BIM/GIS-based Graph Framework for Emergency Response: A Case Simulation for Fire Protection

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Keywords: Digital Twin, CityGML, IoT, Graph

Summary: Effective emergency response requires rapid decision-making supported by accurate and comprehensive spatial information. Traditional risk assessment methods associated with emergency response management (ERM) systems often rely on simplified two-dimensional maps, static models, and experience-based decision-making within the urban context, thus limiting their ability to adapt to dynamic conditions. The core challenge in building emergency response lies in leveraging vast amounts of static and dynamic geographic, urban, and building data for rapid, informed decision-making. The synergy of Building Information Modeling (BIM) and Geographic Information Systems (GIS) offers a powerful foundation for enhancing EM. This paper proposes a conceptual framework for a BIM/GIS-based graph model designed to leverage BIM technology within the comprehensive geospatial context of the urban environment. This model can be used for simulations of situations that are difficult or impossible to perform in a real environment. Guided by a bibliometric analysis of the research landscape concerning BIM/GIS integration, specifically focusing on the application of graph models for ERM, this study aims to advance knowledge on information exchange between BIM and GIS for holistic disaster management within the Prevention, Preparedness, Response, and Recovery (PPRR) framework. The analysis will be confined to publications since 2015 relevant to ERM. Results from this study address common data integration and interoperability challenges through a structured data schema, ensuring a unified network representation for both indoor and outdoor emergency navigation. To validate its feasibility, we estimate room-to-room risk levels by simulating the dynamic spread of fire and smoke within a multistory smart building that incorporates BIM attributes, including occupant density. The resulting framework has potential applications for dynamic risk assessment in emergency response related to natural disasters, emergency medicine, safe construction, and fire protection.

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1. INTRODUCTION

A critical mission aspect for emergency response is the ability to navigate seamlessly through indoor and outdoor spaces. Humans spend most (about 86%) of their time indoors - in residences, offices, and factories - than outdoors (Spalt et al., 2015). Modern buildings are increasingly equipped with diverse sensors and smart devices such as surveillance cameras, motion sensors, and WiFi access points. These sensors enable real-time monitoring of the progression of natural disasters (e.g., rising flood water or fire spread), structural integrity, and the real-time location of occupants, pedestrians or commuters. Such monitoring capabilities represent significant advancement in conventional emergency management and passive safety designs. By providing accurate, real-time situational information, these systems allow both civilians and first responders to adapt their evacuation and rescue strategies more effectively, regardless of whether they are indoors or outdoors.

Digital replicas of interior spaces are defined by the Building Information Model (BIM) (Biswas et al., 2024), while Geographic information System (GIS) represents outdoor spaces. Advances in technologies such as remote sensing, radars, satellite imaging, the Internet of Things (IoT), smartphones, and online social media are now integral to modern disaster management (Baraldo & Di Giuseppantonio Di Franco, 2024). Consequently, they can provide data to monitor, predict disasters, and assess damage in the aftermath of catastrophic events (Esposito et al., 2022). While the synergy between BIM and GIS offers a powerful foundation for emergency response management (ERM), these data models were developed before IoT technologies became prominent. Therefore, they may face limitations when incorporating diverse, real-time data for efficient response. This paper seeks to answer the following questions: a) *What are the challenges of BIM-GIS integration,* and b) *What is an alternate data structure for seamless in/outdoor navigation?* Answers to these two questions allow us to identify challenges in BIM-GIS integration exhibited by the existing techniques and new research opportunities.

We perform a bibliometric analysis to assess the current state of BIM-GIS integration for emergency response. Following an evaluation of the identified limitations in current integration methods, we review position papers on the application of the Knowledge Graph (KG) for seamless indoor/outdoor navigation and advanced emergency response. Section two presents the bibliometric analysis of the BIM-GIS integration, identifying both current limitations and potential advancements, specifically highlighting the role of graph networks as a significant research opportunity for ERM. Section three demonstrates why the basic graph-network is a suitable data model for unifying indoor and outdoor environments. Section four presents a generalized framework for graph networks for emergency management, including simulation results for fire protection. Finally, Section five provides a summary and concluding remarks.

