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Federated Edge-Semantic Learning for Decentralized and Resilient Indoor Evacuation Under Dynamic Hazards

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Abstract

Indoor evacuation under emergency conditions remains a challenging problem due to dynamic hazards, uncertain infrastructure availability, and variability in human behavior. Traditional evacuation systems rely heavily on centralized architectures, making them vulnerable to communication failures and delayed global decision making. To address these limitations, this paper proposes a novel framework termed Federated Edge-Semantic Learning for Decentralized Resilient Evacuation (FESL-DRE). The proposed framework distributes evacuation intelligence across edge nodes, enabling autonomous decision making without dependence on a central controller. It integrates semantic reasoning to transform raw sensor data into interpretable environmental states, federated learning to model behavioral patterns in a privacy-preserving manner, and a gossip-based coordination mechanism to propagate hazard information across neighboring nodes. An adaptive routing strategy is developed to account for hazard levels, crowd density, and human behavioral variability. The framework is evaluated using a simulation-based environment under dynamic hazard conditions and varying levels of node failure. Experimental results demonstrate that FESL-DRE achieves superior performance compared to classical and centralized adaptive methods, with improvements in evacuation success rate, reduced blocked movement attempts, and enhanced resilience under moderate infrastructure degradation. Furthermore, the proposed approach maintains low communication overhead and demonstrates promising scalability characteristics within the evaluated simulation environment. The results highlight the potential of decentralized intelligence for evacuation support and provide a foundation for future validation in realistic smart building and IoT-enabled environments.

Keywords: decentralized evacuation; edge intelligence; federated learning; semantic reasoning; IoT; emergency evacuation; adaptive routing; resilience analysis; smart buildings; multi-agent systems

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1. Introduction

Smart evacuation in indoor spaces is still one of the crucial issues in smart buildings, transportation nodes, shopping centers, hospitals, and other underground spaces. During

an evacuation in case of a fire or other structural emergency, the decision-making process should account for constantly changing conditions related to smoke spreading, obstacles, crowding, low visibility, and partial damage to building infrastructure. Modern research shows that classical algorithms of path planning like Dijkstra's algorithm or A* are still being used in modeling the process of evacuation; however, their efficiency significantly drops due to the lack of account for environmental dangers and obstacles [1,2].

With the increasing use of IoT, edge, and other advanced technologies, more adaptive approaches towards guiding evacuating people have been proposed. For example, evacuation frameworks based on IoT technologies allow for collecting environmental parameters like temperature, smoke, and crowding levels, which helps in making decisions about the best possible escape routes [3,4]. Moreover, recently, there have appeared research efforts related to developing fire-aware and congestion-aware strategies for optimizing evacuation routing in large-scale buildings, shopping malls, subway stations, and ships [5–7]. Nevertheless, most existing approaches still employ a centralized approach where the environmental data and evacuation routes are collected and computed by a single server or building management system. Such an approach leaves the system vulnerable to failures due to loss of communication or damage to the controlling server.

Recent studies have focused on using machine learning techniques such as deep reinforcement learning and multi-agent reinforcement learning in the area of evacuation and emergency management [8–10]. Although these approaches offer the advantage of adapting to dynamically changing situations, they often rely on centralized training processes, high computation capabilities, or even knowledge of the whole environment. Learning-based models used in evacuations also make assumptions regarding the behavior of evacuees, considering them rational beings that will always follow a given path without question. In reality, evacuees may choose routes depending on what others do, go with familiar roads, hesitate, panic, or disobey orders. Evacuation experiments and simulations have both verified that behavioral and route factors significantly impact evacuation performance [11,12].

Modern studies emphasize the importance of integrating human behavioral aspects into evacuation procedures. Studies have proven that behavioral models considering the effect of risk perception, social influence, and uncertainty have a notable impact on evacuation outcomes [13,14]. At the same time, Internet-of-Things-powered evacuation systems employing crowd sensing techniques and real-time environmental information perform much better when facing dynamic environments [15]. Multi-agent simulations are also widely used in evacuation research due to their ability to analyze complicated evacuation dynamics [16]. While decentralized evacuation systems address many of the scalability and single-point-of-failure limitations associated with centralized architectures, they also introduce several challenges. In particular, decentralized approaches may suffer from incomplete global situational awareness, communication delays, inconsistent local decisions, and reduced effectiveness under severe network fragmentation. Furthermore, coordination quality depends heavily on local connectivity and the timely exchange of information among neighboring nodes. As a result, designing decentralized evacuation frameworks requires balancing resilience, scalability, communication overhead, and decision consistency. These challenges motivate the integration of semantic reasoning, federated learning, and gossip-based coordination within the proposed FESL-DRE framework to improve decentralized decision making under dynamic emergency conditions.

To address these limitations, this paper proposes a Federated Edge-Semantic Learning for Decentralized Resilient Evacuation (FESL-DRE). The proposed framework distributes evacuation intelligence across edge nodes, including smart sensors, smart lights, and user devices. Instead of relying on a centralized controller, each node performs local perception,

semantic reasoning, decentralized coordination, and adaptive path planning. The framework integrates ontology-driven reasoning to convert raw sensor data into meaningful states, federated learning to capture behavioral patterns without centralizing private data, and gossip-based coordination to propagate hazard information across neighboring nodes.

The main contributions of this paper are as follows:

1. A decentralized evacuation framework that integrates edge intelligence, semantic reasoning, federated learning, and gossip-based coordination.
2. A semantic hazard interpretation mechanism that converts raw environmental signals into interpretable evacuation states.
3. A decentralized hazard propagation strategy that maintains situational awareness under partial node and communication failures.
4. An adaptive routing mechanism that accounts for hazard level, crowd density, and behavioral variability.
5. A simulation-based evaluation demonstrating improved evacuation success rate, reduced blocked attempts, and enhanced resilience compared to centralized baselines.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 presents the proposed methodology. Section 4 reports the experimental results and evaluation. Section 5 concludes the paper and outlines future research directions.

2. Related Work

2.1. Classical and Dynamic Evacuation Path Planning

Classical evacuation routing schemes are traditionally presented as graph-based shortest path problems. Dijkstra and A* algorithms are commonly used due to their efficiency and relative ease of implementation [1,2]. In recent times, the performance of such algorithms in fire evacuation has been evaluated, covering underground transportation systems and multi-level buildings [1,17]. Yet, the conventional shortest path schemes usually rely on static edge weights and full information about the environment, limiting their use in dynamically changing circumstances related to emergencies.

In order to overcome such a drawback, current scientific efforts include the inclusion of fire hazards, smoke movement, congestion, and other considerations in the routing process. For instance, Liu et al. have introduced an optimization approach for real-time evacuation route finding using the modified Dijkstra's algorithm along with fire dynamics simulation [5]. Other work has included fire evacuation route planning considering hazards for indoor fires, subway evacuations, shopping malls, and ships [6,7,18]. However, all of the above approaches incorporate central processing or environmental information as a whole.

2.2. IoT-Enabled and Smart Building Evacuation Systems

An IoT-based evacuation system uses sensor nodes to sense environmental information and assist in making decisions in real-time. Mohammadi Ounotikandi et al. introduced a smart building fire evacuation and control system based on an IoT infrastructure and a hybrid intelligent optimization approach [3]. Saini et al. designed a disaster emergency response system for smart buildings based on IoT, fog, and cloud computing layers [19]. Zhang et al. discussed an IoT-driven evacuation path optimization and tracking system for managing fires in large shopping centers [4].

These studies show the application of the IoT infrastructure to improve the performance of an evacuation process. However, several IoT-based approaches still use the fog or cloud layer for coordinating the operation of their systems on a global scale. In case of connection failures, such an approach may be inefficient during a disaster scenario.

Therefore, the suggested FESL-DRE framework emphasizes decentralized coordination of systems without the need for a centralized control point.

2.3. Learning-Based Evacuation and Human Behavior Modeling

Learning-based evacuation models have gained popularity due to their flexibility in dealing with various kinds of environments. For example, deep reinforcement learning has been used in rescue path planning and emergency navigation [8]. Additionally, reinforcement learning has been applied in modeling evacuation in response to fire hazards in multi-agent systems [9,10]. More recently, reinforcement learning has been used in creating environments for evacuation modeling, including PyroRL for wildfire evacuation [20].

While providing great flexibility, such algorithms often require large amounts of training samples and computation power. In addition, these systems tend to have centralized training or be based on a completely observable world. Modeling human behavior remains an open problem. Fire drills at multiple scales and analysis of behavior during evacuations have demonstrated that evacuation decisions can depend on such factors as the level of familiarization with the environment, perceived risks, social behavior, and guidance following [11,12]. Therefore, it is worth incorporating human-centric aspects into evacuation modeling.

Recently, research on evacuation modeling has increasingly emphasized the importance of including elements related to behavioral uncertainty and adaptive decision making. For instance, research which takes into account human perception and risk awareness, and the impact of social behavior has proven that behavioral variability affects evacuation outcomes more than routing optimization [13,14]. Additionally, using multi-agent modeling helps in analyzing different behaviors and interactions during evacuation [16].

FESL-DRE tries to solve this issue by introducing a federated learning-based approach to modeling behavioral patterns while keeping observations local.

2.4. Federated Learning and Edge Intelligence

Federated learning represents an attractive solution to privacy-preserving distributed learning in edge and Internet of Things (IoT) networks. Specifically, Abreha et al. present a survey on federated learning in edge computing, highlighting its ability to perform distributed intelligence while not centralizing the raw data [21]. Federated compressed learning for edge computing applications was proposed by Putra et al., showcasing the merits of privacy-preserving learning through effective communication [22]. Further research has investigated the use of federated learning for smart decision making in IoT edge–fog–cloud ecosystems [23].

In line with edge intelligence capabilities, edge-based computation and decision making can be executed in a real-time manner in distributed environments. Recent studies have highlighted the importance of edge computing and its application in supporting low-latency and scalable IoT deployments [24]. In addition, federated learning can enhance edge computing through collaborative learning in a privacy-preserving and communication-efficient manner [25]. Various smart environment applications have successfully employed such methods and show promise in building decentralized evacuation guidance systems.

Overall, from these studies, it becomes apparent that federated learning represents an appropriate approach in the context of distributed IoT systems, particularly when privacy, scalability, and communication are concerned. However, its application to decentralized evacuation guidance is still limited. By utilizing the observations collected locally in the environment, the proposed FESL-DRE framework introduces federated learning to evacuation systems.

