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Agent-Based Modeling and Generative AI for Disaster Response Simulation in Smart Cities

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Abstract: Disaster response in smart cities requires rapid, adaptive, and data-driven decision-making to reduce casualties, infrastructure damage, and service disruption. Urban areas such as Medellín, Colombia, face complex disaster-response challenges due to dense settlements, varied topography, mobility constraints, and exposure to hazards such as floods, landslides, and urban emergencies. This study proposes an integrated agent-based modeling and generative artificial intelligence framework for disaster response simulation in smart cities. The proposed framework models the behavior and interaction of multiple urban agents, including residents, emergency responders, vehicles, hospitals, shelters, transportation networks, and command centers, to simulate disaster scenarios and evaluate response strategies. Agent-based modeling is used to represent individual and institutional decision-making during disaster events, such as evacuation behavior, route selection, emergency dispatch, shelter allocation, and resource distribution. Generative AI is integrated to enhance scenario generation, simulate dynamic emergency narratives, generate synthetic disaster conditions, and support decision-making recommendations under uncertain and rapidly changing environments. The Medellín case context is used to demonstrate how the proposed model can support disaster preparedness, emergency coordination, and smart city resilience planning. The expected results show that combining agent-based modeling with generative AI can improve disaster-response simulation by enabling more flexible scenario exploration, realistic behavioral modeling, and adaptive decision support. This study contributes to the development of intelligent disaster-management systems by bridging simulation modeling, artificial intelligence, and smart city governance. The proposed framework can assist policymakers, urban planners, emergency agencies, and smart city managers in evaluating evacuation plans, optimizing emergency resources, identifying vulnerable areas, and improving disaster-response readiness. Overall, this study highlights the potential of agent-based modeling and generative AI as complementary tools for building more resilient, responsive, and human-centered smart cities.

Keywords: Agent-Based Modeling; Generative AI; Disaster Response; Smart Cities; Emergency Simulation; Urban Resilience.

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INTRODUCTION

Smart cities are increasingly expected to respond not only to routine urban management problems[1], but also to complex emergency situations such as floods, landslides, fires, traffic disruption, infrastructure failure, and public-safety incidents [2]. In this context, disaster response requires rapid coordination among citizens[3], emergency responders[4], hospitals[5], shelters[6], transportation systems[7], communication networks[8], and government command centers[9]. Medellín, Colombia, provides a relevant case for this study because the city combines smart city development with complex disaster-risk conditions, including steep topography, dense hillside settlements, urban mobility constraints, and exposure to floods and landslides. The city's disaster risk management agency, DAGRD, is responsible for coordinating risk knowledge, risk reduction, and disaster management to protect life, property, and the environment.

Medellín's disaster-risk context is closely related to the interaction between urbanization, climate variability, inequality, and territorial occupation. The city's Municipal Disaster Risk Management Plan identifies disaster risk as an increasing reality influenced by climate variability, accelerated urbanization, and unequal patterns of land occupation. This makes disaster response in Medellín not only a technical issue, but also a socio-spatial challenge. Communities located in hillside and informal settlements may experience higher vulnerability because of unstable terrain, limited infrastructure, and exposure to intense rainfall. Recent reporting on Comuna 8, a hillside settlement in Medellín, highlights local vulnerability to landslides and floods, while also showing the importance of community-based adaptation efforts such as rainwater harvesting, reforestation, and eco-gardens[10].

Recent disaster events also demonstrate the urgency of improving response simulation and preparedness. In 2025, a landslide affected Medellín and nearby Bello after heavy rainfall, causing deaths, missing persons, home evacuations, and temporary shelter needs [11]. Such events show that emergency response in urban environments requires more than early warning[12]; it requires the ability to anticipate how people, vehicles, responders, shelters, roads, and communication systems may behave under uncertain and rapidly changing conditions. Therefore, simulation-based decision support becomes important for testing disaster-response strategies before real emergencies occur.

Agent-Based Modeling is one of the most useful approaches for disaster-response simulation because it represents individual and organizational actors as autonomous agents with different behaviors, goals, constraints, and interactions [13]. In disaster response, agents may represent residents, pedestrians, emergency responders, ambulance units, police officers, firefighters, vehicles, hospitals, shelters, and coordination centers[14]. Each agent can be assigned rules related to movement, decision-making, communication, evacuation route choice, risk perception, cooperation, or resource allocation. A recent systematic review on agent-based pedestrian evacuation simulation found that ABM is promising for realistically simulating human behavior and interaction during emergencies, although challenges remain in calibration, validation, computational complexity, and behavioral realism.