2. BIBLIOMETRIC ANALYSIS

This section describes the bibliometric analysis, beginning with a four-stage Systematic Literature Review (SLR) of published journal articles that explore techniques for integrating BIM and GIS data to support efficient emergency management. Stages five through seven involve data assessment, extraction, and analysis to address the research questions. The primary objective is to identify a data structure that enables the integration of BIM, GIS, and IoT technologies.

Figure 1 illustrates our strategy for conducting the bibliometric analysis. We began by constructing search strings for the SLR, which forms the foundation of our study. These strings were developed through an iterative process, combining relevant keywords and phrases associated with the research questions using Boolean operators and parentheses for clustering. The search query **('BIM' OR 'Building Information Model') AND ('GIS' OR 'Geographic Information System') AND ('Integration') AND ('Emergency Response' OR 'Disaster Management' OR 'Evacuation')** was executed across five databases: Crossref, OpenAlex, PubMed, Scopus, and Semantic Scholar.

The initial dataset was cleaned to remove duplicates and irrelevant records, ensuring the accuracy of the selected papers. In Figure 1, the numerical values on the arrows denote the number of search results and retained papers following each phase. To minimize false positives, we restricted the search to article titles, abstracts, and keywords. After merging the findings into a comprehensive spreadsheet and removing duplicates, 904 articles remained for further analysis.

Following the initial retrieval in Stage 1, we applied specific inclusion and exclusion criteria (Stages 2–4). Articles were included based on their procedural approach to BIM-GIS integration, while review articles were eliminated. The primary objective was to identify and categorize studies such as programs, frameworks, and integration processes that specifically applied to seamless navigation, disaster recovery, and published in English between 2015 and 2025.

In Stage 2, papers were screened based on their titles. Stage 3 involved a secondary, more rigorous screening of the remaining 148 papers through a reading of their abstracts. Stage 4 involved a manual review of the reference lists of the selected papers to identify relevant studies that may have been missed during the automated search. Collectively, these four selection stages yielded a total of 67 primary studies.

Stage 5 focused on scrutinizing the robustness of the evidence presented in each article which reduced to 42 studies. Stage 6 centered on aligning the data with the research questions. Finally, Stage 7 involved an analysis for answers to the research questions.