2.5. Gossip-Based Coordination and Decentralized Communication

A decentralized form of coordination is essential for the successful functioning of evacuation systems during partial disruption of the network. Gossip protocols have long been used in distributed and fault-tolerant computing architectures owing to their scalability, fault tolerance, and ability to spread information through local peer-to-peer communications [26,27]. Moreover, context-aware gossip protocols have been considered in IoT systems with the aim to increase information distribution while reducing communication costs [28].

Coordination in multi-agent systems has been widely studied as a method that helps achieve improved scalability and resilience in terms of communication restrictions. Modern research has focused on distributed decision making based on local information and communication between agents [29]. In particular, it was shown that in IoT conditions, distributed decision making contributes to greater resilience against failures [30].

Gossip-based coordination plays an important role in evacuation problems as it allows nodes to share local hazard maps without the need for centralized control. This allows the system to preserve knowledge about the situation in the network even if some parts of it malfunction. However, current evacuation systems rarely use gossip-based communication along with semantic reasoning and adaptive routing. The proposed solution seeks to fill this gap by incorporating gossip propagation in decentralized hazard awareness.

2.6. Semantic Reasoning and Knowledge-Driven Evacuation

Semantic reasoning is increasingly being explored in IoT and smart environment applications because of its ability to turn raw data from sensors into knowledge. Semantic reasoning based on ontology has been applied to help develop context-aware IoT applications, situational awareness, and semantic query [31,32]. The application of semantic approaches in evacuation studies has involved developing methods for dynamic route planning that utilize data from both IoT and a Building Information Model (BIM) [33].

Moreover, current research efforts have focused on integrating artificial intelligence into edge computing, making wireless and IoT applications able to make decisions independently. This highlights the importance of having scalable, privacy-preserving, and efficient communication systems [34,35], which are goals that the FESL-DRE framework seeks to achieve.

While the above-mentioned semantic approaches increase the level of explanation, they mostly operate in a centralized or BIM-based framework. What sets FESL-DRE apart is that it applies semantic reasoning in edge devices, which means that each node can compute high-level information like blocked passages, risky areas, and overcrowded paths.

Recent research has increasingly explored decentralized and distributed approaches for emergency management and evacuation support. Multi-agent coordination frameworks have been investigated to improve adaptive decision making under dynamic hazards [36], while IoT-enabled intelligent evacuation systems have been proposed to enhance resilience and reduce dependence on centralized infrastructure [37]. Similarly, federated learning has emerged as a promising paradigm for privacy-preserving distributed intelligence. These developments motivate the integration of semantic reasoning, federated learning, and distributed coordination within the proposed FESL-DRE framework.

2.7. Research Gap

From the literature reviewed above, the following areas have seen significant progress regarding evacuation path planning: evacuation path planning for IoT-enabled evacuation, learning-based guidance systems, federated edge intelligence, gossip-based communication, and semantic reasoning. However, there are various weaknesses in the existing body

of knowledge. First, some of the existing solutions are based on central coordination, making them highly prone to failures caused by communication and controller issues. Secondly, many learning-based solutions do not consider privacy challenges and also require data collection from a central point. Thirdly, semantic reasoning solutions lack decentralized coordination. Finally, few studies consider hazard dynamics, varying human behavior, communication costs, and resilience against node failures simultaneously.

This paper suggests the FESL-DRE framework, which adopts semantic reasoning, federated learning, gossip-based coordination, and route guidance as its components to create a resilient evacuation solution.

3. Methodology

3.1. System Overview

The proposed FESL-DRE framework models the evacuation environment as a distributed graph, as shown in Equation (1):

$$G = (V, E) \tag{1}$$

where V denotes the set of nodes and E represents communication links. Also, each node $v_i \in V$ represents an intelligent edge agent (sensor, actuator, or user device), and edges E represent local communication links. This formulation is critical because it enables decentralized computation; no node requires global knowledge of the entire graph.

Each node operates under partial observability, meaning that it only has access to local information and neighbor updates. Therefore, all subsequent equations and algorithms are designed to progressively approximate global awareness through local interactions.

3.2. Local Perception and Hazard Representation

Each node $v_i \in V$ continuously acquires multimodal sensory inputs, as shown in Equation (2):

$$S_i(t) = \left\{ s_i^{(1)}(t),\ s_i^{(2)}(t), \ldots, s_i^{(m)}(t) \right\} \tag{2}$$

where $s_i^{(k)}(t)$ represents the $k - th$ sensor modality (e.g., smoke density, temperature, vibration, crowd density) at time t.

These raw inputs are heterogeneous and noisy; hence, they cannot be directly used for decision making. To address this, Equation (3) defines the transformation as a structured hazard representation:

$$H_i(t) = f_{hazard}(S_i(t),\ N_i(t)) \tag{3}$$

where

$H_i(t)$ is the local hazard estimate at node v_i;
$f_{hazard}(.)$ integrates

- sensor readings (e.g., smoke, heat);
- contextual neighbor information $N_i(t)$.

The architecture of FESL-DRE is shown in Figure 1. It comprises a five-layer hierarchical model that provides a basis for fully decentralized and smart evacuation guidance services. Specifically, raw data from diverse sources, such as smoke sensors, crowd density sensors, and users' smartphones, are collected in the Perception Layer at the bottom tier. In the Semantic Reasoning Layer, an ontology-enabled reasoner establishes a knowledge graph to represent raw sensor data as semantically interpretable high-level states, such as zones of hazards and blocked routes. The semantic interpretations are then used in the Federated Coordination Layer, where edge devices establish their own local models

and communicate among themselves based on the gossip protocol for efficient and fault-resistant hazard spreading. This situational awareness can be further capitalized upon in the Decision Layer that deploys an adaptive A* optimization algorithm to provide optimal evacuation routes based on the combination of hazards, crowd density, and behavioral aspects. Finally, personalized guidance is sent to individual gadgets via the Interaction Layer by implementing privacy-friendly means, namely, zero-knowledge proofs.

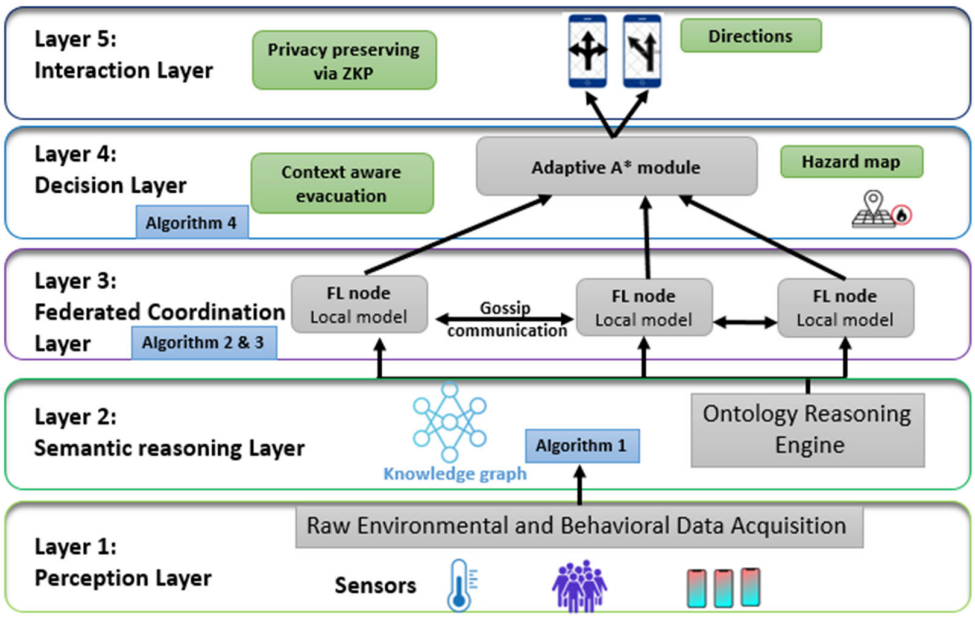


Figure 1. End-to-end architecture of the proposed FESL-DRE framework.

At the beginning of an evacuation scenario, each node constructs an initial local hazard map using its own sensor observations and immediate environmental measurements. Hazard levels are estimated from available sensing modalities, including smoke concentration, temperature, and crowd density. These observations are transformed into local hazard scores according to Equation (3). The resulting local hazard maps serve as the initial knowledge state of each node before any gossip-based information exchange occurs. As communication progresses, neighboring nodes iteratively merge their local maps through the decentralized propagation mechanism described in Section 3.5, gradually building a broader view of the evacuation environment.

3.3. Semantic Reasoning at the Edge

To ensure interpretability and robustness, raw sensor data is transformed into a semantic representation using an ontology-driven reasoning engine deployed at each node.

Let O denote the ontology and R the set of reasoning rules. Each node constructs a local knowledge graph, as seen in Equation (4):

$$K_i(t) = \{(s, p, o)\} \tag{4}$$

where (s, p, o) are RDF triples representing semantic relationships.

The reasoning process is defined in Equation (5):

$$K_i^*(t) = K_i(t) \cup Infer(K_i(t), R) \tag{5}$$

where

$K_i(t)$ represents the raw semantic facts derived from sensors;

$K_i^*(t)$ represents enriched knowledge after reasoning;

R represents the rule set (e.g., "IF smoke high AND temperature rising THEN corridor blocked").

The algorithm depicted in Algorithm 1 shows how the sensor readings are processed to extract knowledge from them. First, the readings are normalized, and then they are mapped to ontology-based concepts, thus obtaining the knowledge graph $K_i(t)$. The rule set R is used on $K_i(t)$ iteratively until no new triples can be generated according to any rule. Each rule contains knowledge associated with some environmental conditions that imply a high-level state. If the conditions for a rule are true, then new triples are generated and added to the knowledge graph to create $K_i^*(t)$. This is the direct implementation of the reasoning model defined in Equation (5), where each node converts numeric values to states usable for decision-making purposes.

Algorithm 1: Edge Semantic Reasoning

Input: Sensor data $S_i(t)$, ontology O, rule set R
Output: Semantic knowledge graph $K_i^*(t)$
1: Initialize $K_i(t)$ from sensor observations
2: Normalize sensor values into semantic concepts
3: for each rule r $\in$ R do
4: if conditions of r are satisfied in $K_i(t)$ then
5: infer new triples and add to $K_i(t)$
6: end if
7: end for
8: return $K_i^*(t)$

Before semantic reasoning is performed, heterogeneous sensor measurements are transformed into ontology-compliant semantic concepts. Raw observations collected from temperature, smoke, hazard, and crowd-monitoring sensors are first normalized according to their corresponding operating ranges. The normalized values are then mapped to semantic categories using predefined thresholds. For example, temperature measurements may be classified as Normal, Elevated, or Critical, while crowd density values may be represented as Sparse, Moderate, or Congested. These semantic concepts are subsequently encoded as ontology entities and used by the reasoning engine to infer higher-level evacuation conditions and routing recommendations. This transformation enables the integration of heterogeneous sensor data into a unified semantic representation suitable for decentralized decision making.