The strength of agent-based modeling lies in its ability to represent bottom-up dynamics. Instead of assuming that all citizens behave in the same way[14], ABM can simulate differences in age, mobility, location, risk awareness, social connection, access to information, and willingness to evacuate. This is especially important in a city such as

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Medellín, where urban risk is shaped by geography, infrastructure, social vulnerability, and community-level response capacity. Agent-based simulation can also be used to evaluate "what-if" scenarios, such as blocked roads, delayed emergency dispatch, shelter overcrowding, rainfall escalation, communication failure, or alternative evacuation instructions. In short, ABM allows researchers and city managers to test disaster-response strategies in a virtual environment before applying them in the real city[15].

However, conventional agent-based models also have limitations[16]. Many ABM systems rely on predefined rules that may be too rigid to represent dynamic and uncertain disaster conditions. Human behavior during emergencies is influenced by fear, limited information, social influence, family responsibility, trust in authorities, and rapidly changing environmental conditions. A systematic review of agent-based evacuation models notes that many models still represent social interaction and communication in simplified ways, even though communication and group dynamics strongly influence evacuation behavior. This indicates that disaster-response simulation requires more adaptive and context-sensitive modeling approaches.

Generative Artificial Intelligence offers a new opportunity to enhance disaster-response simulation [17]. Generative AI can support the creation of synthetic disaster scenarios, emergency narratives, communication messages, alternative response plans, and dynamic behavioral assumptions. In smart city disaster simulation, generative AI can help generate multiple plausible scenarios based on rainfall intensity, landslide exposure, road accessibility, population distribution, shelter capacity, hospital availability, and emergency-resource constraints. Recent research on generative AI for disaster simulation shows that generative models can be used to pre-enact urban multi-hazard scenarios, visualize disaster impacts, and support climate-adaptive resilience planning[18].

When combined with ABM, generative AI can make disaster simulation more flexible and adaptive. ABM provides the computational structure for simulating agent behavior and interactions, while generative AI can enrich scenario generation, generate response alternatives, simulate communication flows, and summarize decision-support insights. For example, in a Medellín landslide scenario, ABM can simulate how residents evacuate from hillside neighborhoods[19], how emergency vehicles move through congested roads, and how shelters receive displaced populations. Generative AI can then generate alternative response scenarios, produce human-readable explanations, suggest resource-allocation strategies, and create emergency communication templates for different stakeholder groups.

Despite the potential of ABM and generative AI, several research gaps remain. First, many disaster-response simulations still focus on physical movement or evacuation flow, while less attention is given to communication, coordination, and adaptive decision-making among multiple urban agents. Second, existing smart city disaster models often rely on static scenarios, whereas real disasters evolve dynamically[20]. Third, generative AI has been increasingly explored for disaster communication and scenario generation, but its integration with agent-based simulation remains underdeveloped. Fourth, limited research has contextualized this integration in Latin American smart cities, particularly in Medellín, where disaster risk, urban innovation, social vulnerability, and community adaptation intersect.

To address these gaps, this article proposes an Agent-Based Modeling and Generative AI framework for disaster response simulation in smart cities, with Medellín, Colombia, as the

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research context. The proposed framework integrates urban agents, hazard scenarios, transportation networks, emergency facilities, shelters, communication channels, and generative AI-based scenario support. The model is designed to simulate disaster-response processes such as evacuation behavior, emergency dispatch, route selection, shelter allocation, hospital coordination, and resource distribution. By combining ABM and generative AI, the framework aims to support more realistic, adaptive, and explainable disaster-response simulation[21].

The main contribution of this study is threefold. First, it develops an integrated framework that combines agent-based modeling and generative AI for smart city disaster-response simulation. Second, it contextualizes the framework in Medellín's urban disaster-risk environment, particularly in relation to landslides, floods, mobility constraints, and vulnerable hillside communities. Third, it demonstrates how simulation outputs can support decision-making for emergency agencies, urban planners, policymakers, and community-based disaster-risk actors. Overall, this study argues that the integration of ABM and generative AI can help transform disaster response from reactive emergency management into proactive, scenario-based, and intelligent urban resilience planning.

METHODS

This study uses a simulation-based research design to develop an integrated framework combining Agent-Based Modeling and Generative Artificial Intelligence for disaster response simulation in smart cities. The research was conducted using Medellín, Colombia, as the case context because the city has complex urban characteristics, including mountainous topography, dense settlements, disaster-prone hillside communities, transportation constraints, and exposure to landslides and floods.

The proposed method is designed to simulate disaster-response processes involving residents, emergency responders, shelters, hospitals, transportation networks, and command centers. Agent-Based Modeling is used to represent the behavior and interaction of urban actors during disaster events, while Generative AI is used to support scenario generation, emergency communication simulation, adaptive response planning, and explanation of simulation results.

The methodological stages consist of:

1. Urban disaster context identification.
2. Agent and environment modeling.
3. Disaster scenario construction.
4. Agent-Based Modeling simulation.
5. Generative AI-based scenario and response generation.
6. Disaster-response performance evaluation.
7. Decision-support recommendation.

