional hazard forecasts to building-level digital twins. This disconnect highlights a missed opportunity to translate regional fire dynamics into structure-level risk intelligence.

3.1.2 Sensor-Based Environmental Monitoring

Approximately six studies (≈9% of the corpus) explored the use of sensor networks, including Unmanned Aerial Vehicles (UAVs), Internet of Things (IoT) devices, and satellite platforms, for real-time environmental data collection. For example, Fu, Hu, Sutrave, Beerel, and Raghavan (2024) developed FireLoc, a crowdsensing system that combines ground cameras and landscape data to geolocate wildfires with low latency. Similarly, Govil, Welch, Ball, and Pennypacker (2020) demonstrated a deep learning-based smoke detection system using remote camera images, capable of identifying fires within 15 minutes of ignition. UAV-integrated AI systems for firefighter action recognition (H. Wang et al., 2025) and multi-UAV coverage optimization (Diaz-Vilor, Lozano, & Jafarkhani, 2025) illustrate operational monitoring advances. Some studies proposed digital twin frameworks that could ingest these sensor data streams to simulate fire behavior dynamically. Lewis et al. (2024) developed a Fire and Smoke Digital Twin, integrating air quality, weather, and infrastructure data, while NA, Rajasekar, and Sarvehswaran (2025) combined IoT sensors with a deep CNN in a real-time twin-enabled risk classification system. Despite these advances, most implementations remained at the conceptual or pilot scale, falling short of operational maturity.

3.1.3 Structural Vulnerability Assessment

BIM-cantered studies primarily focused on simulating material performance and structural detailing under fire exposure. Sun and Turkan (2020) developed a BIM-based simulation framework to assess evacuation safety in buildings, while Al-Bashiti et al. (2024) used deep learning to identify ember hotspots on rooftops. Despite BIM's potential for detailed representation, no study demonstrated dynamic feedback loops between fire progression and structural response within a digital twin environment. This reveals a critical integration gap: while BIM offers detailed representations of the built environment, its potential for adaptive risk modelling remains largely untapped.

3.1.4 Evacuation Planning

Evacuation modelling was addressed in eight studies (11% of the corpus), using agent-based simulations, reinforcement learning, and predictive analytics. Ma and Lee (2024) developed machine learning models to predict evacuee behavior based on survey data, while Sharma, Andersen, Granmo, and Goodwin (2020) applied Deep Q-Learning to optimize evacuation strategies in simulated environments. BIM-enhanced evacuation simulations were explored by F. Wang et al. (2021), who modelled stair and elevator strategies in a college canteen, and Sun and Turkan (2020), who validated a BIM-based evacuation framework using the Station nightclub fire case. However, real-time digital twin applications for evacuation remain absent. Most models were static or scenario-based, lacking adaptability to evolving fire conditions or incoming sensor data.

3.2 Enablers and Barriers in AI–BIM–Digital Twin Integration

To address RQ2, the review identified both enabling technologies that support integration and barriers that constrain their effective deployment. Several enabling technologies emerged across the literature. These include cloud and edge computing for data processing, algorithms (e.g., GNN-LSTM, ULSTM, and hybrid deep learning), and visualization platforms for geospatial overlays and interactive decision support. For instance, C. Zhang, Cheng, Kasoar, and Arcucci (2022) combined reduced-order modelling with LSTM and data assimilation to improve real-time wildfire forecasting. Augmented reality was explored for UAV-based fire prevention (Costa et al., 2025), while YOLO-DeepSORT frameworks were integrated into digital twins for real-time occupant tracking (Ding, Zhang, & Huang, 2023). Despite promising developments, recurring challenges were evident. Foremost was the lack of standardized interoperability protocols, which constrained meaningful integration of BIM and real-time sensor data into cohesive digital twin environments. Technical bottlenecks included (i) computational intensity of high-resolution ML and digital twin models, (ii) dependence on historical datasets that may not reflect future fire dynamics, and (iii) cybersecurity vulnerabilities in digital twin deployments (Lewis et al., 2024; NA et al., 2025). Social and institutional dimensions were also underexplored. Only a handful of studies acknowledged governance, equity, or community trust issues, despite their critical role in WUI resilience.