Ontology Structure and Reasoning Rules

The semantic reasoning module is based on a lightweight evacuation ontology that represents key entities and relationships relevant to emergency response. The ontology contains four primary concept groups: Environment, Hazard, Occupant, and Route. Environmental concepts include corridors, exits, rooms, and evacuation zones. Hazard concepts include smoke level, temperature state, congestion level, and blockage status. Occupant concepts describe behavioral characteristics and evacuation states, while route concepts represent path availability and safety conditions.

Reasoning is performed using a rule set (R) that transforms low-level sensor observations into higher-level evacuation knowledge. Table 1 presents representative reasoning rules used by the semantic engine. These rules enable the system to infer corridor conditions, congestion states, and route availability from distributed sensor observations.

Table 1. Representative semantic reasoning rules.

Rule ID	Rule
R1	IF smoke = High AND temperature = Rising THEN corridor = Blocked
R2	IF crowd density = High THEN congestion = Severe
R3	IF corridor = Blocked THEN route availability = False
R4	IF congestion = Severe THEN route cost = Increased
R5	IF hazard level = Critical THEN evacuation priority = High
R6	IF exit accessibility = Low THEN alternative route = Required

The ontology and rule set are intentionally lightweight to support deployment on resource-constrained edge devices while maintaining sufficient expressive power for evacuation decision making.

3.4. Federated Learning for Human-Centric Modeling

To capture human behavioral variability, a federated learning (FL) framework is employed. Each node trains a local model θ_i using private observations (e.g., movement patterns, device interactions).

The global objective is defined in Equation (6):

$$\min_{\theta} \sum_{i=1}^{N} w_i . L_i(\theta, D_i) \tag{6}$$

where $L_i(\theta)$ denotes the local loss function, w_i is a weighting factor reflecting node reliability, and D_i represents the local dataset maintained by node v_i.

Each node v_i performs local training using its private dataset D_i, which includes behavioral and environmental observations collected at the edge.

The model is updated using federated averaging shown in Equation (7):

$$\theta^{(t+1)} = \sum_{i=1}^{N} w_i . \theta_i^{(t)} \tag{7}$$

This process enables the model to learn evacuation compliance behavior, crowd following tendencies, and trust-aware routing preferences from distributed observations.

The local models optimized according to Equation (6) are aggregated using the federated averaging rule in Equation (7).

Algorithm 2 provides a framework for distributed learning in which the behavior of humans can be captured without the necessity of centralized storage of any sensitive information. Every node will update its own model θ_i based on its own dataset D_i, which is defined by Equation (6). The updated models are then combined to form a global model, as shown in Equation (7), often through a weighted average method. Through this repeated process, the system is able to identify any common behavior patterns like obedience and crowd psychology. The distributed nature of the algorithm also makes it scalable and adaptable, allowing further model training even in partially connected networks.

Algorithm 2: Federated Learning Update

Input: Local datasets D_i, initial model θ
Output: Updated global model θ*
1: Initialize θ globally
2: for each communication round do
3: for each node v_i in parallel do
4: $\theta_i \leftarrow$ Train(θ, D_i)
5: end for
6: θ ← Aggregate(θ_i, weights w_i)
7: end for
8: return θ*

Behavioral Compliance Modeling Through Federated Learning

To explicitly incorporate human behavior into evacuation decision making, the federated learning module is designed to predict the probability that an occupant will follow the evacuation guidance generated by the system. Each edge node constructs a local behavioral dataset using observations collected within its sensing region. For each agent, a behavioral feature vector is defined as $x_i = [h_i, d_i, q_i, b_i, c_i]$, where h_i denotes the local hazard level, d_i represents crowd density, q_i is the normalized distance to the nearest exit, (b_i) corresponds to the behavioral profile score, and c_i denotes the local node connectivity degree. These features jointly characterize the environmental conditions and behavioral factors that influence evacuation decisions.

The objective of the federated learning module is to estimate the route compliance probability of each occupant. The predicted compliance probability is expressed as $P_i = f_\theta(x_i)$, where P_i denotes the probability that occupant i follows the recommended evacuation route, x_i is the behavioral feature vector, and f_θ represents the lightweight behavioral model trained through federated learning. A larger value of P_i indicates a higher likelihood of compliance with the provided guidance.

The predicted compliance probability is incorporated into the adaptive routing process through a behavioral penalty term. Accordingly, the path cost is computed as shown in Equation (8).

$$C(p) = e \in p \sum \left(w_h H(e) + w_d D(e) + w_t T(e) + w_p (1 - P_i) \right) \quad (8)$$

where $H(e)$, $D(e)$, *and* $T(e)$ denote the hazard level, crowd density, and travel distance associated with edge (e), respectively. The term $(1 - P_i)$ penalizes routes that are less likely to be followed by occupants. Consequently, the routing algorithm favors paths that are not only safe and efficient but also behaviorally realistic.

Unlike conventional evacuation algorithms that assume perfect compliance with routing instructions, the proposed approach explicitly models behavioral uncertainty. Federated learning enables edge nodes to learn behavioral compliance patterns from local observations without exchanging raw behavioral data. As a result, evacuation decisions are influenced by both environmental conditions and predicted human behavior, thereby improving the realism of route planning under emergency conditions.

3.5. Decentralized Coordination via Gossip Protocol

An important problem that arises in evacuation networks is maintaining global situational awareness in cases where there are failures in the network, communication problems, and damage to nodes. Traditional centralized solutions fail in such scenarios because they

rely on only one coordinator. This problem is solved through the use of a fully decentralized coordination scheme based on a gossip protocol.

As defined in Equation (9), each node v_i maintains a local hazard map:

$$M_i(t) = \{H_i(t), H_j(t) \mid v_j \in N_i\} \tag{9}$$

This representation encapsulates both self-observed hazard states and neighbor-propagated information, forming a progressively expanding view of the environment. The update rule is in Equation (10):

$$M_i(t+1) = M_i(t) \cup \bigcup_{j \in N_i} M_j(t) \tag{10}$$

This defines a set-union-based state fusion mechanism, where nodes iteratively merge their local maps with those received from neighbors.

where

- $M_i(t)$ represents node v_i's local view of the global hazard map;
- The union operation incrementally propagates knowledge.

The update equation outlined in Equation (10) helps ensure a smooth estimation of the global state of hazards through local communication between agents only. This result can be explained by the fact that each agent updates its local map $M_i(t)$ through communications with neighboring agents, as shown in Algorithm 3 (Lines 2–3). Information about hazards is obtained through local communication, without any centralized controller, and involves several iterations of the process. However, most importantly, the consistency check procedure described in Algorithm 3 (Line 4) helps stabilize the system by eliminating old maps of hazards.

Algorithm 3: Gossip-Based Hazard Propagation

Input: Local hazard map $H_i(t)$, neighbor maps
Output: Updated map $M_i(t)$
1: Initialize $M_i(t) \leftarrow H_i(t)$
2: Receive maps $M_j(t)$ from neighbors
3: Merge received maps with $M_i(t)$
4: Remove outdated or inconsistent entries
5: Broadcast updated $M_i(t)$
6: return $M_i(t)$

According to the systems, the decentralized theory of gossiping enables efficient dissemination of information regardless of the changes occurring in the system. Regardless, the information concerning potential threats is bound to be transmitted within graph G irrespective of any failure or disruption. This is imperative for situations where infrastructure disruptions are expected. Therefore, the system continues functioning even after some elements have failed.

Assuming an average node degree (k), a single gossip round requires approximately (O(Nk)) message exchanges, where (N) denotes the number of active nodes. Because communication is restricted to local neighbors, the messaging overhead grows linearly with network size under sparse connectivity assumptions. This property makes gossip-based coordination significantly more scalable than centralized approaches that require frequent global-state dissemination.

Occupant Behavioral Profiles

To capture behavioral variability during emergency situations, occupants are modeled using four behavioral profiles commonly observed in evacuation studies. These profiles do not attempt to represent the full complexity of human decision making; rather, they provide a simplified behavioral abstraction that enables evaluation of routing robustness under heterogeneous occupant responses.

Calm occupants follow the recommended evacuation route with a high probability and are assumed to make rational decisions based on available guidance. These agents prioritize the shortest safe path and exhibit minimal deviation from system recommendations.

Familiar occupants possess partial knowledge of the building layout and may prefer routes that they have previously used. When a recommended route differs substantially from a familiar path, these agents may choose the familiar alternative, provided that no severe hazards are detected.

Panic-driven occupants exhibit reduced compliance with routing instructions and tend to prioritize immediate movement away from perceived hazards. These agents may select locally attractive paths without considering global route optimality, potentially increasing congestion and routing inefficiencies.

Confused occupants represent individuals with limited situational awareness. Their decisions contain a larger random component, and they may hesitate, change directions, or follow nearby occupants rather than strictly adhering to routing recommendations.

The behavioral profiles are incorporated into the simulation through a compliance score that determines the probability of following the recommended route. Higher compliance values increase the likelihood of adhering to evacuation guidance, while lower values introduce deviations that reflect behavioral uncertainty. This mechanism enables the evaluation of evacuation strategies under diverse occupant responses rather than assuming perfect compliance.

3.6. Adaptive Path Planning with Dynamic Cost Function

Evacuation routing is performed using an adaptive A* algorithm where path cost dynamically incorporates hazard, congestion, and trust.

The cost of a path p is defined in Equation (11):

$$C(p) = \sum_{e \in p} (w1 \cdot H(e) + w2 \cdot D(e) + w3 \cdot T(e)) \quad (11)$$

where

- $H(e)$: hazard level;
- $D(e)$: crowd density;
- $T(e)$: trust score;
- $w1, w2, w3$: adaptive weights.

Algorithm 4 enhances the traditional A* algorithm by incorporating a dynamic cost function that combines hazards, crowds, and trust, as per Equation (11). In contrast to traditional algorithms, the cost function is no longer dependent only on Euclidean distance; instead, the cost value of every node depends on hazard, crowd, and trust factors. During the route search process, the cost function is regularly updated based on the latest data available from the hazard map (Algorithm 3) and behavioral modeling algorithms (Algorithm 2).