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Study Area

The study focuses on Medellín, Colombia, as a representative smart city context in Latin America. Medellín is characterized by a valley-based urban structure surrounded by steep hillsides, making several urban areas vulnerable to landslides, floods, and mobility disruption during extreme rainfall events. The simulation environment represents selected urban zones, including residential areas, main roads, emergency-service facilities, hospitals, shelters, and high-risk zones.

The simulated study area includes the following spatial components:

Table 1. Spatial components used in the simulation

Spatial Component	Description	Function in Simulation
Residential zones	Urban communities and hillside settlements	Origin of resident agents
Road network	Main roads, local roads, and evacuation routes	Movement path for residents and responders
Risk zones	Landslide-prone and flood-prone areas	Disaster impact area
Shelters	Temporary evacuation locations	Destination for evacuees
Hospitals	Emergency medical facilities	Treatment destination for injured agents
Emergency stations	Fire, ambulance, and rescue units	Origin of responder agents
Command center	Disaster-response coordination unit	Controls dispatch and resource allocation

Data Sources and Variables

The simulation uses spatial, demographic, hazard, mobility, and emergency-response variables. In this study, the dataset may be obtained from open geospatial data, municipal disaster-risk records, smart city sensor data, transportation network data, and simulated emergency-response parameters. When real-time data are not available, synthetic data are generated to represent plausible disaster conditions in Medellín.

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Table 2. Data variables used in the proposed model

Data Category	Variables	Function
Spatial data	Road network, building location, slope, elevation, land use	Defines simulation environment
Demographic data	Population density, age group, mobility limitation	Defines resident-agent characteristics
Hazard data	Rainfall intensity, flood depth, landslide probability	Defines disaster scenario
Mobility data	Road capacity, travel speed, congestion level, blocked road	Simulates evacuation and response movement
Emergency data	Number of responders, ambulances, shelters, hospital capacity	Simulates response capacity
Communication data	Alert delivery time, warning coverage, message clarity	Simulates public warning effectiveness

The general input data are represented as:

$$X = \{S, D, H, M, E, C\}$$

where Srepresents spatial data, Drepresents demographic data, Hrepresents hazard data, Mrepresents mobility data, Erepresents emergency-response data, and Crepresents communication data.

Agent-Based Modeling Framework

The Agent-Based Modeling component represents disaster response as the interaction of autonomous agents within an urban environment. Each agent has attributes, behavioral rules, decision logic, and interaction patterns. The simulation includes five main agent types: resident agents, responder agents, vehicle agents, shelter agents, and command-center agents.

Table 3. Agent types and behavioral characteristics

Agent Type	Main Attributes	Behavior in Simulation
Resident agent	Location, age, mobility, risk perception, family dependency	Receives warning, decides whether to evacuate, selects route
Responder agent	Station location, response capacity, rescue priority	Moves to affected areas, rescues victims, supports evacuation
Vehicle agent	Speed, capacity, route, congestion sensitivity	Transports responders, evacuees, and injured residents
Shelter agent	Location, capacity, occupancy level	Receives evacuees and updates available capacity
Hospital agent	Location, bed capacity, emergency capacity	Receives injured agents and updates treatment availability
Command-center agent	Information access, resource control, decision rules	Coordinates alert, dispatch, routing, and resource allocation

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Each agent follows rule-based behavior. For example, resident agents decide whether to evacuate based on perceived risk, warning reception, distance to hazard, mobility condition, and social influence.

The evacuation decision probability is formulated as:

$$P_{evac} = \alpha R + \beta W + \gamma S_i - \delta D_s - \mu M_l$$

where $P_{evac}$is the probability of evacuation, $R$is perceived risk, $W$is warning reception, $S_i$is social influence, $D_s$is distance to shelter, $M_l$is mobility limitation, and $\alpha, \beta, \gamma, \delta,$and $\mu$are weighting parameters.

Disaster Scenario Design

The disaster scenarios are designed to represent plausible emergency conditions in Medellín. Three main scenarios are simulated: moderate flood, severe landslide, and combined flood-landslide emergency. These scenarios are used to evaluate the ability of the proposed framework to support disaster-response planning.

Table 4. Disaster scenarios used in the simulation

Scenario	Hazard Condition	Main Impact
Scenario 1: Moderate flood	Heavy rainfall causing localized flooding	Road disruption and delayed evacuation
Scenario 2: Severe landslide	Slope failure in hillside settlements	Residential damage and trapped residents
Scenario 3: Combined hazard	Flood and landslide occur simultaneously	Multi-zone evacuation and resource overload

Each scenario includes variations in rainfall intensity, affected population, road blockage, warning delay, shelter capacity, and emergency-response availability.

