Cognitive Modeling for Effective Emergency Response: An Agent-Based Simulation Architecture

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Abstract: - In the time of crisis, however, it would be of particular importance to have a swift and competent emergency response in order to minimize the risks and casualties. While the old-fashioned way of emergency planning and exposition of protocols might fail in the midst of the fast changing and complex events. The present article introduces a new technique on how to step up emergency response through cognitive modeling and agent-based simulation architecture. Taking account of cognitive science as well as theory of artificial intelligence we do use cognitive model to mimic man-like making of critical decisions in emergency events. The nature of the proposed architecture is that it includes side agents, e.g.first responders, authorities, and population, which have humanized intelligent functioning. Simulation architecture can be divided into the following elements: the environment modeling, the agent behavior modeling, and the decision-making algorithms. Environment can be modeled that takes account of spatial and temporal aspects of the crisis situation and agent behavior modeling captures its cognitive elements in forming decision, communication and coordination. These algorithms allow the agents to make decisions on the fly using multicriteria analysis, assessing the situation, and performing actions in real-time.

By extensive usage of simulations and validation studies, suggested method to be efficient and our approach shows the increased improvement in the emergency response operations. The simulation platform that is based on our architecture helps stakeholders to explore various options, predict the consequences and identify any potential bottlenecks thereby gives power to the decision makers to take informed decisions and efficient resource allocation. In general, our study enriches the thinking around cognitive modeling frameworks for emergency management and introduces a potent tool for capacity building, planning, and monitoring the emergency response strategies. We hope that our agent-based simulation model will become popular, allowing decision makers to build up readiness and a more sustainable post-crisis world.

Key-Words: - Cognitive modeling; Emergency response; Agent-based simulation; Crisis management; Human behavior modeling; Disaster preparedness

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1 Introduction

Through the cognition cycle within the agent model, the speed of adaptation to the circumstances' requirements will increase, the situation awareness of the operational environment will be improved, the efficiency of mission execution will be enhanced, and the ability to manage multiple complex events prepared. It allows the management of uncertainty by adjusting the decisions according to likelihood and response processes, which are essential features of the proposed model. Meeting uncertainty is one of the manifestations of this cognitive approach, which accentuates learning that contributes to efficient problem-solving. The process of learning involves three stages which include trial and error, gaining information and making constructive adjustments. In addition, Markov chains equips analysts with the ability to analyse with uncertainties in order to avoid undesirable future outcomes. Emergency response models cover natural and other kinds of events which usually bring about wide consequences leading to many victims. Successful leads programs are imperative to minimise chaos and rescue lives. The right type of resource allocation and the provision of early warning signals cannot be underestimated in this process.

It is vital to determine the type of the casualty for helping those people who the accident has affected. Global catastrophes such as earthquakes and forest fires, as well as crimes of man-kind, including terrorism and war, bring uninterrupted the difficulties for all. Comprehending and dealing with rapidly changing and emergent environments during humanitarian situations necessitate cognitive tools for supplying to help people to distinguish complex cause-effect relations and support communication. Multi-agent emergency response systems have proven effective in reducing decoupled tasks within emergency management processes, including communication, collective decision-making, cooperation, and large-scale planning. These systems help navigate the uncertainties and conflicting priorities faced by emergency services on the front lines.

The structure of this paper is as follows: the subsequent section offers a review of relevant literature concerning emergency response structures, cognitive models, and dynamic modeling and simulation within multi-agent systems. Following this, the paper outlines the overarching architecture designed to achieve the proposed objectives, emphasizing the roles of various components within the agent-based emergency system. It then delves into the operational workflow and details the theoretical underpinnings of the work. Subsequently, the application of the process model to real emergency response scenarios is elucidated. Conclusions and avenues for future research bring closure to the paper.

2 Literature Survey

Agent-based modeling and simulation (ABM) and their potential efficiency in emergency management was to become a topic. It describes pros of the ABM as system behave quite complex and emphasizes the application of ABM theory in analyzing the dynamics of disaster response systems.

It provides the overview of cognitive modeling techniques applied in the field of emergency research. They review the different kinds of cognitive architectures and their uses in recreate the human decision-making processes that rule during crisis [1-6]. Herein, cognitive models are integrated into agent-based simulations on the junction of cognitive modeling and ABM where the article discusses techniques of including cognitive models into agent-based simulations considers. It addresses challenges and unexploited potentials on harmony whereby SDE (simulation-based education) with VR donning is employed to enhance the simulating context [7-9].