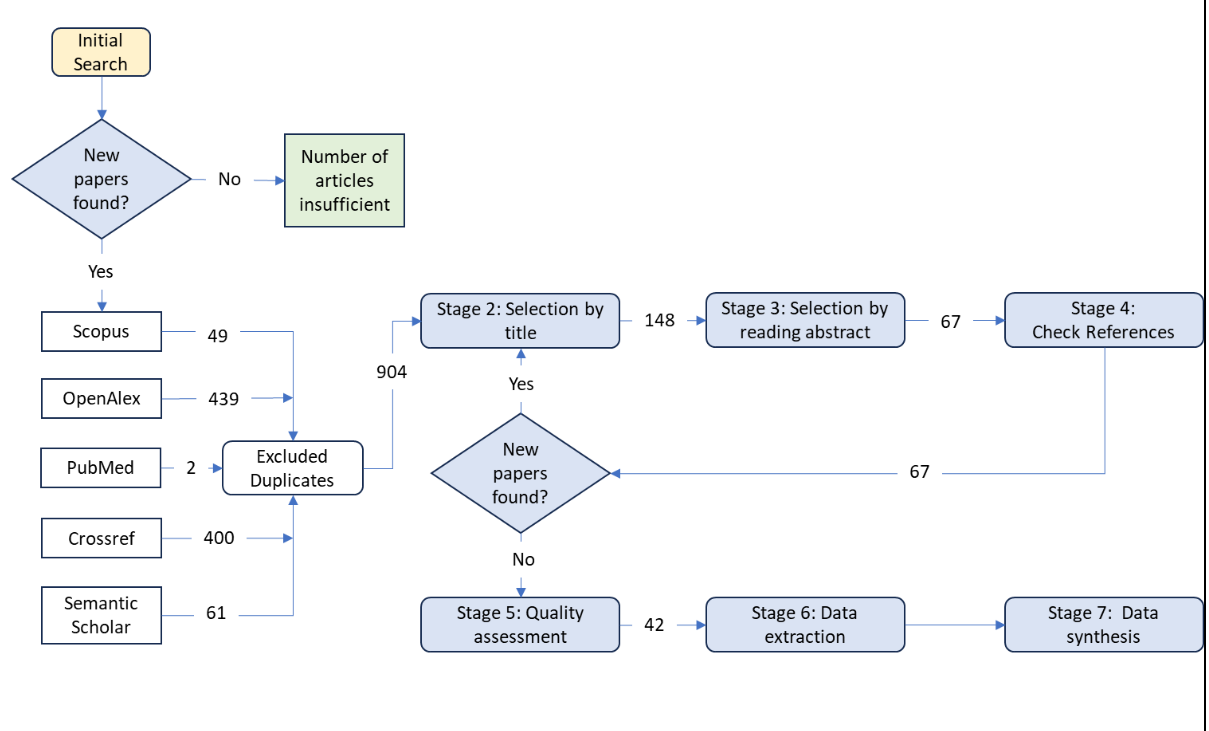

Figure 1: Methodology for paper search and selection

2.1. Findings

2.1.1. <u>Publication Trends and Growth</u>

The analysis confirms a low level of initial research activity before 2015, followed by a sharp increase in the number of publications. This trend signals the maturity of interoperability techniques and the recognition of the technology's application potential. As shown in Figure 2A, there was a peak publication rate in 2020, followed by a gradual decline to an average of approximately 110 publications per year. This decline may suggest that challenges with BIM-GIS integration are increasingly viewed as persistent, potentially necessitating the exploration of alternative data structures.

Figure 2B shows that the top five most cited journals are led by the *Intl. Archives Photo. Remote Sensing & Spatial Info. Sci.*, followed by *ISPRS International Journal of Geo-Information*, *Remote Sensing* , *SPRS Annals of the Photogrammetry*, and *Sustainability*. The most cited article on BIM-GIS integration for natural disaster response is by Amirebrahimi et al. (2016) titled on “A framework for a microscale flood damage assessment and visualization for a building using BIM–GIS integration” published in the *International Journal of Digital Earth*.

2.1.2. Dominant Research Themes

Co-occurrence analysis of keywords identified three main conceptual clusters: integration and interoperability, emergency response application, and inclusion of advanced technologies.

The *Core Integration & Interoperability* cluster focuses on the technical challenges of harmonizing the disparate data structures of BIM and GIS. Conversion of Industry Foundation Classes (IFC) models of BIM into GIS-compatible networks is not a one-to-one mapping. However, the BIM-GIS synergy is increasingly leveraged within the Digital Twin paradigm for simulating post-disaster reconstruction scenarios prior to physical implementation. The upward trajectory of publications on BIM-GIS integration, particularly leading up to 2020, is attributed to the maturation of data exchange standards. Journals such as *Automation in Construction*, *Remote Sensing*, and *Sustainability* have emerged as the primary repositories for this research topic.

The *Emergency Application* cluster highlights the primary practical focus of network models for optimal pathfinding, particularly for building evacuation and first responder access.

The *Advanced Technologies* cluster focusses on the emerging trend of integrating dynamic data (e.g., sensor data on fire, smoke, or occupant movement) into static graph models to enable adaptive, real-time ERM decisions. Recent trends indicate a pivot toward IoT sensors and Artificial Intelligence (AI) with BIM-GIS frameworks. These advancements facilitate the development of dynamic, real-time disaster response systems capable of reacting to evolving environmental conditions.

2.2 Discussion and Research Opportunity

Over the last decade, research has shifted from fundamental data interoperability challenges toward sophisticated applications in disaster resilience, including automated flood damage assessment, seismic vulnerability modeling, and real-time emergency evacuation routing. Key research areas now include data model conversion (e.g., IFC to Graph models), real-time data integration via IoT sensors, and post-disaster damage assessment.