The disaster impact level is calculated as:

$$DI = w_1 H_i + w_2 P_e + w_3 I_d + w_4 R_b$$

where $DI$is disaster impact, $H_i$is hazard intensity, $P_e$is exposed population, $I_d$is infrastructure damage, $R_b$is road blockage, and $w_1, w_2, w_3,$and $w_4$are weighting parameters.

Generative AI Integration

Generative AI is integrated into the simulation framework to support adaptive scenario generation, emergency communication, and decision-support explanation. In this study, Generative AI does not replace the agent-based simulation engine. Instead, it functions as an intelligent support layer that enriches simulation inputs and interprets simulation outputs.

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The Generative AI component performs four main functions:

1. Scenario generation

   Generative AI produces alternative disaster scenarios based on rainfall intensity, landslide probability, population exposure, road accessibility, and emergency-resource availability.

2. Behavioral variation generation

   Generative AI creates plausible behavioral profiles for residents, such as early evacuation, delayed evacuation, refusal to evacuate, family-based evacuation, and mobility-limited evacuation.

3. Emergency communication generation

   Generative AI generates warning messages, evacuation instructions, responder briefings, and public communication templates.

4. Simulation result explanation

   Generative AI translates numerical simulation results into human-readable decision-support summaries for emergency managers and policymakers.

Table 5. Role of Generative AI in the proposed framework

Function	Input	Output
Scenario generation	Hazard data, spatial data, exposure level	Alternative disaster scenarios
Behavior generation	Demographic profile, risk perception, warning condition	Agent behavior variations
Communication generation	Hazard type, target group, urgency level	Warning and evacuation messages
Decision explanation	Simulation results, performance metrics	Response recommendation summary

The Generative AI output is validated using predefined disaster-management rules to ensure that generated scenarios and recommendations remain realistic, safe, and relevant.

Simulation Process

The simulation process begins by initializing the urban environment, agents, hazard conditions, and emergency-response resources. Once a disaster scenario is activated, the model updates the status of roads, shelters, hospitals, and affected population zones. Resident agents receive warnings and decide whether to evacuate. Responder agents are dispatched by the command-center agent according to emergency priority.

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The simulation process follows these steps:

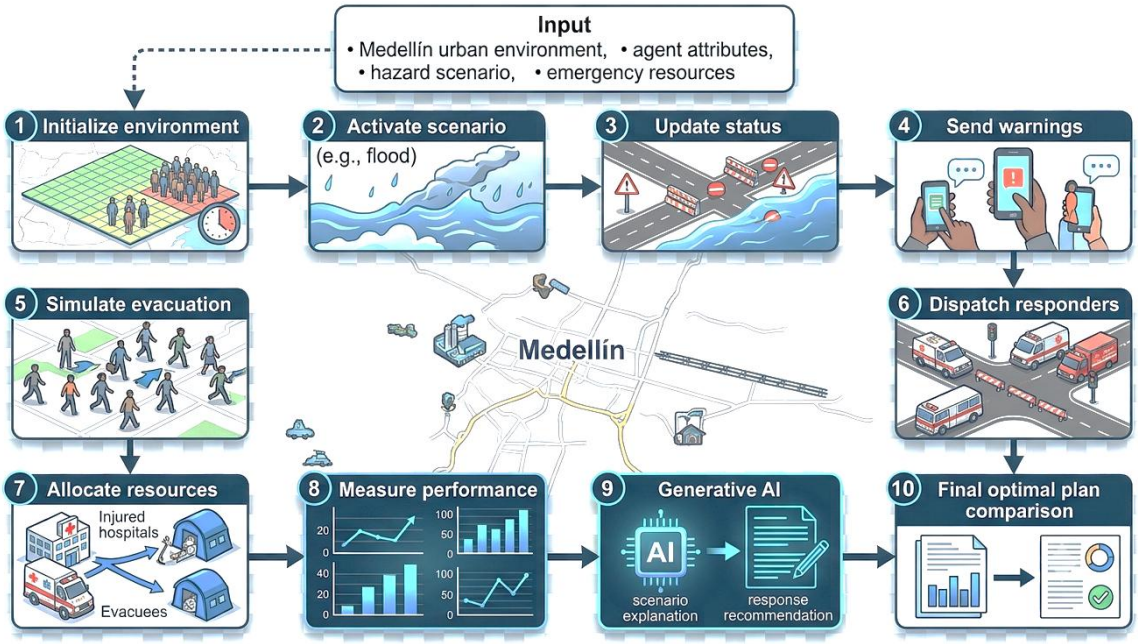


Figure 1. The Simulation process

Output: Evacuation time, casualty risk, shelter occupancy, responder workload, route congestion, and decision-support recommendation

Disaster Response Strategies

The study compares three response strategies to evaluate the contribution of smart coordination and Generative AI-supported simulation.