Algorithm 4: *Adaptive A* Evacuation Routing*

```
Input: Graph G, start node s, goal node g, cost weights w
Output: Optimal evacuation path p*
Initialize open set with s
while open set is not empty do
        select node with lowest f(n) = g(n) + h(n)
            if n = g then
                return reconstructed path
            end if
        for each neighbor n' do
            compute cost using hazard, density, trust
            update scores and parent pointers
    end for
end while
```

3.7. Privacy-Preserving Interaction via Zero-Knowledge Proofs

To address privacy concerns during emergency response, user devices share only the minimum information required for evacuation coordination through Zero-Knowledge Proofs (ZKPs). Rather than transmitting precise coordinates, each occupant proves membership within a valid evacuation zone without revealing the actual location. Formally, the proof is expressed as shown in Equation (12).

$$Prove(x \in Z_k)\ without\ revealing\ x \tag{12}$$

where x denotes the exact user location and Z_k represents the evacuation zone to which the user belongs.

The generated proof allows for neighboring edge nodes to verify that the occupant is located within a legitimate zone while preventing disclosure of precise spatial coordinates. Consequently, the system can utilize location-related information for congestion estimation, hazard awareness, and route optimization without exposing sensitive personal data.

The verification process can be represented as shown in Equation (13).

$$\boldsymbol{Verify}(\boldsymbol{\pi_i}) = \begin{cases} 1, & \boldsymbol{\pi_i\ is\ valid} \\ 0, & \boldsymbol{otherwise} \end{cases} \tag{13}$$

where $\boldsymbol{\pi_i}$ denotes the zero-knowledge proof generated by occupant $\boldsymbol{i}$. Successful verification confirms that the occupant satisfies the zone membership condition $x \in Z_k$ without disclosing their exact spatial coordinates $\boldsymbol{x}$. Consequently, neighboring edge nodes can utilize location-related information for evacuation coordination while preserving user privacy.

By using this privacy-preserving mechanism, the proposed framework achieves three objectives: (i) protecting the anonymity of occupants, (ii) supporting compliance with privacy regulations and data protection requirements, and (iii) enabling secure participation in decentralized evacuation optimization. As a result, user devices can contribute to real-time hazard assessment and routing decisions while maintaining location privacy.

3.8. Complexity and Resilience Analysis

This section evaluates the computational efficiency, communication overhead, and resilience of the proposed FESL-DRE framework, with emphasis on its decentralized coordination (Section 3.5) and adaptive routing (Section 3.6).

3.8.1. Computational Complexity

Each node performs three primary operations: semantic reasoning, local federated learning updates, and gossip-based information exchange. The computational burden of semantic reasoning depends on the size of the local knowledge graph and the number of active reasoning rules, both of which remain limited because reasoning is performed locally at edge nodes. Similarly, federated learning is executed using lightweight local models trained on node-specific observations, resulting in modest computational requirements. Consequently, the proposed framework is suitable for distributed execution on resource-constrained edge devices without requiring centralized processing resources.

3.8.2. Communication Complexity and Convergence

The communication cost of the proposed framework is governed by the gossip-based coordination mechanism. Unlike centralized architectures that require global dissemination of state information, each node exchanges information only with its immediate neighbors. This localized communication strategy substantially reduces messaging overhead while enabling progressive propagation of hazard information throughout the network. As information is repeatedly exchanged and merged, neighboring nodes gradually develop consistent views of the evacuation environment, supporting adaptive routing decisions even under partial communication failures.

3.8.3. Resilience and Robustness

To quantify robustness, the resilience of the system is defined in Equation (14):

$$Resilience \propto 1 - \frac{|\, V_{failed} \,|}{|\, V \,|} \tag{14}$$

Unlike the catastrophic failure of a traditional, centralized system, our approach to distributed hazard detection gracefully degrades as node failures or broken communications become more pronounced, and individual nodes continue to have a coherent local view of what is happening. Furthermore, we show that decentralized coordination algorithm (Section 3.5) steers a hazard message through alternative routes should necessary capacities fail. The routing policies (Section 3.6) can operate with significant incompleteness in the information provided by neighbor propagation (Equation (8)) and are supported by the removal of stale information, which is performed during each gossip iteration (Algorithm 3).

3.8.4. Summary

In summary, the proposed FESL-DRE model is characterized by negligible computation and communication cost while maintaining resilience. The decentralized nature of the model makes it highly scalable and reliable, which makes it suitable for use during evacuations.

4. Results and Evaluation

4.1. Experimental Setup

4.1.1. Simulation Environment

As safety is paramount during evacuations and gathering empirical data from emergencies can be difficult, the simulation technique is used for the evaluation process. This method of evaluation is highly recommended in the evacuation literature, as experiments in evacuation research require control and repeatability for reliable analysis under different scenarios.

The performance of the designed FESL-DRE framework is tested in a graph-based indoor environment that represents a structural indoor building plan. The indoor environment is modeled using the graph topology G = (V, E), where nodes represent the location in space (room, corridor, intersection) and edges represent the connections between nodes. Furthermore, each edge will carry dynamic parameters such as distance, hazard, and number of people in the area.

The simulation environment consists of a 12 × 12 grid-based indoor topology comprising 144 interconnected nodes. The graph structure represents a medium-scale building environment with multiple possible evacuation routes and two designated exit nodes. Hazard conditions, dynamic blockages, crowd density, and occupant behavior are simulated over the network to evaluate the effectiveness of the proposed FESL-DRE framework under varying emergency scenarios.

4.1.2. Agent Modeling and Behavioral Profiles

A group of synthesized agents is created to mimic the behavior of the human individuals inside of the building environment. Each agent starts its journey from a randomly chosen non-exit point in the environment and possesses some predefined behavioral characteristics to reflect the differences in humans' decisions. These behaviors include the following:

- **Calm agents**, who tend to follow optimal evacuation paths;
- **Panic-driven agents**, who exhibit crowd-following behavior;
- **Familiar agents**, who prefer known or shortest routes;
- **Confused agents**, who demonstrate stochastic or suboptimal movement patterns.

This is a dynamically maintained condition consisting of the current position of each agent, evacuation conditions, and elapsed time. This behavioral deviation is essential when evaluating the resilience of the proposed model in light of real-world behavioral departure from perfect routing conditions.

Occupants were randomly assigned behavioral profiles according to the distributions shown in Table 2. These profiles influence route compliance probabilities and evacuation decisions throughout the simulation.

Table 2. Behavioral profiles used in the simulation.

Behavioral Profile	Compliance Probability	Primary Decision Characteristic
Calm	0.85–0.95	Follows recommended route
Familiar	0.70–0.90	Prefers known routes
Panic-Driven	0.40–0.70	Moves away from hazards with reduced compliance
Confused	0.30–0.60	Randomized or follower-based decisions

4.1.3. Hazard Modeling

In order to create emergencies within the system, dynamic hazards are introduced into the environment. The hazard magnitude is considered to be a function with different

magnitudes that are generated by some source nodes in the graph and distributed throughout the environment. Specifically, the intensity of the hazard in each edge is computed using an exponential decay function depending on distance from the source node.

Using such a model allows for simulating real-world situations where evacuation decisions depend on dynamically changing environment conditions. The proposed hazard model is implemented directly in the local perception model (see Section 3.2) and distributed through the network using the gossiping technique (see Section 3.5).

4.1.4. Crowd Density Estimation

Crowd density is dynamically obtained from the spatial distribution of the agents at each time step of the simulation. The density for each edge is obtained by taking into consideration the ratio of the number of agents in the neighboring cells. Such a congestion measure enables the inclusion of crowd density into the cost function, which is defined in Equation (10). Through this inclusion, it is possible to circumvent areas of high congestion while distributing evacuation routes in an efficient manner.

4.1.5. Implementation Details

The simulation environment is coded using Python 3.11 language and makes use of the NetworkX module to model the graph structure and conduct pathfinding. A common processing chain has been used for data synthesis, hazard modeling, and agent-based simulation in order to maintain consistency in all experimentation environments. All experiments are performed using fixed random seeds to make sure that results are reproducible. Parameters of the simulation, such as number of agents, number of hazards, and network architecture, are reported in the dataset.

4.1.6. Summary

In this paper, we present an experimental environment that helps make the FESL-DRE challenging yet realistic to test and evaluate. This experimental environment facilitates constructing an overall system performance assessment model, where system behavior is captured by a graph model, dynamics are modeled by temporal dynamic hazards, and agents in the system exhibit heterogeneous behavior. This environment is then utilized for conducting experiments and analysis of the FESL-DRE system.

4.2. Baseline Methods

To evaluate the performance of FESL-DRE, we compare it with several baseline algorithms designed to function as traditional evacuation algorithms as well as state-of-the-art evacuation methods that incorporate decentralization, adaptability, and even human-related behavior.

4.2.1. Centralized Shortest Path (Dijkstra)

We discussed the option of the simplest solution for computing shortest paths, which is Dijkstra's algorithm. This solution only takes into account the static structure of the graph and the weights of the nodes and edges but makes no considerations of dynamics such as danger and crowd density. However, it is easy to compute, which is one of the reasons it is commonly used for systems where we have complete knowledge of the system, and it cannot adapt to any changes that may occur.

4.2.2. Centralized A* Routing

To provide a stronger baseline, a centralized A* routing approach is implemented. This method incorporates heuristic-guided searching to identify shortest paths more efficiently than Dijkstra's algorithm. However, similar to the previous baseline, it relies

on a centralized view of the environment and assumes reliable communication with a global controller.

Although A* can be extended to include weighted costs, in this study, it operates under a centralized paradigm and lacks the distributed coordination and real-time adaptability of the proposed framework.

4.2.3. Centralized Adaptive Routing (Hazard-Aware A*)

To ensure a fair comparison, a hazard-aware centralized routing model is also considered. In this approach, the A* algorithm is extended to incorporate hazard and congestion information into the path cost function, similar to Equation (10). However, all hazard and density information is assumed to be aggregated at a central entity.

This baseline isolates the effect of decentralization by comparing

- centralized adaptive intelligence vs.
- decentralized adaptive intelligence (FESL-DRE).

4.2.4. Discussion of Baseline Selection

The selected baselines collectively represent three key categories of evacuation strategies:

- **Static centralized methods**, which rely on fixed shortest paths;
- **Heuristic-based centralized methods**, which improve computational efficiency but remain non-adaptive;
- **Adaptive centralized methods**, which incorporate dynamic information but depend on global coordination.

By comparing against these baselines, the evaluation is designed to isolate the contributions of the proposed framework, particularly the following:

- Decentralized coordination via gossip protocol;
- Real-time hazard propagation without a central controller;
- Integration of behavioral and contextual factors into routing decisions.

4.3. Evaluation Metrics

In order to thoroughly examine the effectiveness of the proposed FESL-DRE approach, several metrics have been defined to assess efficiency, adaptiveness, resiliency, and communication cost. Such metrics have been selected in light of their ability to measure both classic goals of evacuation and specific attributes of decentralization.