Challenges with BIM-GIS integration persist because information exchange between the two domains remains problematic, particularly regarding data resolution and semantic consistency. BIM comprises micro-level information on design and construction as required by Architecture, Engineering, and Construction (AEC) professionals (Cuellar et al., 2023). Conversely, GIS operates on macro-level geospatially referenced information for outdoor urban objects such as roads, bridges, and tunnels (Kolbe et al., 2021). While integrating BIM and GIS offers a powerful platform to bridge this information gap, unifying these technologies inevitably leads to an exponential growth in project data volume (Xia, 2022).

A significant hurdle is the conceptual mismatch in LoD between BIM and GIS. LoD for BIM denotes data for construction management, whereas LoD for GIS refers to spatial resolution for 3D representation. Mapping these disparate concepts is not a direct one-to-one process. Furthermore, BIM primarily uses solid modeling while GIS relies on surface-based modeling. Converting BIM data to GIS-equivalent CityGML requires decomposing solids into surfaces, a process that often introduces geometric errors or the loss of topological relationships essential for spatial analysis.

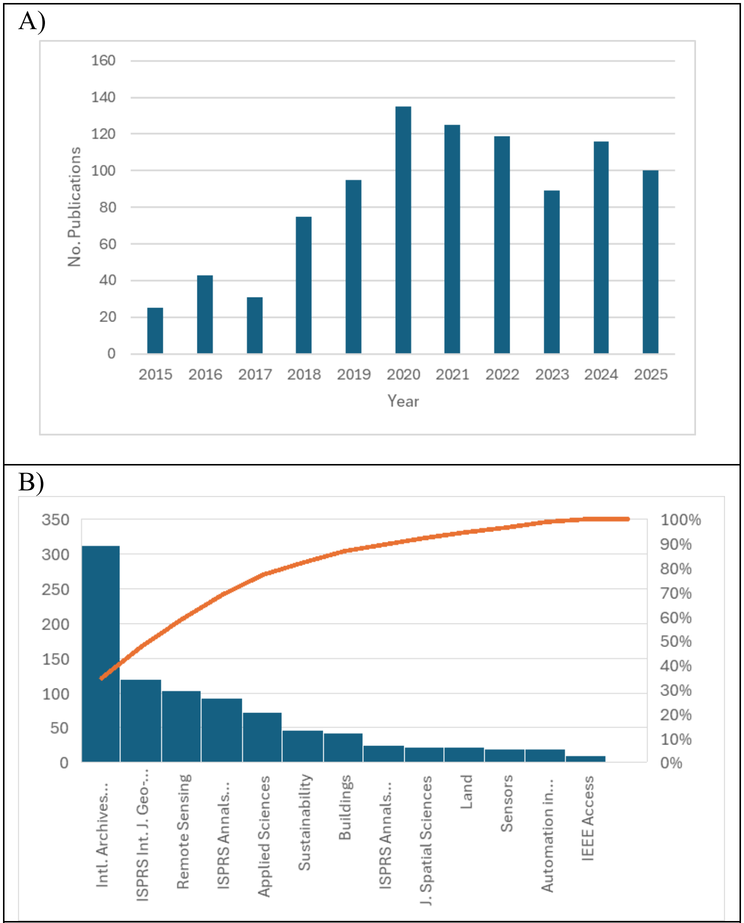

Figure 2. BIM-GIS integration analysis A) Articles published, B) Journals with the highest number of publications on BIM-GIS integration applications.

Additional challenges include establishing automated semantic alignment given that the two models use different ontologies to classify building elements. Furthermore, the local coordinate system of the BIM model must be accurately transformed and georeferenced to align with the global GIS coordinate system to achieve integration (Tan et al., 2023).

Results from the bibliometric analysis indicate that CityGML is primarily designed for 3D urban visualization and thematic modeling. While it handles building exteriors effectively, it often lacks the topological connectivity required to guide a first responder from a street-level coordinate to a specific room within a complex structure. This data incompatibility creates significant barriers to seamless indoor/outdoor navigation, which is crucial for reliable emergency response services.