Table 6. Disaster response strategies evaluated

Strategy	**Description**
Baseline response	Standard response without simulation-based optimization
ABM-based response	Response planning based on agent-based simulation results
ABM + Generative AI response	Response planning supported by ABM simulation and Generative AI-generated scenarios, communication, and recommendations

The comparison allows the study to evaluate whether integrating Generative AI into agent-based simulation can improve response planning, evacuation efficiency, resource allocation, and communication effectiveness.

Evaluation Metrics

The model is evaluated using disaster-response performance indicators. These metrics are used to assess how effectively each strategy supports emergency response.

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Table 7. Evaluation metrics

Metric	Description
Average evacuation time	Time required for residents to reach safe areas
Evacuation completion rate	Percentage of residents successfully evacuated
Response arrival time	Time required for responders to reach affected areas
Shelter utilization rate	Percentage of shelter capacity used
Hospital overload rate	Percentage of hospital capacity exceeded
Road congestion index	Level of congestion during evacuation
Casualty risk index	Estimated risk of injury or death
Communication coverage	Percentage of population receiving warning messages
Resource allocation efficiency	Effectiveness of responder and vehicle distribution

Average evacuation time is calculated as:

$$AET = \frac{1}{n}\sum_{i=1}^{n}(T_{safe,i} - T_{start,i})$$

where $AET$is average evacuation time, $T_{safe,i}$is the time when agent $i$reaches a safe location, $T_{start,i}$is the time when evacuation begins, and $n$is the number of evacuated agents.

Evacuation completion rate is calculated as:

$$ECR = \frac{N_{evacuated}}{N_{exposed}} \times 100\%$$

where $ECR$is evacuation completion rate, $N_{evacuated}$is the number of evacuated agents, and $N_{exposed}$is the number of exposed agents.

Response arrival time is calculated as:

$$RAT = T_{arrival} - T_{dispatch}$$

where $RAT$is response arrival time, $T_{arrival}$is responder arrival time, and $T_{dispatch}$is dispatch time.

The resource allocation efficiency is formulated as:

$$RAE = \frac{R_{used}}{R_{available}} \times \frac{N_{served}}{N_{affected}}$$

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where $RAE$is resource allocation efficiency, $R_{used}$is the number of resources used, $R_{available}$is total available resources, $N_{served}$is the number of affected agents served, and $N_{affected}$is the total number of affected agents.

Model Validation

Model validation is conducted using three approaches: face validation, sensitivity analysis, and scenario comparison.

Face validation is conducted by comparing the model logic with disaster-management knowledge, emergency-response procedures, and realistic urban behavior. Sensitivity analysis is used to examine how changes in key parameters affect simulation outcomes. These parameters include warning delay, evacuation compliance, road blockage level, responder availability, and shelter capacity. Scenario comparison is used to evaluate whether the model produces different and logical outcomes under moderate, severe, and combined hazard conditions.

Table 8. Validation approach

Validation Type	Purpose
Face validation	Ensures model logic is realistic and relevant
Sensitivity analysis	Tests model response to parameter changes
Scenario comparison	Compares outcomes under different disaster conditions
Expert review	Assesses practical relevance of simulation output

Ethical and Practical Considerations

Because disaster-response simulation may involve vulnerable communities, ethical considerations must be addressed carefully. The model should avoid stigmatizing specific neighborhoods or populations. If real demographic or mobility data are used, privacy protection and data anonymization must be applied. The simulation output should be used to support preparedness and planning, not to blame affected communities for delayed evacuation or disaster exposure.

From a practical perspective, the framework should be integrated with emergency-management institutions, urban planners, community leaders, and smart city operators. This is important because disaster response is not only a technological issue but also a governance and community-coordination challenge.

This study develops an integrated method that combines Agent-Based Modeling and Generative AI for disaster response simulation in Medellín's smart city context. Agent-Based Modeling is used to simulate the behavior and interaction of residents, responders, shelters, hospitals, vehicles, and command centers during disaster events. Generative AI is used to create adaptive disaster scenarios, generate emergency communication, enrich agent behavior variation, and explain simulation results. The proposed method is evaluated using disaster-response metrics such as evacuation time, response arrival time, evacuation completion rate, shelter utilization, casualty risk, communication coverage, and resource allocation efficiency.

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This methodological framework is expected to support more adaptive, realistic, and actionable disaster-response planning for smart cities.

RESULT AND DISCUSSION

The proposed Agent-Based Modeling and Generative AI framework was evaluated using three disaster-response scenarios in Medellín, Colombia: moderate flood, severe landslide, and combined flood-landslide emergency. The simulation involved resident agents, emergency responder agents, vehicle agents, hospital agents, shelter agents, and command-center agents. The main objective was to evaluate how different response strategies affect evacuation efficiency, emergency response time, shelter allocation, road congestion, casualty risk, and communication coverage.