3.3 Conceptual Framework

Building upon the thematic synthesis of the literature and in response to RQ3, this study advances a conceptual framework (Figure 2) to guide the integration of AI, BIM, and digital twins in enhancing wildfire resilience within WUI communities. The framework envisions a layered and interoperable system that continuously monitors, predicts, and responds to wildfire hazards while simultaneously supporting long-term community adaptation. The framework is motivated by evidence that most existing work concentrates on hazard modelling at regional scales, with limited coupling of BIM and digital twins, highlighting the need for end-to-end integration across phases, scales, and decision contexts (Sun & Turkan, 2020).

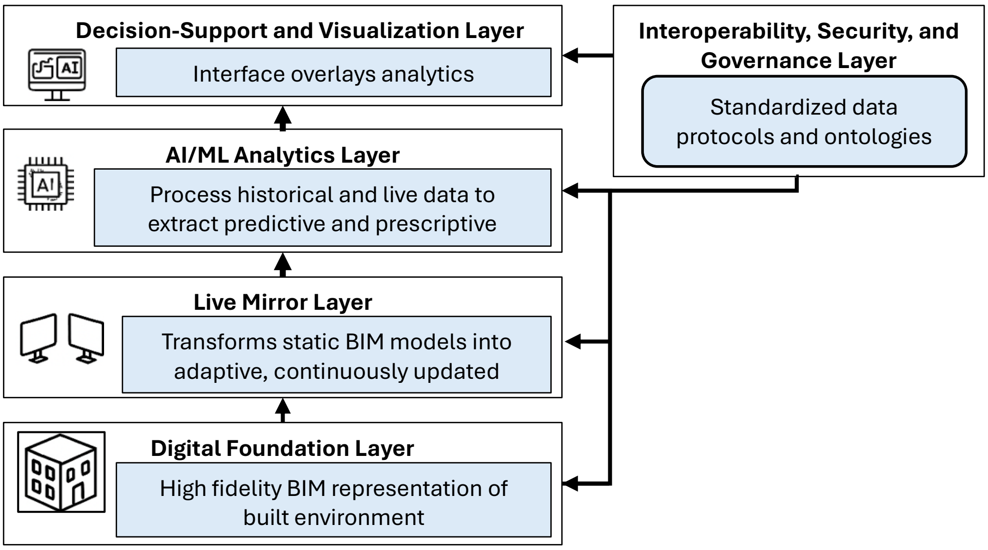

Figure 2. Conceptual Framework: AI–BIM–Digital Twins for WUI Wildfire Resilience.

Digital Foundation Layer: At its foundation, the framework is anchored in a high-fidelity BIM representation of the built environment, capturing spatial layout, structural details, material properties, defensible space configurations, and patterns of occupancy across WUI communities. This foundation provides a means of cataloguing vulnerabilities, thereby serving as a reference point for integrating dynamic data streams. BIM objects should be encoded using open schemas and enriched with fire-relevant attributes such as material fire ratings and defensible space buffers to enable downstream AI and digital-twin services (Al-Bashiti et al., 2024; Sun & Turkan, 2020). While BIM has demonstrated value for evacuation and safety analysis at the building scale, its application to community-scale WUI risk remains limited unless paired with geospatial layers (Heeren, Dennison, Campbell, & Thompson, 2023; J. Wang, Wei, & Dong, 2021).

Live Mirror Layer: Extending from this foundation, the digital twin environment transforms static BIM models into adaptive, continuously updated systems. By ingesting real-time data from weather stations, remote sensing platforms, sensor networks, and IoT devices, the digital twin functions as a dynamic mirror of evolving wildfire conditions. Emerging municipal-scale twins demonstrate integration of smoke dispersion physics with city geometries and live data streams, but also highlight cybersecurity concerns that must be engineered from the outset (Lewis et al., 2024). IoT-integrated twins can operate as real-time risk classifiers, routing sensor events such as heat, smoke, and wind conditions to predictive services for rapid warnings (NA et al., 2025). For pre-deployment testing and firefighter training, Augmented reality /Virtual reality-enabled twin sandboxes incorporating mixed reality UAVs offer safe rehearsal of procedures without field exposure (Costa et al., 2025).