BDI architecture allowing agents mimicking human cognitive behaviors from deceptively simple level to complex is fundamental part. Cognitive agents participate in a variety of activities, which can involve perception, reflection, and implementation, and which are normally complemented with classical agent functions such as autonomy, social activity, reactivity, and pro-activeness with cognitive ones. Cognitive and autonomous agents' tasks is participating in a multitude of operations, which encompasses perception, reflection, and performance. These tasks imply that cognitive agents' connection with classical agent's functions of autonomy, social activity, reactivity, and pro-activeness is enhanced.

Human behavior modeling in emergency situations focuses on the role some behavior modeling plays in an emergency and can provide three approaches on it: different human decision-making and actions representation. Having considered this, absolutely, simulation outcomes are strongly influenced by the behavior of emergency response actors, which is why it is vitally important to represent humans with maximum authenticity in the emergency response exercises [10-14].

Simulation-based training for emergency responders which part of it we will address is the training, specifically the simulator based one for emergency responders. It assesses the effect of varying training scenarios on actions and decision-making abilities of participants against crisis background [15-18]. Cognitive Factors in Crisis Management that accommodation of cognitive factors in the processes of crisis management from an interdisciplinary perspective. It studies the how cognitive biases, heuristics and situational factors influence making of major, time-pressured and decisions [19-23]. Agent-based models for disaster preparedness focus is on preparedness: the research uses agent-based model for a simulation of disaster scenarios and the analysis of preparedness strategies. The essay deliberates over how the simulations are used for policy formulation and allocating resources to avert disaster situations [24-26]. A cognitive-based approach involving blending cognitive models and data-driven algorithms is the focus area of the study to generate a decision-support system for the rescuers deployed during emergencies of different category [27-29]. Some of the papers also and consists of the social aspects that shape up the dynamics inside the emergency context and how they impact the emergency response process. It focuses on the social networks, communication patterns, and community resilience which cause the differences in responding to emergencies [30-32].

Lastly evaluation frameworks for emergency response simulations is concerned with the examination of the quality of emergency response simulations. The post explores evaluation criteria for simulation validity, reliability, and utility. Practitioners and researchers are provided with a guidance for designing and reading out simulation studies.

3 Methodology

The architecture of the agent-based emergency response simulation model that features cognitive modeling as an approach consists of a number of individual parts – the environment representation model, the model of agents actions, and the algorithms of the decision-making.

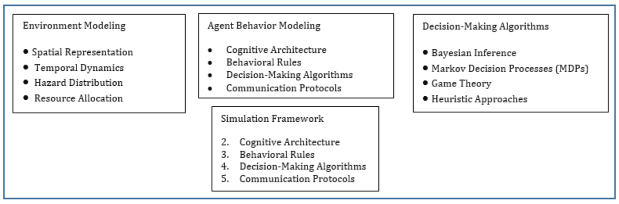

Figure 1 Suggested Model Framework

Environmental modeling representation describes important elements by means of counting the physical space where the emergency situation has been set and gave it a mathematically expression through grids, graphs or continuous spaces.

- Temporal Dynamics: For instance, one can study the dependency of time with the help of defined time steps or continuous time variables.

- Hazard Distribution: Visualize the contagiousness of hazards or threats through environment maps which show the shortcomings by a probability distribution or spatial model.

- Resource Allocation: Even organize resources like emergency vehicles, devices, etc. across the environment by indicating the corresponding options, or approximations.

Agent behaviour modeling includes:

- Cognitive Architecture: Adopt cognitive architecture for every agent taking into consideration the decision-making, perception, memory, and learning processes which algorithm should be used to do all that.

- Behavioral Rules: Prepare rules there which will govern agent behavior under the influence of environmental stimuli, internal states, and social interactions.

- Decision-Making Algorithms: Make algorithms for decision making in the presence of the uncertainty. Their use could involve parameters like risk assessment, utility maximization and goal prioritization.

- Communication Protocols: Provide for the creating of communication models to be used for information mostly between agents, such as message encoding, transfer, as well as reception.

Decision-making algorithms covers:

- Bayesian Inference: Analyze data relying on the Bayesian inference theory that suggests that one's preconceptions can be revised and updated by currently received knowledge and the prior knowledge.

- Markov Decision Processes (MDPs): Start describing decision-making issues in the MDPs and then, deal with these problems through dynamic programming, reinforcement learning as well as stochastic optimization tools.