4.3.1. Evacuation Success Rate

The success rate of the evacuation indicates how many of the individuals managed to evacuate from a given location through an assigned safe exit in the time frame used for simulations. The success rate can be calculated as the ratio between the number of people evacuated and the total number of individuals in the model. It represents the effectiveness of the chosen evacuation procedure, especially in failure cases.

4.3.2. Average Evacuation Time

Average evacuation time refers to the average time required by the agents to exit the building. It is calculated for all agents that have been evacuated successfully, and it is used as a measure of the efficiency of the routing algorithm. The lower the evacuation time, the higher the efficiency.

4.3.3. Path Cost

The path cost is the total cost incurred due to the routes used by the agents based on the cost dynamic function defined in Equation (10). The cost function takes into consideration

factors such as hazards, congestion, and distance travelled. Unlike distance-based costs, this metric accounts for safety-driven routing.

4.3.4. Latency to Redirection

Latency to redirection refers to the amount of time needed by the system to adjust itself to any sudden changes in the environment, including emergence of a new threat or blocking off an escape route. Latency represents the period of time that elapses between a change and the update of the routing decision made on its basis. This criterion plays a vital role in evaluating the effectiveness of decentralized coordination (Section 3.5) and adaptive routing (Section 3.6).

4.3.5. Resilience Metric

The resilience metric, which was previously introduced in Equation (14), is used in order to evaluate the robustness of the system when some failures occur. Resilience quantifies the fraction of the network that continues to function when part of the network fails. In addition to the formula presented, empirical evaluation of resilience takes place by evaluating the evacuation rate while different types of failures take place.

4.3.6. Communication Overhead

Communication overhead is the total amount of data exchanged between nodes in the gossip protocol algorithm process. Communication overhead is measured based on the number of communications between neighbors of each node within an iteration. It reflects the scalability of the system and how well it can be deployed in environments with limited resources.

4.3.7. Discussion of Metrics

As for the metrics selected, they all include several aspects that can be considered when discussing the performance of the system. Standard metrics are evacuation time and cost measure efficiency, while latency time before redirection and resilience measure the ability of the system to perform under dynamic and unpredictable circumstances.

4.4. Performance Comparison

4.4.1. Quantitative Results

Table 3 presents the comparative performance of the proposed FESL-DRE framework against the baseline methods under dynamic evacuation conditions.

Table 3. Performance comparison under dynamic hazard conditions.

Method	Success Rate (%)	Avg. Evacuation Time (Steps)	Path Cost	Blocked Attempts
Centralized Dijkstra	57.0	8.31	36,174.00	267
Centralized A*	57.0	8.31	36,174.00	267
Centralized Adaptive A*	85.2	14.36	29,123.35	95
FESL-DRE (Proposed)	92.4	12.57	28,049.48	70

4.4.2. Analysis of Results

The results shown in Table 3 clearly show the effectiveness of the suggested FESL-DRE algorithm in handling dynamic and uncertain evacuation situations. In relation to the success rate, the suggested algorithm achieves the highest success rate at 92.4%, significantly exceeding both the classical and adaptive approaches. Compared with the centralized adaptive A* algorithm, FESL-DRE has an increase in the success rate above 7%, reflecting better performance of guiding the agents towards safe exits when there are hazardous

conditions. Considering the average time needed for evacuation, FESL-DRE has a shorter evacuation time compared with the centralized approach while being decentralized. Even though classical methods have shorter times for evacuation, their performance is mainly because of the tendency to choose a dangerous or unsafe route, resulting in a significantly smaller success rate. As expected, the improvement in the path cost can be seen as another benefit of the proposed algorithm. Through the incorporation of semantic hazard detection, crowds, and adaptive algorithms, FESL-DRE provides safer and more efficient routes compared with the three other baseline approaches. It is worth noting that the suggested algorithm has the least blocked attempts, which reflects its ability to detect unsafe areas and avoid any possible dangers.

4.4.3. Impact of Decentralized Intelligence

It is clear that the improvements in performance that were achieved were primarily due to the decentralized and adaptive nature of the FESL-DRE architecture. This is because contrary to centralized approaches that rely on global knowledge, which may be stale or insufficient, the proposed approach makes use of localized semantic reasoning and distributed coordination for environment representation.

This enables the following:

- Early detection of hazardous regions;
- Proactive rerouting decisions;
- Improved alignment with human behavioral dynamics.

As a result, FESL-DRE achieves a better balance between safety and efficiency, which is critical in real-world evacuation scenarios.

4.4.4. Summary

Overall, the results confirm that the proposed FESL-DRE framework outperforms both classical and adaptive centralized methods across key performance metrics. The combination of decentralized coordination, semantic reasoning, and human-centric modeling leads to more reliable and effective evacuation outcomes.

4.5. Resilience Analysis

4.5.1. Quantitative Results

Table 4 presents the resilience performance of the evaluated methods under varying levels of node failure.

Table 4. Resilience analysis.

	Failure Rate (%)	Method	Success Rate (%)	Avg. Evacuation Time (Steps)	Path Cost	Failed Nodes	Blocked Attempts
0	0.0	Centralized Dijkstra	57.00	8.31	36,174.00	0	267
1	0.0	Centralized A*	57.00	8.31	36,174.00	0	267
2	0.0	Centralized Adaptive A*	85.20	14.36	29,123.35	0	95
3	0.0	FESL-DRE (Proposed)	92.40	12.57	28,049.48	0	70
4	10.0	Centralized Dijkstra	62.36	16.64	63,868.00	14	204
5	10.0	Centralized A*	62.36	16.64	63,868.00	14	204
6	10.0	Centralized Adaptive A*	82.93	15.99	35,247.66	14	100
7	10.0	FESL-DRE (Proposed)	87.53	15.17	37,250.77	14	88
8	30.0	Centralized Dijkstra	66.67	15.86	56,494.00	42	137

Table 4. *Cont.*

	Failure Rate (%)	Method	Success Rate (%)	Avg. Evacuation Time (Steps)	Path Cost	Failed Nodes	Blocked Attempts
9	30.0	Centralized A*	66.67	15.86	56,494.00	42	137
10	30.0	Centralized Adaptive A*	82.26	16.21	34,364.07	42	81
11	30.0	FESL-DRE (Proposed)	87.10	15.48	39,142.85	42	31
12	50.0	Centralized Dijkstra	11.62	3.54	197.00	71	213
13	50.0	Centralized A*	11.62	3.54	197.00	71	213
14	50.0	Centralized Adaptive A*	11.62	3.04	90.46	71	213
15	50.0	FESL-DRE (Proposed)	11.62	2.61	25,934.24	71	787
16	70.0	Centralized Dijkstra	5.00	1.62	18.00	99	152
17	70.0	Centralized A*	5.00	1.62	18.00	99	152
18	70.0	Centralized Adaptive A*	5.00	1.62	9.42	99	152
19	70.0	FESL-DRE (Proposed)	5.00	1.62	16,133.15	99	948

4.5.2. Analysis of Moderate Failure Scenarios (0–30%)

The findings show that the suggested FESL-DRE framework is capable of maintaining high efficiency levels in the presence of moderate levels of failure. In case there is a failure level of 10%, the FESL-DRE model is able to achieve a success rate of 87.53%, which outperforms the adaptive A* algorithm using a centralized design. A similar trend is observed when the level of failure reaches 30%, where the FESL-DRE model continues to maintain a success rate of more than 87%. Additionally, the suggested model is able to maintain shorter evacuation times and lower numbers of blocked attempts compared to baseline models.

Figure 2 provides further evidence of the findings reported in Table 2 by showing the evacuation success rate with respect to the node failure rate. These findings suggest that the proposed FESL-DRE technique always performs better than other approaches in moderate levels of failure (up to 30%). In particular, FESL-DRE shows a higher success rate compared to the central adaptive A* technique, proving its ability to cope with infrastructure damage in an adaptive manner. Please note that, in Figure 2, the line of the centralized Dijkstra is overlapped with centralized A* since the two algorithm have the same performance.

At higher failure rates beyond 30%, all of the tested techniques exhibit poor performance because graph partitioning renders the evacuation routes infeasible. At such critical failure rates, the difference in performance between all techniques becomes very small, implying that success rates are mostly determined by the structure of the graphs themselves rather than the evacuation strategies employed. It is, however, clear from Figure 2 that FESL-DRE is more successful at moderate failure rates.

Figure 3 demonstrates the effect of node failures on evacuation efficiency by showing the variance in the mean time of evacuation depending on the failure rate. For moderate levels of failure (in the range of 0% to 30% failure), the introduced FESL-DRE outperforms the adaptive A* algorithm in terms of speed of evacuation. The reason for such performance is the decentralized process of coordination, which allows agents to make a decision according to current information and not wait for global information because of its high updating delay. With the increasing failure rate, all approaches have approximately equal time of evacuation due to a lower number of available paths. At high failure rates, an increase in the speed of evacuation is achieved owing to premature termination of agent mobility. The line of the centralized dijkstra in Figure 3 is overlapped with centralized A* since the two algorithm have the same performance.

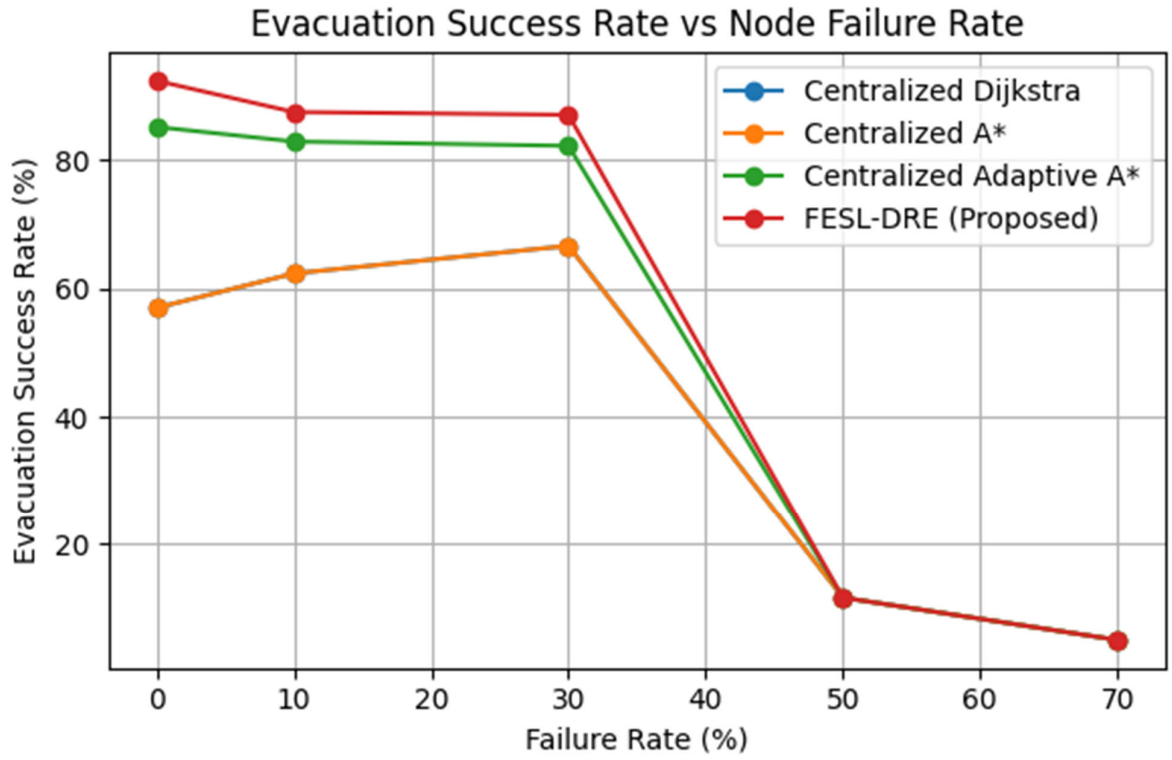


Figure 2. Evacuation success rate as a function of node failure rate. The proposed FESL-DRE framework consistently outperforms baseline methods under moderate failure conditions (0–30%), demonstrating superior resilience through decentralized coordination and adaptive routing. At higher failure rates, all methods exhibit performance degradation due to structural fragmentation of the environment.