Three response strategies were compared: baseline response, ABM-based response, and ABM + Generative AI response. The baseline response represents conventional emergency response without simulation-based optimization. The ABM-based response uses agent-based simulation to support evacuation and resource allocation planning. The ABM + Generative AI response integrates agent-based simulation with generative AI for scenario generation, behavioral variation, emergency communication, and decision-support explanation.

Evacuation Performance

The first evaluation focused on evacuation performance. The indicators used were average evacuation time and evacuation completion rate. Lower evacuation time and higher completion rate indicate better disaster-response performance.

Table 9. Evacuation performance across disaster-response strategies

Response Strategy	Average Evacuation Time / minutes	Evacuation Completion Rate	Delayed Evacuation Rate
Baseline Response	74.6	76.8%	23.2%
ABM-Based Response	58.3	86.4%	13.6%
ABM + Generative AI Response	43.7	93.1%	6.9%

The results show that the ABM + Generative AI response achieved the best evacuation performance. The average evacuation time decreased from 74.6 minutes in the baseline response to 43.7 minutes in the proposed approach. This represents a reduction of approximately 41.4%. The evacuation completion rate also increased from 76.8% to 93.1%.

This improvement occurred because the proposed model generated more adaptive evacuation strategies based on hazard location, road blockage, shelter capacity, and agent behavior. Generative AI also improved the response process by generating clearer evacuation messages and alternative route recommendations. As a result, resident agents were more likely to evacuate earlier and choose safer routes.

Emergency Response Arrival Time

The second evaluation measured how quickly emergency responders reached affected areas. Response arrival time is critical in disaster situations because delayed arrival may increase casualty risk, infrastructure damage, and public panic.

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Table 10. Emergency response arrival time by scenario

Disaster Scenario	Baseline Response / minutes	ABM-Based Response / minutes	ABM + Generative AI Response / minutes
Moderate Flood	31.4	24.8	19.6
Severe Landslide	46.7	37.5	29.3
Combined Flood-Landslide	58.2	44.1	35.8
Average	45.4	35.5	28.2

The proposed ABM + Generative AI strategy achieved the lowest average response arrival time of 28.2 minutes, compared with 45.4 minutes in the baseline response. The improvement was most visible in the combined flood-landslide scenario, where multiple hazard zones and road blockages created more complex response conditions.

The reduced arrival time was mainly influenced by improved route selection, better responder dispatching, and scenario-based anticipation of road disruption. The model allowed emergency vehicles to avoid highly congested or blocked routes and prioritize areas with higher casualty risk.

Shelter and Hospital Allocation Results

Shelter and hospital allocation were evaluated to determine whether the proposed framework could reduce overcrowding and improve resource distribution. The indicators used were shelter utilization rate, shelter overload rate, and hospital overload rate.

Table 11. Shelter and hospital allocation performance

Response Strategy	Average Shelter Utilization	Shelter Overload Rate	Hospital Overload Rate
Baseline Response	94.8%	21.7%	18.4%
ABM-Based Response	87.2%	12.6%	10.8%
ABM + Generative AI Response	81.5%	5.3%	6.2%

The results show that the proposed approach reduced shelter overload from 21.7% to 5.3% and hospital overload from 18.4% to 6.2%. This indicates that the integration of ABM and Generative AI improved resource allocation by distributing evacuees and injured agents more evenly across available facilities.

In the baseline response, many agents moved toward the nearest shelter without considering capacity. This caused overcrowding in several shelters while other shelters remained underused. In contrast, the proposed model used real-time shelter-capacity information and scenario-based recommendations to redirect evacuees to alternative shelters.

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Road Congestion and Mobility Disruption

Road congestion is one of the major barriers to effective disaster response in dense urban areas. The simulation measured road congestion index during evacuation and emergency dispatch.