AI/ML Analytics Layer: AI serves as the analytical engine of the framework, processing both historical and live data to generate predictive and prescriptive insights. Machine-learning models estimate ignition probabilities, forecast fire propagation trajectories, and assess ember transport risks, while reinforcement learning techniques support dynamic evacuation planning. Examples include GNN-LSTM forecasts of Fire Weather Index (Shahriar et al., 2025), CNN-based spread models (Jiang et al., 2023), interpretable hybrid predictors for large fires (Li et al., 2024), ensemble ignition mapping (Tong & Gernay, 2023), and ember hotspot detection for roof geometries (Al-Bashiti et al., 2024). A "sense–predict–decide–act" loop connects crowd-sensed geolocation systems with digital-twin resident forecasts and evacuation routing agents, enabling time-aware course-of-action recommendations (Fu et al., 2024; Sharma et al., 2020). Uncertainty quantification and explainability techniques should be embedded to support stakeholder trust and calibration (Qiu, Chen, Fan, Sun, & Zheng, 2022).

Decision-Support and Visualization Layer: A visualization and decision-support interface overlays the analytics, transforming multi-source data into actionable knowledge. Interactive dashboards, immersive 3D visualizations, and geospatial risk maps make the system accessible to emergency managers, urban planners, and community residents alike, ensuring translation of technical outputs into practical decision-making. Field-validated tools in use include crowd-sensed wildfire geolocation, UAV-assisted firefighter activity recognition, and post-event damage classifiers that can feed directly into digital twins for surge assessments (Fu et al., 2024; J. Wang et al., 2021). Augmented reality-integrated interfaces can overlay sensor feeds and tactical overlays for UAV-based prevention and patrol operations (Costa et al., 2025).

Interoperability, Security, and Governance Layer: The outermost layer emphasizes interoperability and governance. Standardized data protocols and ontologies are essential to connect BIM, GIS, sensor networks, and AI models into a unified architecture. Operational studies highlight cyber-risks in 3D twins and connectivity constraints in crowdsensing systems, making security-by-design and offline-first fallbacks essential (Fu et al., 2024; Lewis et al., 2024). Continuous learning pipelines should be embedded, linking model retraining and MLOps workflows to post-event assessments (e.g., UAV-satellite burn-severity mapping and infrastructure recovery trajectories), ensuring that the twin evolves over time (Schmidt, Ellsworth, Tilt, Thiel, & Hiner, 2025). Governance mechanisms must institutionalize human factors, including community needs and vulnerabilities, evacuation behavior, warning response, and shelter utilization, to reduce gaps between modelled scenarios and real-world WUI response (Ma & Lee, 2024; X. Zhang, Zhao, Xu, Nilsson, & Lovreglio, 2024).

4 Discussion

This review demonstrates that the integration of AI, BIM, and digital twins for wildfire resilience in WUI communities remains highly fragmented, with a strong skew toward hazard modelling and a relative neglect of evacuation and recovery phases. This imbalance mirrors trends in the broader wildfire science literature, which historically emphasized fire behavior prediction and suppression effectiveness, often at the expense of long-term adaptation and post-disaster recovery (Moritz et al., 2014; Syphard et al., 2007). While predictive models, particularly machine-learning approaches, have delivered important advances in wildfire forecasting (Reichstein et al., 2019), their reliance on historical datasets presents a significant limitation. As climate change reshapes ignition patterns, fuel structures, and fire regimes, models that cannot accommodate non-stationarity risk and emerging trends becoming increasingly unreliable (Abatzoglou et al., 2021).

The relative absence of BIM and digital twins in the reviewed studies is striking. BIM has been widely adopted in construction and facility management for safety and hazard assessment (Succar & Kassem, 2015), yet its application to wildfire resilience remains nascent. Only a few studies applied BIM for evacuation modelling or structural performance assessment (Sun & Turkan, 2020; F. Wang et al., 2021). Even fewer extended these models into dynamic digital twin environments, despite growing evidence that real-time, data-driven twins can significantly enhance disaster preparedness and situational awareness (Fuller et al., 2020). The lack of coupling between regional fire dynamics and building-level intelligence reflects a missed opportunity for multi-scale risk management, where hazard forecasts could directly inform structural adaptations and occupant decision-making. Sensor-based monitoring studies, using UAVs, IoT devices, and satellite platforms, represent another promising but underdeveloped pathway. Work such as FireLoc (Fu et al., 2024) and smoke-detection systems (Govil et al., 2020) illustrate the feasibility of near-real-time detection, but most implementations remain pilots or conceptual frameworks. Operational maturity is hindered by computational costs, data heterogeneity, and lack of interoperability standards, challenges that align with broader critiques in the smart city and digital twin literature (Kitchin, Young, & Dawkins, 2021). Without standardized ontologies and integration protocols, BIM, GIS, AI, and IoT remain siloed systems, undermining the vision of an interoperable resilience infrastructure. Social and institutional considerations were markedly underrepresented across the reviewed literature. Very few studies explicitly addressed governance, community trust, or equity dimensions, despite evidence that social vulnerability is a critical determinant of wildfire risk in WUI communities (Radeloff et al., 2018). The reliance on technical solutions without embedding them in socio-technical systems risks producing innovations that fail to translate into meaningful, actionable, and sustained resilience outcomes. Prior disaster informatics research underscores that decision-support systems must align with user needs, organizational capacity, and governance frameworks to achieve adoption (Comes, Mayag, & Negre, 2014).