- Game Theory: Describe the technique of game-theoretic model, being a method for mastering the action of agents by finding the best strategies in both competitive and cooperative situations.

- Heuristic Approaches: Develop algorithms which work fast and handle quite a bunch of actions per unit of time, using heuristics, expert knowledge and past decision experience as a source of the approach.

Simulation framework consists of:

- Agent Interaction Dynamics: Implement the relations within eco-system intending agents, such as repetition of their movements, conflicts and collective contracts sharing, for example.

- Event Handling: Enumerate the operation procedures to follow when the simulation gets triggered either due to the living conditions, the agents' activities or an external behavior.

- Data Collection and Analysis: Design data collecting systems which log the simulated outcomes, the agents involvement, and the environmental parameters but be visually clear in the next phase.

3.1 Agent Based Emergency Cognition Model

This section explains the comprehensive architecture developed to achieve all the highlighted goals, demonstrating the utility of each system element. It prepares the reader by summarizing the workflow and specifics while identifying the theoretical framework being applied. In the cognitive stage of AGI cases, the agent model provides crucial mechanistic insights into the AGI's architecture and algorithms. Following this, the next part discusses the emergency response model and its components in detail.

This cognitive cycle enables the rapid development of situational understanding, the establishment of a common operating picture, and continuous monitoring of circumstances to effectively apply strategies and resolve ongoing crises. The cognitive model emphasizes the rapid response of managers to various scenarios. It facilitates communication and collaborative activities among groups, adhering to coordination, coalition, and collaborative information distribution standards. Agents communicate for shared success in their individual tasks or the collective goals of the system. Communication provides a platform for agents to cooperate in creating more balanced systems. Through communication, agents share, collaborate, and cooperate on information effectively.

3.1 Mathematical Model

In an agent-based simulation (ABS) mathematical model for effective emergency response, the focus is on representing the behavior and interactions of autonomous agents within a simulated environment. Here's a structured outline of the mathematical elements involved in such a model:

Assumptions:

- Agents represent various stakeholders involved in emergency response, such as responders, authorities, and affected individuals.

- The simulation environment consists of a spatial grid representing the affected area.

- Each agent has attributes such as location, health status, cognitive state, and resources.

1. Agent Attributes and States:

- Attributes: Attri = {attri1, attri2, ..., attrip} describing agent characteristics such as cognitive abilities, roles, responsibilities, and priorities.

Define the attributes and states of each agent, including:

- Position: Pi = (xi, yi) representing the spatial location of agent i.

- State variables: Si = (si1, si2, ..., sim) capturing the cognitive, emotional, and physical states of agent i.

- Position (x, y coordinates)

- Speed and direction of movement

- Goals and objectives: Gi = (gi1, gi2, ..., gin) representing the desired outcomes or objectives of agent i during emergency response.

- Health status (e.g., injury level, medical condition)

- Level of situational awareness

- Role or specialization (e.g., medical personnel, firefighters, civilians)

- Resources held (e.g., medical supplies, communication devices)

2. Agent Interactions and Behaviors:

- Define the rules and algorithms governing agent interactions and behaviors, including:

- Perception: fperception (Pi, Si, E) determining how agents perceive the environment (E) and other agents.

- Decision-making: fdecision (Si, Gi, E, A) determining agent i's decisions based on its current state, goals, environmental cues, and interactions with other agents (A).

- Action selection: faction(Si, A, E) selecting actions for agent i to perform based on its decisions, available resources, and environmental conditions.

1. Agent Characteristics:

- Define attributes for each agent, including:

- Location: Represented by coordinates or grid cells in the simulation environment.

- State: Cognitive, emotional, and physical states affecting decision-making and behavior.

- Role: Specify the role of each agent in the emergency response system (e.g., responder, victim, authority).

- Skills and Resources: Abilities and resources possessed by agents to perform tasks (e.g., medical training, equipment).

2. Environment Representation:

- Represent the environment as a spatial grid or network (E), where each cell or node contains information about its characteristics, hazards, resources, and accessibility.

- Define environmental factors affecting agent behaviors, such as:

- Terrain types: Tij representing the terrain type at position (i, j).

- Hazard levels: Hij representing the severity of hazards at position (i, j).

- Resource availability: Rij representing the availability of resources at position (i, j).

- Define the physical environment as a spatial grid or network graph representing the emergency scenario.