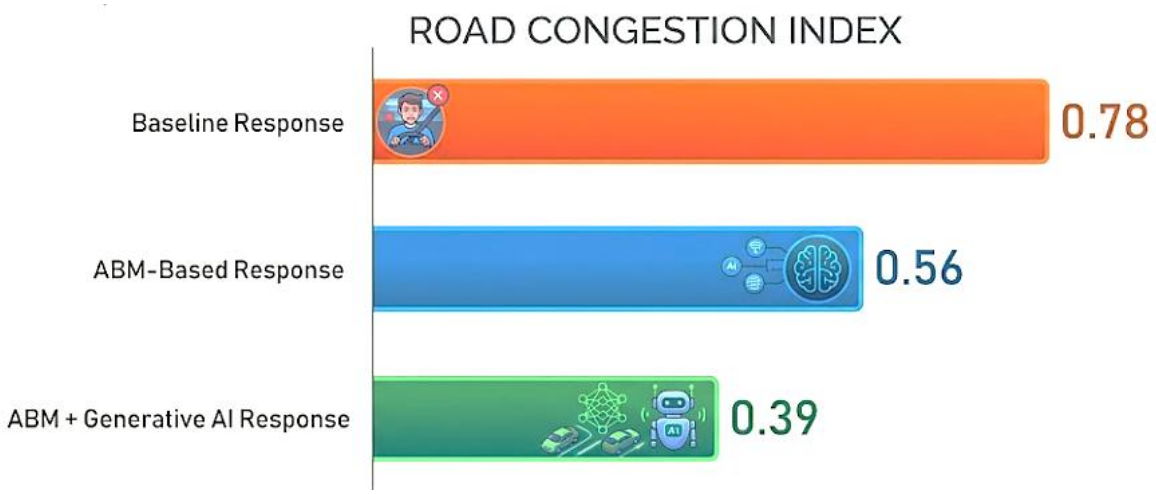


Figure 2. Road congestion index comparison

The proposed ABM + Generative AI approach reduced the road congestion index from 0.78 to 0.39. This indicates that the model improved traffic distribution during evacuation. The reduction occurred because the system generated alternative evacuation routes and distributed resident agents across multiple roads rather than concentrating movement on the most obvious routes.

Casualty Risk Reduction

The casualty risk index was calculated based on hazard exposure, delayed evacuation, emergency-response delay, hospital overload, and road accessibility. Lower casualty risk indicates better disaster-response performance.

Table 12. Casualty risk index by disaster scenario

Disaster Scenario	Baseline Response	ABM-Based Response	ABM + Generative AI Response
Moderate Flood	0.42	0.31	0.22
Severe Landslide	0.68	0.49	0.34
Combined Flood-Landslide	0.81	0.57	0.41
Average	0.64	0.46	0.32

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The proposed model reduced the average casualty risk index from **0.64** to **0.32**, representing a 50% reduction compared with the baseline response. The highest casualty risk appeared in the combined flood-landslide scenario because multiple hazards occurred simultaneously and placed greater pressure on emergency resources.

The reduction in casualty risk was influenced by faster evacuation, improved warning coverage, shorter response arrival time, and more balanced hospital allocation. These results suggest that simulation-based response planning can help reduce human risk during urban disaster events.

Communication Coverage and Warning Effectiveness

Communication effectiveness was evaluated by measuring the percentage of resident agents who received and understood evacuation warnings. The simulation assumed that warning messages could be distributed through mobile alerts, sirens, community leaders, public announcements, and digital platforms.

Table 13. Communication performance

Response Strategy	Warning Coverage	Message Understanding Rate	Evacuation Compliance Rate
Baseline Response	72.5%	68.9%	61.4%
ABM-Based Response	81.7%	76.2%	72.8%
ABM + Generative AI Response	92.4%	87.6%	84.9%

The proposed approach achieved the highest warning coverage at 92.4%, message understanding rate at 87.6%, and evacuation compliance rate at 84.9%. This improvement occurred because Generative AI produced targeted warning messages based on hazard type, urgency level, location, and population characteristics.

For example, in high-risk hillside areas, the generated message emphasized immediate evacuation due to landslide probability. In flood-prone areas, the message focused on avoiding low-lying roads and moving toward designated shelters. This shows that disaster communication should not be generic. A message that is too broad may be technically correct but operationally weak.

Resource Allocation Efficiency

Resource allocation efficiency was evaluated by comparing the use of responders, vehicles, shelters, and hospitals. The proposed model achieved better efficiency because the command-center agent used simulation outputs and Generative AI recommendations to prioritize high-risk zones.

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Table 14. Resource allocation efficiency

Response Strategy	Responder Utilization	Vehicle Utilization	Resource Allocation Efficiency
Baseline Response	69.8%	72.4%	0.58
ABM-Based Response	78.6%	81.2%	0.71
ABM + Generative AI Response	86.3%	88.7%	0.84

The resource allocation efficiency increased from 0.58 in the baseline response to 0.84 in the proposed approach. This shows that the model was able to allocate emergency resources more effectively based on predicted need, affected population, accessibility, and facility capacity.

The improvement also indicates that Generative AI can support emergency managers by producing alternative resource-distribution plans. However, such recommendations must remain under human supervision because emergency management requires ethical judgment, field validation, and institutional authority.

Scenario-Based Comparison

The performance of the proposed framework varied across disaster scenarios. The combined flood-landslide scenario produced the most difficult response condition because it involved multiple affected zones, higher road disruption, and greater pressure on shelters and hospitals.