These findings indicate that while technical progress is being made in wildfire prediction, monitoring, and evacuation simulation, integration across scales, phases, and socio-technical domains remains the central challenge. The conceptual framework directly responds to this gap by outlining a layered, interoperable architecture that bridges BIM-based structural representations with live data streams and AI-driven analytics. The proposed "sense–predict–decide–act" loop aligns with calls for adaptive, data-driven resilience strategies that extend beyond suppression to encompass preparedness, evacuation, and recovery (Tierney, 2020).

5 Conclusions

This systematic review reveals an uneven landscape of innovation in applying AI, BIM, and digital twins to wildfire resilience in WUI communities. The overwhelming focus on predictive hazard modelling reflects the field's historical roots but leaves major gaps in evacuation, recovery, and structural vulnerability assessment. While promising advances in machine learning, UAV-enabled sensing, and BIM-based evacuation modelling exist, their integration into dynamic, interoperable digital twin systems remains limited. The conceptual framework developed in this paper offers a pathway toward closing these gaps. By layering BIM-based representations, real-time data ingestion, AI analytics, visualization, and governance, the framework envisions an end-to-end system that supports proactive wildfire preparedness, adaptive emergency response, and long-term community resilience. Such integration could transform WUI fire management from reactive suppression to a continuous cycle of sensing, prediction, decision-making, and adaptation.

Nevertheless, several limitations remain. First, the maturity of AI-enabled BIM–digital twin systems is still low, with most studies limited to prototypes or simulations. Second, socio-technical dimensions, such as community trust, institutional capacity, and policy frameworks, are insufficiently addressed. Third, interoperability standards for linking BIM, GIS, IoT, and AI systems are still emerging, constraining scalability. Future research should therefore prioritize three directions: (1) operationalizing integrated AI–BIM–digital twin systems in real-world WUI testbeds, (2) embedding socio-technical perspectives to ensure adoption and equity, and (3) advancing open standards for data interoperability and model governance. By addressing these priorities, researchers and practitioners could accelerate the deployment of intelligent, adaptive digital infrastructures that safeguard vulnerable WUI communities from escalating wildfire risks.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

References

AAbatzoglou, J. T., Battisti, D. S., Williams, A. P., Hansen, W. D., Harvey, B. J., & Kolden, C. A. (2021). Projected increases in western US forest fire despite growing fuel constraints. *Communications Earth & Environment, 2*(1), 227. https://doi.org/10.1038/s43247-021-00299-0

Al-Bashiti, M. K., Nguyen, D., Naser, M., & Kaye, N. B. (2024). Predicting Wildfire Ember Hot-Spots on Gable Roofs via Deep Learning. *Fire, 7*(5), 153. https://doi.org/10.3390/fire7050153

Arango, E., Nogal, M., Sousa, H. S., Matos, J. C., & Stewart, M. G. (2024). Improving societal resilience through a GIS-based approach to manage road transport networks under wildfire hazards. *Transportation Engineering, 15*, 100219. https://doi.org/10.1016/j.treng.2023.100219

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Comes, T., Mayag, B., & Negre, E. (2014). *Decision support for disaster risk management: Integrating vulnerabilities into early-warning systems.* Paper presented at the International Conference on Information Systems for

Crisis Response and Management in Mediterranean Countries. https://doi.org/10.1007/978-3-319-11818-5_16