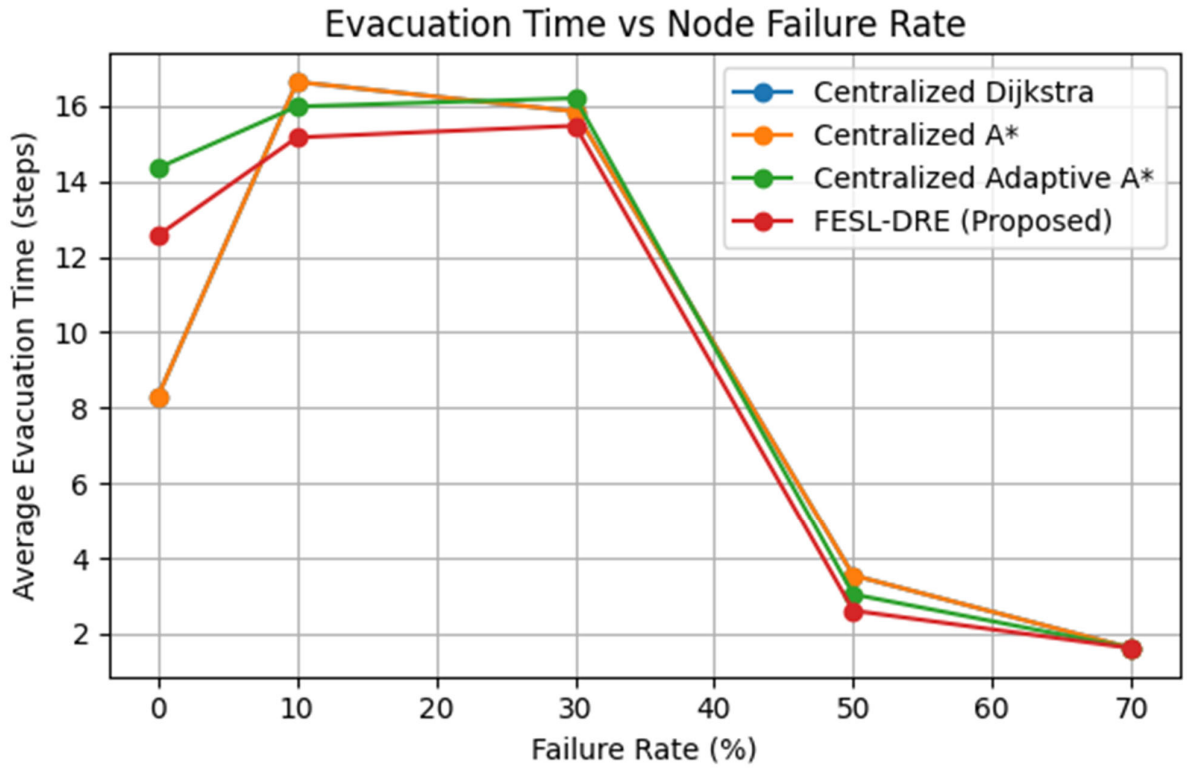


Figure 3. Average evacuation time as a function of node failure rate.

Figure 4 depicts another test of the proposed algorithm's robustness in terms of the number of blocked movements depending on different failure probabilities. From the data shown in Figure 4, it is evident that when the system faces medium-level failures ranging from 0% to 30%, the proposed algorithm gives a lower number of blocked attempts compared to other methods, which implies that the new approach performs better in predicting dangerous areas. The higher performance is a result of enhanced local decisions made possible by semantic knowledge and decentralized coordination.

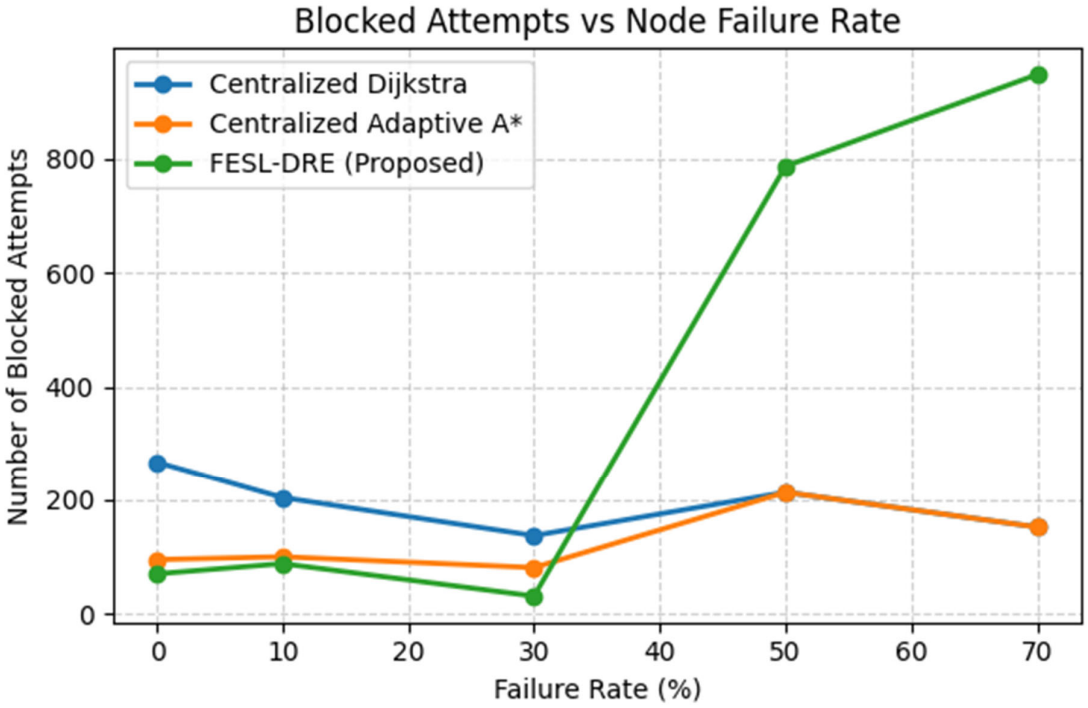


Figure 4. Number of blocked movement attempts as a function of node failure rate. Centralized A* is omitted because it produced results identical to those of Centralized Dijkstra under the adopted static distance-based cost function. The proposed FESL-DRE framework consistently reduces the number of blocked attempts under moderate failure conditions compared to baseline methods, indicating improved hazard awareness and more effective path selection. At higher failure rates, the increase in blocked attempts reflects the limited availability of feasible paths due to structural fragmentation of the environment.

4.5.3. Behavior Under Severe Failure (50–70%)

The results indicate that the proposed framework remains effective under moderate and substantial infrastructure disruptions. Up to a 30% node failure rate, FESL-DRE maintains a success rate exceeding 87%, demonstrating robust decentralized coordination despite partial communication loss and dynamic topology changes. However, the results also reveal a critical transition between 30% and 50% failure rates. At 50% node failures, network fragmentation becomes dominant, resulting in a significant reduction in evacuation success. When the failure rate reaches 70%, the communication graph becomes highly disconnected, limiting the availability of feasible evacuation paths and reducing the effectiveness of distributed coordination mechanisms.

These observations are consistent with the expected behavior of decentralized systems operating on sparse communication topologies. Although semantic reasoning, federated learning, and adaptive routing continue to function within connected network components, large-scale fragmentation restricts information propagation and route availability. Consequently, the results suggest that the proposed framework is resilient to moderate

and substantial failures but, like other distributed evacuation systems, ultimately remains constrained by the connectivity of the underlying communication network.

4.5.4. Summary

Overall, it can be concluded that the FESL-DRE paradigm does show better resilience in practical failure situations. This is especially true for moderate levels of failure where the use of decentralization and intelligence enables the system to respond effectively.

4.6. Communication Overhead Analysis

Effective communication is an essential requirement for a distributed evacuation system, particularly in limited-resource settings like edge nodes and IoT networks. In the case of the suggested FESL-DRE model, communication is achieved through a light-weighted gossip protocol, where nodes only communicate with their direct neighboring nodes. This eliminates the need to aggregate states globally, which simplifies communication significantly.

In terms of calculating communication cost, we used the number of communication events between neighboring nodes per node simulated. This is shown in Table 5.

Table 5. Communication overhead statistics of the proposed FESL-DRE framework.

Metric	Value
Average neighbor exchanges per node	3.67
Minimum neighbor exchanges	2.00
Maximum neighbor exchanges	4.00
Total communication exchanges	528.00

The results presented in Table 5 indicate that the communication burden imposed by the decentralized gossip protocol remains modest throughout the evacuation process. On average, each node exchanges information with approximately 3.67 neighboring nodes, while the maximum observed number of exchanges remains limited to four. This behavior reflects the localized nature of gossip-based communication, where information propagates incrementally through neighboring nodes rather than relying on network-wide broadcasts.

The total number of communication exchanges observed during the simulation was 528, demonstrating that the proposed framework can maintain distributed situational awareness without generating excessive communication traffic. Unlike centralized architectures that require continuous transmission of global state information, the proposed approach confines most communication to local neighborhoods. Consequently, communication overhead grows primarily with local connectivity rather than total network size, improving scalability in large deployments.