Furthermore, the analysis identifies that KGs emerge as a compelling alternative modeling method for BIM-GIS integration. In a graph structure, nodes and edges represent objects and their complex relationships (Zhu et al., 2022). KGs preserve multimodal design data including geometry, attributes, and topology within a structure that can be embedded into high-dimensional vectors. This allows learning algorithms to detect statistical patterns and support a wide range of downstream tasks, such as link prediction and graph generation. Ultimately, KGs represent a paradigm shift in navigation, bridging artificial intelligence and IoT technologies to enhance disaster resilience and recovery.

3. KNOWLEDGE GRAPH FOR BIM-GIS INTEGRATION

Contemporary living and work environments of humans are getting increasingly complex, combining structures above and below the ground, indoor and outdoor. Agents (e.g., pedestrians, first responders, etc.) may wish to negotiate a navigation path from one kind of environment to another or through interiors spaces into the outside environment.

Graphs bridge the fundamental gap between the micro-level interior (BIM) and the macro-level exterior (GIS) without the data loss or rigid hierarchies inherent in CityGML. Furthermore, an integrated knowledge graph (Listl et al., 2024) facilitates rapid, multi-scale, and intelligent spatial analysis, which is critical for time-sensitive tasks such as optimal evacuation route calculation, resource allocation, and real-time situational awareness during a crisis. A KG framework addresses common data interoperability challenges through a structured data schema, ensuring a unified network representation for both indoor and outdoor emergency navigation.

3 1 Graph Model Construction

The heart of the issue is the creation of a navigable 3D graph network that links indoor building spaces to the outdoor street network.

Indoor Graph Generation: Rooms and spaces from the BIM model are represented as **nodes**. Connection elements (doors, stairs, elevators) are represented as **edges**. Attributes like traversal time, width, and hazard risk are assigned to the edges.

Outdoor Graph Generation: The GIS Street network (roads, sidewalks) forms the graph for navigation outdoors, with intersections as nodes and street segments as edges, including attributes like traffic capacity and current hazard status.

Inter-Domain Connection (Gateway Edges): Crucially, gateway nodes (building entrances/exits from BIM are linked to the nearest corresponding outdoor street nodes in the GIS graph. These gateway edges allow for continuous pathfinding from any point inside a building to any location in the city. Figure 3 illustrates the concept.

Formally, a graph is defined as $G = (V; E)$, where V is a set of vertices and E consists of edges, each edge being a pair $(v; w)$ where $v; w \in V$. In the context of geospatial analytics, a network-based graph nodes indicate the location and semantic information about the place (such as name, type or decision points) and edges between them represent their spatial relationships (Yan et al., 2021).