Costa, C., Gomes, E., Rodrigues, N., Gonçalves, A., Ribeiro, R., Costa, P., & Pereira, A. (2025). Augmented reality mobile digital twin for unmanned aerial vehicle wildfire prevention. *Virtual Reality, 29*(2), 1-18. https://doi.org/10.1007/s10055-025-01145-w

Diaz-Vilor, C., Lozano, A., & Jafarkhani, H. (2025). A Reinforcement Learning Approach for Wildfire Tracking with UAV Swarms. *IEEE Transactions on Wireless Communications*. https://doi.org/10.1109/TWC.2024.3524324

Ding, Y., Zhang, Y., & Huang, X. (2023). Intelligent emergency digital twin system for monitoring building fire evacuation. *Journal of Building Engineering, 77*, 107416. https://doi.org/10.1016/j.jobe.2023.107416

Fu, X., Hu, Y., Sutrave, P., Beerel, P. A., & Raghavan, B. (2024). *FireLoc: Low-latency Multi-modal Wildfire Geolocation*. Paper presented at the Proceedings of the 22nd ACM Conference on Embedded Networked Sensor Systems. https://doi.org/10.1145/3666025.3699318

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: enabling technologies, challenges and open research. *IEEE access, 8*, 108952-108971. https://doi.org/10.1109/ACCESS.2020.2998358

Govil, K., Welch, M. L., Ball, J. T., & Pennypacker, C. R. (2020). Preliminary results from a wildfire detection system using deep learning on remote camera images. *Remote Sensing, 12*(1), 166. https://doi.org/10.3390/rs12010166

Gu, Y., Csiszar, I., Tsidulko, M., & Guo, W. (2025). Using multispectral information and machine learning to improve daytime fire radiative power estimation from METImage measurements. *Ecological Informatics*, 103358. https://doi.org/10.1016/j.ecoinf.2025.103358

Heeren, A. J., Dennison, P. E., Campbell, M. J., & Thompson, M. P. (2023). Modeling wildland firefighters' assessments of structure defensibility. *Fire, 6*(12), 474. https://doi.org/10.3390/fire6120474

Jiang, W., Qiao, Y., Su, G., Li, X., Meng, Q., Wu, H., . Quan, W., Wang, J. & Wang, F. (2023). WFNet: A hierarchical convolutional neural network for wildfire spread prediction. *Environmental Modelling & Software, 170*, 105841. https://doi.org/10.1016/j.envsoft.2023.105841

Kitchin, R., Young, G. W., & Dawkins, O. (2021). Planning and 3D spatial media: Progress, prospects, and the knowledge and experiences of local government planners in Ireland. *Planning theory & practice, 22*(3), 349-367. https://doi.org/10.1080/14649357.2021.1921832

Lewis, R. H., Jiao, J., Seong, K., Farahi, A., Navratil, P., Casebeer, N., & Niyogi, D. (2024). Fire and smoke digital twin–a computational framework for modeling fire incident outcomes. *Computers, Environment and Urban Systems, 110*, 102093. https://doi.org/10.1016/j.compenvurbsys.2024.102093

Li, F., Zhu, Q., Yuan, K., Ji, F., Paul, A., Lee, P., Radeloff, V.C. & Chen, M. (2024). Projecting large fires in the western US with an interpretable and accurate hybrid machine learning method. *Earth's Future, 12*(10), e2024EF004588. https://doi.org/10.1029/2024EF004588

Ma, F., & Lee, J. Y. (2024). Understanding Evacuation Behavior During Wildfires: Exploring Key Factors Affecting Evacuee Behaviors and Developing Predictive Models for Decision-Making. *Fire Technology*, 1-42. https://doi.org/10.1007/s10694-024-01683-w

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Bmj, 339*. https://doi.org/10.1136/bmj.b2535

Moritz, M. A., Batllori, E., Bradstock, R. A., Gill, A. M., Handmer, J., Hessburg, P. F., Leonard, J., McCaffrey, S., Odion, D.C. & Schoennagel, T. (2014). Learning to coexist with wildfire. *Nature, 515*(7525), 58-66. https://doi.org/10.1038/nature13946

NA, I. S., Rajasekar, V., & Sarvehswaran, V. (2025). Real-time Fire Risk Classification using Sensor Data and Digital Twin-Enabled Deep Learning. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. https://doi.org/10.1109/JSTARS.2025.3593138