These findings suggest that the gossip-based coordination mechanism provides a practical balance between information dissemination and communication efficiency, enabling resilient decentralized operation while avoiding excessive messaging overhead.

4.7. Federated Behavioral Model Evaluation

To further clarify the contribution of the federated learning component, an additional experiment was conducted to evaluate the behavioral compliance model. The model was trained using behavioral samples generated from the same simulation environment used throughout the evacuation experiments. The dataset contained 1250 samples derived from agent behavior profiles, local hazard levels, crowd density measurements, distances to exits, and node connectivity information.

Table 6 summarizes the predictive performance of the federated behavioral model. The model achieved an accuracy of 66.00%, precision of 70.47%, recall of 82.93%, an F1-score of 76.19%, and an AUC of 67.11%. These results indicate that the model provides a useful behavioral signal for estimating route compliance. In particular, the high recall value demonstrates the model's ability to identify occupants who are likely to follow evacuation guidance, which is particularly important for human-aware route planning.

Table 6. Performance of the federated behavioral compliance model.

Metric	Value
Accuracy	0.6600
Precision	0.7047
Recall	0.8293
F1-score	0.7619
AUC	0.6711

Figure 5 illustrates the convergence behavior of the federated learning process over 30 communication rounds. Both accuracy and F1-score stabilize after approximately 20 rounds, indicating effective aggregation of local behavioral models and stable distributed learning. Although the model is not intended to serve as a standalone behavioral classifier, its output provides an estimate of occupant compliance that is directly incorporated into the routing cost function. Consequently, the federated learning component contributes to evacuation decision making by enabling adaptive routing that accounts for behavioral variability while preserving data privacy through decentralized training.

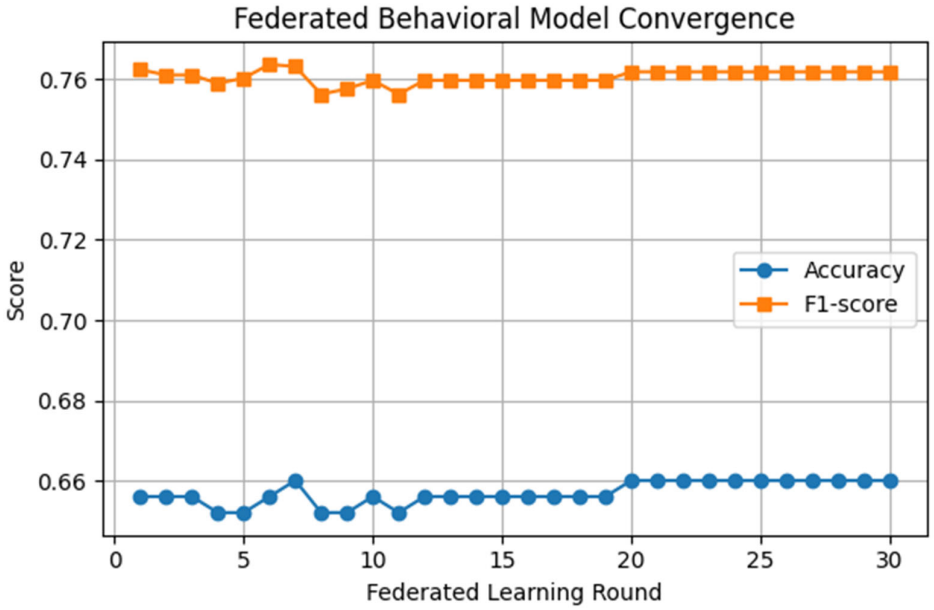


Figure 5. Convergence of the federated behavioral compliance model across communication rounds.

4.8. Statistical Stability Analysis

To assess the robustness of the reported results and address potential sensitivity to random initialization, the simulation was repeated across ten independent runs using different random seeds. Table 7 reports the mean and standard deviation of the primary performance metrics.

Table 7. Statistical stability analysis.

Method	Success Rate (%)	Avg. Evacuation Time (Steps)	Path Cost	Reroutes	Blocked Attempts
Centralized A*	58.58 ± 2.71	8.29 ± 0.17	37,891.40 ± 2678.17	5503.70 ± 240.32	273.60 ± 15.04
Centralized Adaptive A*	86.56 ± 1.98	13.94 ± 0.58	29,391.45 ± 1726.07	6255.50 ± 256.47	91.80 ± 10.21
Centralized Dijkstra	58.58 ± 2.71	8.29 ± 0.17	37,891.40 ± 2678.17	5503.70 ± 240.32	273.60 ± 15.04
FESL-DRE (Proposed)	90.74 ± 1.51	12.46 ± 0.54	27,267.76 ± 1732.96	5863.20 ± 278.38	88.50 ± 9.20

The results demonstrate consistent performance across multiple runs. FESL-DRE achieved the highest average evacuation success rate (90.74% ± 1.51%), outperforming Centralized Adaptive A* (86.56% ± 1.98%) and substantially exceeding both Centralized Dijkstra and Centralized A* (58.58% ± 2.71%). In addition, FESL-DRE maintained lower path costs and fewer blocked attempts than the baseline approaches while exhibiting relatively small standard deviations. These findings indicate that the observed performance improvements are not dependent on a specific random seed and that the proposed framework maintains stable behavior under varying simulation conditions.

4.9. Discussion

According to the experimental findings, the suggested FESL-DRE architecture proves to be an efficient and reliable solution for evacuations within partially degraded and dynamically changing environments. Thanks to the application of decentralized cooperation mechanisms, semantic reasoning, and adaptive routing, the proposed approach outperforms classical adaptive and centrally coordinated approaches in multiple ways.

First, FESL-DRE exhibits significantly greater evacuation success rates compared to other architectures, which is achieved regardless of the degree of environmental degradation. Contrary to centrally coordinated approaches, which heavily rely on outdated and insufficiently detailed data concerning the status of the environment, the proposed architecture leverages distributed interactions between agents, thus creating a more up-to-date and reliable map that provides additional insights into the agent's decision-making process and increases the evacuation success rate even under partial environmental degradation.

Moreover, besides being effective, FESL-DRE is more efficient than alternative approaches as it requires less time and path cost to evacuate all agents. Due to its ability to make routing decisions adaptively and based on the current state of the environment, FESL-DRE is able to avoid hazards more successfully. However, despite being faster in some cases, classical approaches are unable to guarantee high success rates because of dangerous routing decisions.

Finally, analysis of blocked attempts reveals one more advantage of the proposed framework—it produces fewer of them, which indicates better path quality and increased awareness of potential dangers. Such an ability proves to be very useful while working with a highly dynamic and unpredictable environment, because any errors during movement may lead to disastrous consequences.

Based on the resilience analysis, the performance benefits of the proposed framework can be observed when failures occur moderately (up to around 30% of nodes). In such a case, FESL-DRE outperforms both baseline approaches due to the ability to operate in the partially disrupted network infrastructure. Beyond that range, performance of all approaches drops dramatically as the graph becomes fragmented. This finding shows that beyond some point, feasibility of evacuation depends more on connectivity in the infrastructure than the routing method used. It should be noted that despite the fact that algorithms can provide performance gains, severe disruptions in the infrastructure remain a critical issue that cannot be solved only using routing algorithms.

Considering scalability issues, the results of the communication overhead analysis suggest that the proposed framework works efficiently in the decentralized setup. Avoiding excessive communication by limiting it to the neighboring areas enables scaling up the algorithm to large systems. Such a feature makes the system especially interesting from the point of view of real-life applications in which it needs to work with edge devices.

However, some limitations of the approach should be noted. First, the experiment is conducted using simulations that do not accurately reflect real human behavior but are widely used in evacuation research studies. Second, behavioral models that are implemented in the simulation are quite diverse and still simplified abstractions that might miss some psychological aspects of human behavior. Third, communication between local areas is assumed to happen reliably, while in real-life scenarios it could face various problems related to latency, loss, or other limitations of hardware infrastructure. An important observation from the resilience analysis is the existence of a connectivity threshold beyond which decentralized coordination becomes significantly degraded. While FESL-DRE maintains strong performance under moderate and substantial node failures, severe network fragmentation reduces the effectiveness of information exchange and adaptive routing. Future work will investigate recovery strategies such as mobile relay nodes, temporary communication bridges, and opportunistic peer-to-peer forwarding mechanisms to improve operation under extreme failure conditions. An additional limitation of the present study is that the performance evaluation primarily compares the proposed framework against established centralized routing algorithms, including Dijkstra, A*, and Adaptive A*. Although these methods provide well-known reference points for evacuation path planning, future work should include comparisons with emerging decentralized and multi-agent evacuation approaches to further assess the relative advantages and trade-offs of the proposed architecture.

In future work, we will focus on addressing these limitations by considering more realistic behavior models, expanding the framework for heterogeneous and irregular buildings, and implementing more advanced privacy-preserving mechanisms and communication strategies.

The current evaluation is based on a synthetic graph-based environment and therefore does not fully capture the architectural complexity of real buildings, including corridors, rooms, staircases, multi-floor structures, and other layout-specific constraints. Furthermore, the experiments were conducted using a single topology, which limits the ability to assess generalization across diverse building configurations. While the chosen environment enables controlled evaluation of decentralized coordination, semantic reasoning, federated learning, and adaptive routing under dynamic hazards, additional validation using multiple floorplans, digital twins, and realistic evacuation simulators is necessary. Consequently, the reported results should be interpreted as evidence of feasibility under controlled conditions rather than proof of universal applicability across all building types.

5. Conclusions and Future Work

In this study, a new indoor evacuation framework called Federated Edge-Semantic Learning for Decentralized Resilient Evacuation (FESL-DRE) is proposed. Using decentralization and autonomy in edge nodes, this new model overcomes some limitations inherent to traditional centralized models of evacuation. This work combines the principles of edge computing, semantic learning, federated learning, and gossip communications into one system that takes advantage of the knowledge and adaptiveness of evacuating agents.

According to the experimental evidence presented, the proposed FESL-DRE framework outperforms both traditional and centralized adaptive systems in all considered measures. Thus, it obtains the best success rates of evacuation attempts, the lowest number

of blocked attempts, and optimal routing. In terms of resilience to node failures, the new system demonstrates superior performance even at moderate levels of damage. Finally, the analysis of communication overhead shows that the framework can enable efficient information sharing while minimizing network usage.

Several limitations should be acknowledged. First, the evaluation relies on a synthetic graph-based simulation and therefore does not fully represent the geometric and operational complexity of real buildings. Second, the behavioral models are simplified abstractions intended to evaluate routing robustness rather than comprehensive representations of human decision making. Third, the privacy-preserving component is evaluated conceptually and does not include implementation-specific cryptographic benchmarking. Consequently, the reported results should be interpreted as evidence of feasibility within a controlled simulation environment. Furthermore, the resilience analysis demonstrates that the proposed framework maintains effective evacuation coordination under moderate and substantial node failures, although extreme network fragmentation remains a challenging scenario for future investigation. Finally, some assumptions made for communication protocols might not hold true in reality.