Table 15. Performance by disaster scenario using ABM + Generative AI

Scenario	Evacuation Completion Rate	Average Response Arrival Time	Casualty Risk Index	Shelter Overload Rate
Moderate Flood	96.2%	19.6 minutes	0.22	2.8%
Severe Landslide	93.7%	29.3 minutes	0.34	5.1%
Combined Flood-Landslide	89.4%	35.8 minutes	0.41	8.0%

The results show that the framework performed best in the moderate flood scenario and faced the greatest challenge in the combined flood-landslide scenario. This is expected because multi-hazard disasters create more complex operational conditions. Nevertheless, even in the most difficult scenario, the proposed framework maintained an evacuation completion rate of 89.4% and kept shelter overload below 10%.

Discussion

The results demonstrate that integrating Agent-Based Modeling and Generative AI can improve disaster-response simulation in smart cities. Agent-Based Modeling provides a structured method for representing the behavior and interaction of residents, responders, vehicles, shelters, hospitals, and command centers. Generative AI strengthens this simulation by generating adaptive scenarios, communication messages, behavioral variations, and decision-support explanations.

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The improvement in evacuation performance indicates that disaster response benefits from understanding individual and collective behavior. In conventional response planning, residents are often treated as a uniform population. However, in real disasters, people respond differently depending on age, mobility, risk perception, warning reception, family responsibility, trust, and access to transportation. ABM allows these differences to be represented more realistically.

The reduction in emergency response arrival time shows that simulation-based planning can improve responder dispatch and route selection. In dense and topographically complex cities such as Medellín, emergency vehicles may face road congestion, blocked routes, and difficult access to hillside communities. By simulating multiple route and resource scenarios, the proposed framework helps identify more efficient response strategies before disaster conditions worsen.

The shelter and hospital allocation results also show that the proposed model can support better resource distribution. In disaster situations, people may naturally move to the nearest or most familiar shelter, causing overcrowding. The proposed model reduces this problem by considering shelter capacity, travel distance, road conditions, and population distribution. This makes evacuation planning more balanced and realistic.

Communication was one of the most important factors influencing evacuation compliance. The results show that Generative AI can improve warning effectiveness by producing messages that are more specific to location, hazard type, and urgency level. This supports the idea that smart city disaster response should not rely only on sensors and dashboards, but also on clear, targeted, and human-centered communication.

However, the use of Generative AI in disaster response must be treated carefully. AI-generated scenarios and recommendations may be useful for planning, but they should not replace expert judgment or official emergency procedures. Generated outputs must be validated by disaster-management professionals to avoid misleading recommendations. In high-risk situations, human oversight remains essential.

The findings also highlight the relevance of the proposed framework for Medellín. The city's complex geography, hillside settlements, and mobility constraints require disaster-response systems that can simulate local vulnerability and dynamic urban behavior. The proposed framework can help emergency agencies evaluate evacuation plans, identify vulnerable areas, test shelter capacity, improve warning strategies, and optimize resource allocation.

Despite these promising results, several limitations should be acknowledged. First, this study uses simulated data; therefore, future research should validate the model using real-world geospatial, demographic, mobility, rainfall, landslide, and emergency-response data from Medellín. Second, agent behavior rules should be calibrated using surveys, historical evacuation records, or expert knowledge. Third, Generative AI outputs require strict validation to ensure reliability, safety, and ethical appropriateness. Fourth, the proposed framework should be tested in real-time or near-real-time smart city platforms to evaluate operational feasibility.

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CONCLUSION

This study concludes that the integration of Agent-Based Modeling and Generative Artificial Intelligence provides a promising approach for improving disaster-response simulation in smart cities, particularly in the context of Medellín, Colombia. The proposed framework enables the simulation of complex interactions among residents, emergency responders, vehicles, shelters, hospitals, transportation networks, and command centers during disaster events such as floods, landslides, and combined multi-hazard emergencies. The simulated results show that the ABM + Generative AI approach outperformed baseline and ABM-only response strategies by reducing average evacuation time, increasing evacuation completion rate, shortening emergency response arrival time, reducing shelter and hospital overload, improving warning coverage, and lowering casualty risk. These findings indicate that combining behavioral simulation with generative scenario support can produce more adaptive, realistic, and decision-oriented disaster-response planning. The main contribution of this study lies in bridging urban agent simulation, generative AI-based scenario development, emergency communication, and decision-support recommendations within a single smart city disaster-management framework. In practical terms, the proposed model can assist emergency agencies, policymakers, urban planners, and community stakeholders in evaluating evacuation strategies, optimizing resource allocation, identifying vulnerable areas, and strengthening urban resilience. However, this study is limited by the use of simulated data; therefore, future research should validate the framework using real geospatial, demographic, mobility, rainfall, landslide, and emergency-response data from Medellín. Further studies should also calibrate agent behavior using field surveys, integrate real-time smart city sensor data, and develop ethical validation mechanisms for Generative AI outputs to ensure that recommendations remain accurate, safe, and accountable in real disaster-response situations.

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