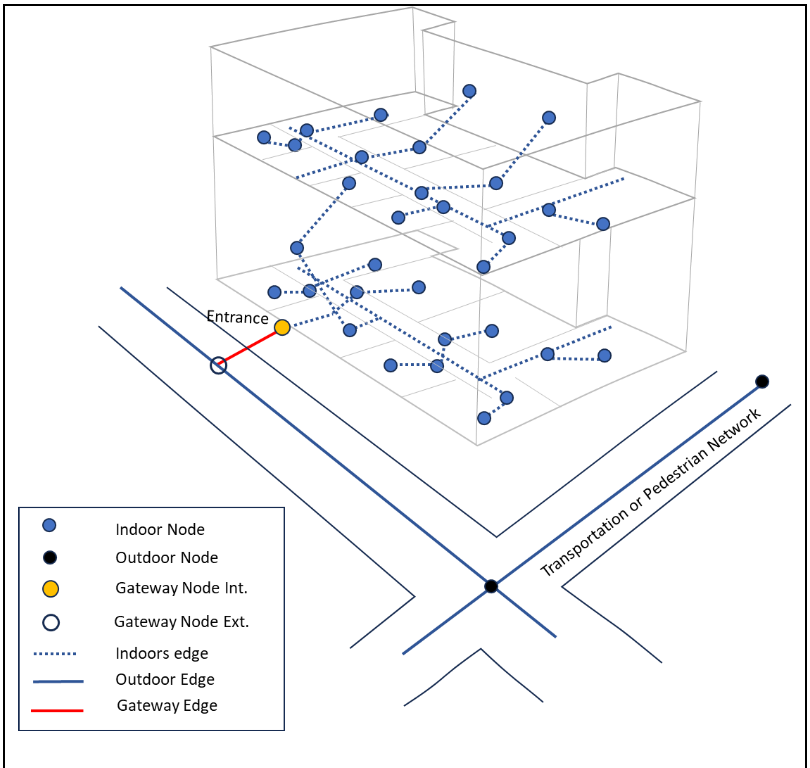

Figure 3. Representing connections between indoor and outdoor spaces. Adapted from (Teo & Cho, 2016)

Applications of graph networks include multi-commodity flow models, emergency logistics etc. A generalized graph combines indoor spaces with outdoor street-based networks through a gateway node at the building entrance and its connection with the street network. An interior gateway node (indoors) can be a room or functional area while an exterior gateway node (outdoors) is related to transportation networks (sidewalk, intersection of a road, etc.).

To perform navigation calculations between indoor and outdoor spaces, the graph must specify a adjacency matrix between an outdoor object and a building or structure

$$A^{(structure)} \in \{0,1\}^{N \times N},$$

where $A^{(structure)} = 1$ if objects i and j share a direct physical connection; otherwise, 0.

Indoor structural adjacency focuses on compartmentalized spaces (rooms connected by doors) while outdoor navigation graphs focus on continuous free space interrupted by obstacles (buildings, water, walls). The two mathematical worlds can be connected via the Graph Union (Claridades & Lee, 2021) expressed as

$$G_{Total} = G_{indoors} \cup G_{outdoors} \cup E_{gateway}$$

where $E_{gateway}$ edge connect the room node in the indoor graph to the specific node (the building entrance) in the outdoor graph. The resulting integrated graph model will be able to facilitate rapid, multi-scale, and intelligent spatial analysis, which is critical for time-sensitive tasks such as optimal emergency response operations during a crisis. This framework has potential applications for dynamic risk assessment and emergency response to natural disasters, and emergency medicine (Li et al., 2025), safe construction (Chen et al., 2025), and fire protection (Pramanik et al., 2025).

4. SIMULATION EXPERIMENT

We simulated fire protection in a multistory smart building that incorporates BIM attributes including occupant density to estimate room-to-room risk levels from dynamic spread of fire and smoke (Pramanik et al., 2025).

Let N be the number of rooms in a building. To capture the main pathways through which fire and smoke propagate, we focus on two dominant types of adjacency information: structural adjacency and airflow adjacency. These are chosen because they represent the primary mechanisms of spread—flames and heat transfer through shared physical boundaries, and smoke or hot gases traveling through ventilation systems. Other possible connections (e.g., plumbing shafts or electrical conduits) are generally less influential and can be subsumed under these two categories described below:

Structure adjacency matrix represents the physical adjacency of rooms, i.e., rooms sharing walls, doors, corridors, or windows.

Airflow adjacency matrix. This matrix captures airflow-based adjacency, i.e., connectivity between rooms through ventilation ducts, HVAC systems, or similar channels

$$A^{(airflow)} \in \{0,1\}^{N\times N},$$

where $A^{(airflow)} = 1$ if rooms *i* and *j* are connected through conduit, ventilation duct or HVAC systems, and 0 otherwise.

To create a single and coherent framework for modeling fire spread, we unify the two forms of connectivity (structural and airflow) using a union rule: if two rooms are connected through either pathway, they are treated as adjacent in the unified graph. Formally

$$Adj[*,*] = \min\left(A^{(structure)} + A^{(airflow)}, 1\right).$$

This formulation ensures that $Adj[i,j] = 1$ whenever a connection exists in either the structural or airflow matrix, without prioritizing one type of pathway over the other. Formally, the building is represented as a graph $G = (V, E)$, where V is the set of rooms and E is the set of edges determined by the nonzero entries of the aggregated adjacency matrix $Adj[*,*]$. Here, $Adj[i,j]$ denotes the edge between two rooms i and j, capturing both direct and indirect fire propagation routes