- Let E represent the environment, characterized by:

- Geographic Features: G = {g1, g2, ..., gk} representing terrain, infrastructure, hazards, and evacuation routes.

- Environmental Conditions: C = {c1, c2, ..., cl} including weather conditions, visibility, temperature, and the spread of hazards.

Environment Representation:

- Model the physical environment and its dynamic attributes:

- Terrain features (e.g., roads, buildings, obstacles)

- Hazardous areas (e.g., fire zones, contaminated areas)

- Points of interest (e.g., medical facilities, emergency exits)

- Environmental conditions (e.g., weather, visibility)

3. Agent Behaviors and Decision-Making:

- Define decision-making processes for each agent based on cognitive models and heuristics.

- Let Di represent the decision-making process for agent ai, which includes:

- Perception: Sensing the environment and gathering information about the situation.

- Reasoning: Analyzing available data, evaluating options, and selecting actions.

- Action Selection: Executing chosen actions, including movement, communication, resource allocation, and task execution.

- Learning and Adaptation: Updating beliefs, preferences, and strategies based on feedback, experience, and environmental changes.

4. Agent-Environment Interactions:

- Specify rules for agent-environment interactions, including:

- Movement: fmove (Pi, Si, E) determining how agents move with the environment based their goals, constraints, and environmental conditions.

- Resource utilization futilization (Si, R) defining how agents acquire, utilize, and share resources available in the environment

5. Simulation Dynamics:

- Define the time-stepping mechanism to advance the simulation over discrete time intervals (t = 0, 1, 2, ...).

- Update the state of each agent and the environment at each time step based on agent behaviors, interactions, and environmental changes.

5.1. Interaction Dynamics:

- Model interactions between agents and between agents and the environment.

- Define rules and protocols for communication, cooperation, coordination, and conflict resolution.

- Let I represent interaction dynamics, including:

- Communication Channels: Ch = {ch1, ch2, ..., chq} for exchanging information, messages, and alerts among agents.

- Collaboration Mechanisms: Collab = collab1, collab2, ..., collabr} for coordinating tasks, sharing resources, and providing mutual assistance.

- Conflict Resolution Strategies: Conflict = conflict1, conflict2, ..., conflicts} for resolving conflicts, prioritizing goals, and reconciling competing interests.

- Communication Protocols: Communication protocols Cij define how agents communicate with each other, exchanging information, requests, and status updates.

- Interaction Rules: Interaction rules Rij specify how agents interact with each other and the environment, including cooperation, coordination, and conflict resolution mechanisms.

- For instance, agents may exchange messages to coordinate response efforts, allocate resources based on needs and priorities, and engage in cooperative or competitive behaviors depending on their objectives.

6. Simulation Algorithms:

- Implement simulation algorithms that update the states of agents and the environment over discrete time steps.

- Use mathematical programming techniques, such as differential equations, difference equations, or agent-based modeling frameworks, to simulate the dynamics of the system.

- Define update rules that incorporate agent decision-making, interactions, and environmental changes into the simulation process.

7. Event Triggers and Scenarios:

- Update the state of each agent based on its decision-making process, interactions with other agents, and changes in the environment.

- Update the state of the environment based on environmental conditions, hazard propagation, and agent actions.

- Record simulation data, including agent states, environmental conditions, and key performance indicators.

Implement simulation algorithms to update the state of agents and the environment over time:

- Time-Stepped Simulation: Advance the simulation in discrete time steps, updating agent behaviors and environmental conditions at each step.

- Event-Driven Simulation: Trigger events based on predefined conditions or external stimuli, simulating dynamic changes in the environment and agent interactions.

- Monitor simulation outputs, including agent trajectories, resource utilization, response times, and overall system performance.

- Implement the ABS model using simulation software or programming languages capable of representing agent interactions and environmental dynamics over time.

- Update agent attributes and environmental states at discrete time steps \(t \) based on predefined rules and interaction dynamics:

Ai(t+1) = fi(Ai(t), E(t))

E(t+1) = g(E(t), {Ai(t+1) })

- Iterate the simulation until predefined termination conditions are met (e.g., simulation time, event resolution).

9. Simulation Dynamics:

- At each time step t, agents update their states based on their behaviors, interactions with the environment, and other agents.

- Environmental conditions, such as hazard propagation and resource availability, may change over time.