Qiu, L., Chen, J., Fan, L., Sun, L., & Zheng, C. (2022). High-resolution mapping of wildfire drivers in California based on machine learning. *Science of The Total Environment, 833*, 155155. https://doi.org/10.1016/j.scitotenv.2022.155155

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., . . . Syphard, A. D. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of sciences, 115*(13), 3314-3319. https://doi.org/10.1073/pnas.1718850115

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature, 566*(7743), 195-204. https://doi.org/10.1038/s41586-019-0912-1

Schmidt, A., Ellsworth, L., Tilt, J., Thiel, A., & Hiner, N. (2025). Long-term tracking of recovery of built infrastructure after wildfires with deep network topologies. *Neural Computing and Applications, 37*(14), 8465-8477. https://doi.org/10.1007/s00521-025-11003-0

Shahriar, S. A., Choi, Y., & Islam, R. (2025). Advanced deep learning approaches for forecasting High-Resolution fire weather index (FWI) over CONUS: integration of GNN-LSTM, GNN-TCNN, and GNN-DeepAR. *Remote Sensing, 17*(3), 515. https://doi.org/10.3390/rs17030515

Sharma, J., Andersen, P.-A., Granmo, O.-C., & Goodwin, M. (2020). Deep Q-learning with Q-matrix transfer learning for novel fire evacuation environment. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 51*(12), 7363-7381. https://doi.org/10.1109/TSMC.2020.2967936

Succar, B., & Kassem, M. (2015). Macro-BIM adoption: Conceptual structures. *Automation in Construction, 57*, 64-79. https://doi.org/10.1016/j.autcon.2015.04.018

Sun, Q., & Turkan, Y. (2020). A BIM-based simulation framework for fire safety management and investigation of the critical factors affecting human evacuation performance. *Advanced engineering informatics, 44*, 101093. https://doi.org/10.1016/j.aei.2020.101093

Syphard, A. D., Radeloff, V. C., Keeley, J. E., Hawbaker, T. J., Clayton, M. K., Stewart, S. I., & Hammer, R. B. (2007). Human influence on California fire regimes. *Ecological applications, 17*(5), 1388-1402. https://doi.org/10.1890/06-1128.1

Tierney, K. (2020). *The social roots of risk: Producing disasters, promoting resilience*: Stanford University Press. https://doi.org/10.1515/9780804791403

Tong, Q., & Gernay, T. (2023). Mapping wildfire ignition probability and predictor sensitivity with ensemble-based machine learning. *Natural Hazards, 119*(3), 1551-1582. https://doi.org/10.1007/s11069-023-06172-x

Volk, R., Stengel, J., & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings—Literature review and future needs. *Automation in Construction, 38*, 109-127. https://doi.org/10.1016/j.autcon.2013.10.023

Wang, F., Xu, X., Chen, M., Nzige, J., & Chong, F. (2021). Simulation research on fire evacuation of large public buildings based on building information modeling. *Complex System Modeling and Simulation, 1*(2), 122-130. https://doi.org/10.23919/CSMS.2021.0012

Wang, H., Zhao, C., Feng, Y., Huang, X., Qu, C., Zhu, Y., . . . Guo, W. (2025). Enhancing firefighter safety and efficiency through UAV-assisted AI-based human motion recognition system. *Expert Systems with Applications, 289*, 128176. https://doi.org/10.1016/j.eswa.2025.128176

Wang, J., Wei, G., & Dong, X. (2021). A dynamic fire escape path planning method with BIM. *Journal of Ambient Intelligence and Humanized Computing, 12*(11), 10253-10265. https://doi.org/10.1007/s12652-020-02794-2

Zhang, C., Cheng, S., Kasoar, M., & Arcucci, R. (2022). Reduced order digital twin and latent data assimilation for global wildfire prediction. *EGUsphere, 2022*, 1-24. https://doi.org/10.5194/egusphere-2022-1167

Zhang, X., Zhao, X., Xu, Y., Nilsson, D., & Lovreglio, R. (2024). Situational-aware multi-graph convolutional recurrent network (SA-MGCRN) for travel demand forecasting during wildfires. *Transportation Research Part A: Policy and Practice, 190*, 104242. https://doi.org/10.1016/j.tra.2024.104242