Room attributes are defined as follows: Suppose the given building consists of N rooms, indexed by $i \in \{1, \dots, N\}$. Each room i is associated with two attributes that capture both its physical vulnerability to fire and its operational importance, denoted as follows:

$$Fuel = (Fuel_1, \dots, Fuel_N)$$

$$Critical = (Critical_1, \dots, Critical_N)$$

where $Fuel_i \in [1, \infty)$ denotes fuel load or flammability. Likewise, $Criticality_i \in [1, \infty)$ denotes the functional or human importance of the room within the building. This parameter does not independently cause fire risk; rather is modulated the priority of the intervention when the room is already threatened by fire or smoke.

We assume evidence of fire in each room can be obtained from static sensors (i.e., temperature), dynamic sensors (i.e., mobile robot, drone), and human (occupant or firefighter). Such sensory inputs can be normalized [0,1] and then combined as a proxy on a single room-level estimate of the fire condition expressed as:

$$e_i(t) = \alpha_s static_i(t) + \alpha_d dynamic_i(t) + \alpha_h human_i(t).$$

where $(\alpha_s, \alpha_d, \alpha_h)$ denotes normalized weights. To incorporate criticality and flammability effects, each room's score is determined as $s_i(t) = e_i(t)(\phi Fuel_i + \psi Critical_i)$ where $\phi, \psi \geq 0$ denote coefficients that control the relative influence of feud load and room criticality. Incorporating neighbor influences, the fire risk $fire_i'(t)$ of room i at time t is defined as:

$$fire_i'(t) = s_i(t) + \sum_{j \in N} Adj[i,j] \times s_j(t),$$

where $Adj[*,*]$ is the adjacency matrix encoding connectivity between rooms. The fire risk of room i is expressed as the sum of its own scaled sensor score $s_i(t)$ and the aggregate contribution from its directly connected neighbors j, as given by the i-th row of $Adj[*,*]$ multiplied with the vector $S(t)$ – the room-level scaled sensor score. The SPARK algorithm incorporates multi-hops in graph diffusion to capture potential next neighbor room fire risk contributions. In addition, SPARK algorithm incorporates *zone clustering* to provide actionable decision support for firefighting operations. SPARK defines three risk clusters. Rooms assigned to the cluster with the highest risk are flagged as critical zones, requiring immediate intervention. Rooms in the intermediate cluster correspond to vulnerable zones where fire spread is likely, while those in the lowest-risk cluster represent relatively safe zones.

Fire Dynamics Simulator. We use Fire Dynamics Simulator (FDS), an open-source computational fluid dynamics (CFD) tool developed by National Institute of Standards and Technology (NIST) specifically to simulate fire for our experiment.

FDS is widely used for research and safety engineering studies to model realistic fire growth, smoke propagation, and sensor responses in complex geometries.

Building structure. Doors (modeled as HOLEs) of size ≈ 1.0 m × 2.1 m are placed in all interior partitions on all floors to allow lateral spread. A stairwell provides a direct path for upward transport of fire at each floor.

Fire ignition and simulation time. The 3,600-second simulation initiates fire in a first-floor room via an 8,000 kW/m^2 burner, with subsequent spread occurring naturally through wall heating. A sensor network of 300 devices—measuring temperature, CO, CO_2, soot, and visibility—is distributed across every room to capture readings every 0.5 seconds. All sensors are standardized at a height of 0.3 meters below the ceiling to ensure consistent monitoring of hazardous conditions.

Dynamic sensor data generation: Because the FDS framework lacks native support for mobile sensors like drones, this method introduces a custom approach to simulate dynamic data collection for fire spread. Temperature and smoke values for a moving sensor are calculated by averaging readings from its current location with those of adjacent rooms. To ensure realism, the resulting data is infused with random noise to reflect the inherent uncertainty of real-world hardware.