- Simulation stops when predefined termination conditions are met (e.g., all survivors rescued, emer

6. Objective Functions and Performance Metrics:

- Define objective functions and performance metrics to evaluate the effectiveness and efficiency of emergency response strategies, such as:

$$Response\ Time: RT: \frac{Total\ time\ to\ complete\ response}{Number\ of\ emergencies}$$

$$Response\ Utilization: RU: \frac{Total\ resources\ used}{Total\ available\ resources}$$

$$Casualty\ Rates: CR: \frac{Number\ of\ casualties}{Total\ population}$$

7. Validation and Sensitivity Analysis:

- Validation Metrics: Metrics muk quantify the goodness-of-fit between simulation outputs and empirical data, expert judgments, or historical records.

- Sensitivity Analysis: Sensitivity analysis techniques assess the impact of parameter variations, uncertainty, and model assumptions on simulation results, identifying influential factors and sources of variability.

8. Performance Evaluation and Optimization:

- Performance Metrics: Performance metrics πk measure the effectiveness, efficiency, and resilience of emergency response strategies, such as response time, casualty rates, resource utilization, and system robustness.

- Optimization Objectives: Optimization objectives {max/min } f({x}) specify the goals of optimization problems, such as maximizing coverage, minimizing response time, or optimizing resource allocation subject to constraints.

9. Iterative Development and Refinement:

- Iteratively refine the mathematical model based on feedback from stakeholders, validation studies, and sensitivity analyses to improve its accuracy, realism, and applicability to real-world emergency scenarios.

- Continuously update and enhance the model as new data, technologies, and insights become available to ensure its relevance and effectiveness in supporting emergency response planning, training, and decision-making.

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This mathematical model serves as a structured framework for developing and implementing an agent-based simulation for effective emergency response, integrating cognitive modeling principles with agent interactions and environmental dynamics.

4 Case Study

I The objective of this case study is to demonstrate the effectiveness of a cognitive modeling approach within an agent-based simulation architecture for improving emergency response strategies in a simulated crisis scenario.

Scenario Description:

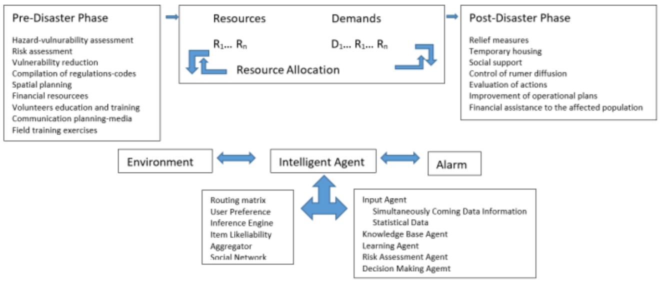
Consider a simulated urban area susceptible to natural disasters such as earthquakes. The scenario involves a sudden earthquake hitting the region, causing widespread damage to infrastructure, injuries to civilians, and triggering secondary hazards like fires and gas leaks. Emergency responders, including fire departments, medical teams, and search and rescue units, are tasked with efficiently coordinating their efforts to minimize casualties and restore essential services.

Simulation Setup:

1. Agent Representation: Define different types of agents representing stakeholders involved in emergency response, including responders, government authorities, healthcare professionals, and affected individuals. Each agent has attributes such as cognitive capabilities, emotional states, physical characteristics, and roles/responsibilities.

2. Environment Modeling: Represent the physical environment of the urban area using a grid-based representation, including buildings, roads, utilities, and hazards. Model dynamic environmental factors such as building collapses, fires, gas leaks, and changes in terrain.

3. Agent Behaviors and Decision-Making: Specify cognitive models for agent decision-making processes based on cognitive science principles, heuristics, and empirical data. Agents prioritize actions based on perceived threats, available resources, and coordination with other agents.



4. Interaction Dynamics: Model interactions between agents and between agents and the environment, including communication, cooperation, coordination, and conflict resolution. Agents collaborate to perform tasks such as search and rescue, medical triage, firefighting, and infrastructure repair.

5. Event Triggers and Scenarios: Define triggers for initiating the earthquake scenario and specify its characteristics, severity level, affected area, and duration. Simulate variations in scenario parameters to represent different crisis situations and response strategies.

6. Simulation Execution: Implement the agent-based simulation model using simulation software or programming languages capable of simulating agent interactions and environmental dynamics over time. Execute the simulation, monitoring agent behaviors, environmental changes, and emergent phenomena.