Future work will focus on such directions as the development of new behavioral models based on realistic decisions of occupants, validation of the system using actual data or smart building platforms, assessment of various privacy-preserving technologies like zero-knowledge proof and secure multi-party computation for their efficiency, and scalability tests. Moreover, future work will investigate practical implementations of zero-knowledge proof protocols and evaluate their impact on latency, energy consumption, and large-scale deployment. Future work will also investigate benchmarking the proposed framework against state-of-the-art decentralized and multi-agent evacuation systems under standardized evaluation settings. Future work will evaluate the proposed framework on multiple building topologies, including multi-floor structures, realistic architectural layouts, and digital-twin-based evacuation environments to assess generalization and deployment readiness.

Overall, the proposed FESL-DRE framework demonstrates the feasibility of integrating semantic reasoning, federated learning, gossip-based coordination, and adaptive routing within a decentralized evacuation architecture. The simulation results indicate that the framework can improve evacuation performance and resilience under controlled dynamic hazard scenarios. However, the current evaluation is limited to a synthetic graph-based environment and should not be interpreted as evidence of deployment readiness. Additional validation using realistic building layouts, digital twins, evacuation simulators, and real-world smart building infrastructures is required before practical adoption. Nevertheless, the proposed framework provides a promising foundation for future research on decentralized and resilient evacuation systems.

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References

1. Kim, H.; Haam, S.; Yoo, M.; Song, W.S. Algorithmic Evaluation of Fire Evacuation Efficiency Under Dynamic Crowd and Smoke Conditions. *Fire* **2026**, *9*, 32. [CrossRef]
2. Bhat, R.; Rao, P.K.; Kamath, C.R.; Tandon, V.; Vizzapu, P. Comparative analysis of Bellman-Ford and Dijkstra's algorithms for optimal evacuation route planning in multi-floor buildings. *Cogent Eng.* **2024**, *11*, 2319394.
3. Mohammadiounotikandi, A.; Fakhruldeen, H.F.; Meqdad, M.N.; Ibrahim, B.F.; Jafari Navimipour, N.; Unal, M. A fire evacuation and control system in smart buildings based on the internet of things and a hybrid intelligent algorithm. *Fire* **2023**, *6*, 171. [CrossRef]
4. Zhang, Z.; Tan, L.; Tiong, R.L. Fire emergency management of large shopping malls: IoT-based evacuee tracking and dynamic path optimization. *Alex. Eng. J.* **2024**, *107*, 652–664.
5. Liu, L.; Zhang, H.; Shi, J.; Geng, J. Real-time evacuation route optimization in the fire scenarios of cruise ships. *Simul. Model. Pract. Theory* **2023**, *129*, 102843. [CrossRef]
6. Haam, S.; Kim, H.; Yoo, M.; Song, W.S. Optimal additional evacuation route analysis in deep underground station structures using Dijkstra's algorithm. *Dev. Built Environ.* **2025**, *24*, 100784.
7. Shih, G.R.; Tsai, P.H. Safest-path planning approach for indoor fire evacuation. *Int. J. Disaster Risk Reduct.* **2023**, *93*, 103760. [CrossRef]
8. Li, X.; Liang, X.; Wang, X.; Wang, R.; Shu, L.; Xu, W. Deep reinforcement learning for optimal rescue path planning in uncertain and complex urban pluvial flood scenarios. *Appl. Soft Comput.* **2023**, *144*, 110543. [CrossRef]
9. Omidbeyk, S.; Ghavami, S.M. Multi-agent simulation of population evacuation during dynamic fire using reinforcement learning based on integration of geographic information systems and building information modeling. *J. Build. Eng.* **2025**, *111*, 113035. [CrossRef]
10. Zhang, Z.; Tan, L.; Tiong, R.L. Evacuation path optimization algorithm for grassland fires based on SAR imagery and intelligent optimization. *Front. Environ. Sci.* **2025**, *13*, 1522933. [CrossRef]
11. Zhang, Y.; Ding, Y.; Chraibi, M.; Huang, X. Multi-scale analysis of fire and evacuation drill in a multi-functional university high-rise building. *Dev. Built Environ.* **2025**, *21*, 100626.
12. Xu, N.; Lovreglio, R.; Kuligowski, E.D.; Cova, T.J.; Nilsson, D.; Zhao, X. Predicting and assessing wildfire evacuation decision-making using machine learning: Findings from the 2019 kincade fire. *Fire Technol.* **2023**, *59*, 793–825. [CrossRef]
13. Lovreglio, R.; Ronchi, E.; Nilsson, D. An Evacuation Decision Model based on perceived risk, social influence and behav-ioural uncertainty. *Simul. Model. Pract. Theory* **2016**, *66*, 226–242.
14. Ronchi, E.; Nilsson, D. Fire evacuation in high-rise buildings: A review of human behaviour and modelling research. *Fire Sci. Rev.* **2013**, *2*, 7. [CrossRef]
15. Nguyen, V.Q.; Vu, H.T.; Nguyen, V.H.; Kim, K. A smart evacuation guidance system for large buildings. *Electronics* **2022**, *11*, 2938. [CrossRef]
16. Senanayake, G.P.; Kieu, M.; Zou, Y.; Dirks, K. Agent-based simulation for pedestrian evacuation: A systematic literature review. *Int. J. Disaster Risk Reduct.* **2024**, *111*, 104705. [CrossRef]
17. Lovreglio, R.; Ronchi, E.; Nilsson, D. A model of the decision-making process during pre-evacuation. *Fire Saf. J.* **2015**, *78*, 168–179. [CrossRef]
18. Huang, Q.; Si, Y.; Wang, H. Fire Evacuation Path Planning Based on Improved MADDPG (Multi-Agent Deep Deterministic Policy Gradient) Algorithm. *Int. J. Adv. Comput. Sci. Appl.* **2024**, *15*, 387. [CrossRef]
19. Saini, K.; Kalra, S.; Sood, S.K. Disaster emergency response framework for smart buildings. *Future Gener. Comput. Syst.* **2022**, *131*, 106–120. [CrossRef]

20. Guman, J.; O'Brien, J.C.; Pondoc, C.; Kochenderfer, M.J. PyroRL: A reinforcement learning environment for wildfire evacua-tion. *J. Open Source Softw.* **2024**, *9*, 6739.
21. Abreha, H.G.; Hayajneh, M.; Serhani, M.A. Federated learning in edge computing: A systematic survey. *Sensors* **2022**, *22*, 450. [CrossRef] [PubMed]
22. Putra, K.T.; Chen, H.C.; Prayitno Ogiela, M.R.; Chou, C.L.; Weng, C.E.; Shae, Z.Y. Federated compressed learning edge computing framework with ensuring data privacy for PM2. 5 prediction in smart city sensing applications. *Sensors* **2021**, *21*, 4586. [PubMed]
23. Rajagopal, S.M.; Supriya, M.; Buyya, R. FedSDM: Federated learning based smart decision making module for ECG data in IoT integrated Edge–Fog–Cloud computing environments. *Internet Things* **2023**, *22*, 100784.
24. Gooi, H.B.; Wang, T.; Tang, Y. Edge intelligence for smart grid: A survey on application potentials. *CSEE J. Power Energy Syst.* **2023**, *9*, 1623–1640. [CrossRef]
25. Li, T.; Sahu, A.K.; Talwalkar, A.; Smith, V. Federated learning: Challenges, methods, and future directions. *IEEE Signal Process. Mag.* **2020**, *37*, 50–60. [CrossRef]
26. Li, G.; Wang, C.; Wang, H. Unreachable Peers Communication Scheme in Decentralized Networks Based on Peer-to-Peer Overlay Approaches. *Future Internet* **2022**, *14*, 290.
27. Singh, J.D.; Singh, N.; Adhikari, M.; Singh, A.K. Decentralized gossip-assisted deep learning model training for re-source-constraint edge devices. *IEEE Trans. Comput. Soc. Syst.* **2024**, *12*, 5526–5535.
28. Altoaimy, L.; Alromih, A.; Al-Megren, S.; Al-Hudhud, G.; Kurdi, H.; Youcef-Toumi, K. Context-aware gossip-based protocol for Internet of Things applications. *Sensors* **2018**, *18*, 2233. [PubMed]
29. Zhang, K.; Yang, Z.; Başar, T. Multi-agent reinforcement learning: A selective overview of theories and algorithms. In *Handbook of Reinforcement Learning and Control*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 321–384.
30. Bandar, A. A Review of Resilient IoT Systems: Trends, Challenges, and Future Directions. *Appl. Sci.* **2026**, *16*, 2079. [CrossRef]
31. Alirezaie, M.; Kiselev, A.; Längkvist, M.; Klügl, F.; Loutfi, A. An ontology-based reasoning framework for querying satel-lite images for disaster monitoring. *Sensors* **2017**, *17*, 2545. [PubMed]
32. Endler, M.; Briot, J.P.; de Almeida, V.P.; Dos Reis, R.; Silva e Silva, F. Stream-Based Reasoning for IoT Applica-tions—Proposal of Architecture and Analysis of Challenges. *Int. J. Semant. Comput.* **2017**, *11*, 325–344.
33. Pang, B.; Shi, J.; Jiang, L.; Pan, Z. A semantic approach to dynamic path planning for fire evacuation through BIM and IoT data integration. *Adv. Civ. Eng.* **2024**, *2024*, 8839865. [CrossRef]
34. Li, H.; Ge, L.; Tian, L. Survey: Federated learning data security and privacy-preserving in edge-Internet of Things. *Artif. Intell. Rev.* **2024**, *57*, 130.
35. Chang, Z.; Liu, S.; Xiong, X.; Cai, Z.; Tu, G. A survey of recent advances in edge-computing-powered artificial intelligence of things. *IEEE Internet Things J.* **2021**, *8*, 13849–13875.
36. Su, H.; Zhong, Y.D.; Chow, J.Y.; Dey, B.; Jin, L. EMVLight: A multi-agent reinforcement learning framework for an emergency vehicle decentralized routing and traffic signal control system. *Transp. Res. Part C Emerg. Technol.* **2023**, *146*, 103955.
37. Ma, Y.; Gelenbe, E.; Liu, K. Impact of IoT System imperfections and passenger errors on cruise ship evacuation delay. *Sensors* **2024**, *24*, 1850. [CrossRef] [PubMed]

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