Sensor data fusion: This process fuses five sensor modalities—temperature, carbon monoxide, carbon dioxide, soot, and visibility—by normalizing raw readings into a 0 to 1 range and applying specific fixed weights. Multi-hop risk is then calculated using a weighted resolvent formula to account for how fire conditions influence neighboring areas. Additionally, the simulation incorporates environmental variance by designating 20% of the rooms as containing combustible materials to reflect different flammability levels.

Accuracy evaluation: To evaluate accuracy, a room is defined as burning if it reaches specific thresholds for temperature, gas concentration, or low visibility. Every 0.5 seconds, the SPARK algorithm analyzes non-burning candidate rooms and clusters them by risk levels to identify which are most likely to ignite next. The final accuracy is determined by the percentage of these high-risk predictions that correctly match the actual ignition events recorded in the simulation.

4.1 Simulation Results

Figure 4 and Table 1 show the performance of the SPARK algorithm. Each experiment highlights a different aspect of its predictive capability.

Experiment 1 tracks prediction accuracy by comparing which rooms are forecasted to ignite within a 60-second window against the rooms that catch fire every 0.5 seconds. While initial accuracy is slightly lower due to the limited data available at the start of the fire, the model's performance improves and stabilizes as more rooms ignite. Ultimately, the SPARK algorithm demonstrates high reliability, maintaining an average prediction accuracy of approximately 96% throughout the simulation.

Experiment 2 examines SPARK's ability to model multi-floor fire spread by plotting risk trajectories for representative rooms on each level. These trajectories visualize how risk scores accumulate over time, with rooms that ignite earlier showing faster and steeper rises in risk compared to those igniting later. The results confirm that fire risk propagates sequentially from the first-floor up through the building.

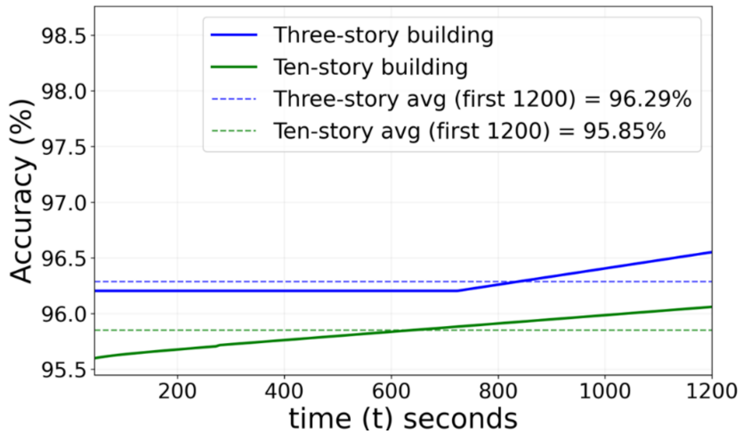

Figure 4. SPARK Prediction Accuracy over time.

Experiment 3 is an ablation study that compares the predictive accuracy of three sensor configurations: static-only, dynamic-only, and a combined dynamic+static approach. By measuring the success of next-ignition predictions within a 60-second window, the experiment demonstrates that integrating all five sensor types leads to the highest performance. The findings, focused on the first 1200 seconds of simulation, confirm that combining stationary and mobile data sources consistently outperforms using either signal in isolation.

Table 1: Prediction accuracy (%) of the SPARK algorithm under different sensor settings for three-story and ten-story buildings.

Building	Static-Only	Dynamic-Only	Dynamic + Static
Three-floor	97.12	94.77	98.09
Ten-floor	95.31	91.67	97.06

5. SUMMARY AND CONCLUSION

Drawing from a bibliometric analysis of five major academic databases, this research addresses the BIM-GIS integration gap by moving beyond static LOD frameworks toward a Graph-based Knowledge Network (KGN). While traditional CityGML-based alignment often fails due to geometric decomposition errors, the KGN approach, demonstrated through a multi-floor fire spread simulation, creates an intelligent computational framework for emergency response management and for Digital Twins.

By fusing BIM, GIS, and real-time IoT data, this framework enables seamless indoor-outdoor navigation and autonomous reasoning for emergency response, shifting the focus from basic data storage to real-time, time-series resilience for natural disasters and medical emergencies.

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