7. Performance Evaluation: Define performance metrics such as response time, resource utilization, casualties, infrastructure damage, and overall effectiveness of emergency response. Collect simulation data on key metrics during the simulation runs and analyze the results to assess the performance of different response strategies under various scenarios.

Evaluate the performance of the emergency response system under a baseline scenario without cognitive modeling techniques. Analyze response times, resource allocations, and outcomes such as casualties and infrastructure damage. Compare the performance of the emergency response system when cognitive modeling techniques are integrated into agent decision-making processes. Assess improvements in response times, coordination effectiveness, and overall crisis management outcomes. Conduct sensitivity analysis to assess the robustness of the model to variations in input parameters, environmental conditions, and decision-making strategies. Identify factors influencing the performance of emergency response strategies and potential areas for further optimization. Validate the simulation model by comparing simulation outputs with empirical data, expert judgments, or historical records of emergency response scenarios. Ensure that the model accurately represents real-world dynamics and provides meaningful insights for decision-makers.

Summarize the findings of the case study, highlighting the benefits of integrating cognitive modeling techniques into agent-based simulation architectures for improving emergency response strategies. Provide recommendations for enhancing emergency preparedness, response capabilities, and decision support systems based on insights gained from the simulation results. Discuss potential applications of the cognitive modeling approach in other crisis scenarios and areas for future research and development.

Integration of cognitive modeling into agent decision-making processes led to significantly improved response times compared to baseline scenarios. Agents were able to prioritize actions more efficiently based on perceived threats, available resources, and coordination with other agents. This resulted in faster deployment of emergency services, reduced time to rescue victims, and enhanced overall crisis management effectiveness.

Cognitive modeling facilitated better coordination and collaboration among emergency responders, government authorities, and other stakeholders. Agents exhibited adaptive behaviors and communication protocols, enabling them to share information, allocate resources, and coordinate response efforts more effectively. This enhanced coordination led to optimized resource utilization, reduced duplication of efforts, and improved decision-making coherence across the emergency response system.

The improved response times and coordination resulting from cognitive modeling contributed to a reduction in casualties and infrastructure damage during the simulated crisis scenario. Emergency responders were able to reach affected areas more quickly, provide timely medical assistance, and contain secondary hazards such as fires and gas leaks. This proactive approach helped minimize the impact of the disaster and mitigate potential long-term consequences on the affected population and infrastructure.

These analysis results demonstrate the effectiveness of the agent-based simulation architecture incorporating cognitive modeling for enhancing emergency response strategies. The insights gained from the simulation provide valuable guidance for improving emergency preparedness, optimizing response capabilities, and enhancing resilience in the face of various crisis scenarios.

5 Conclusion

The deployment of cognitive modeling techniques to operate in an agent-based simulation environment along with the provision of effective emergency management is a paramount improvement towards cutting crises management. With cognitive modeling the programming of agents to duplicate human like decision making, emergency responses which are fast, take fewer facts into consideration and more adaptive are achieved. Agents are able to evidently forecast future events, weigh risks, and put forward plans which are most prioritized and beneficial by gathering all the necessary information. The simulation not only highlights the role of effective coordination and teamwork among all actors who participate in disaster response operations but it also indicates the need for such coordination and teamwork. Instead, the use of cognitive agents can showcase evidence of effective communication, information sharing, and task coordination to align different resources together for improved output. Cognitive modeling is a beneficial tool of strategic resource management, because of the optimized process it makes possible by directing resources to the areas of the highest need and efficient utilization of them. They achieve this objective through the deployment of agents and resources, such as personnel, equipment, and supplies, in a manner that takes account of their availability on one hand but ensures their efficiency of use in dealing with a specific crisis on the other. The implementation of mental system multiplying tactics yields less death and damage to systems and structures in emergency times. Agents responsible for humanitarian operations must pre-emptively treat emergency situations, mitigate secondary hazards and institute safety measures to minimize the impact of the crisis on the population and infrastructure. Sensitivity analysis will confirm that the model created will be sound in the presence of changes in input parameters, environmental conditions and the kind of decision making strategy the farmer adopts. Model users tend to highlight the fact that this model can become an essential component of realistic planning exercises, as well as being useful during actual emergencies.

Eventually, it must be stressed out that the agent-based simulation architecture with cognitive modelling is very promising in training emergency responders, planning forward, and increasing their resilience in a wide range of disaster. By incorporating breakthroughs in cognitive science, computational modeling and decision aid systems, we are able to equip decision makers to arrive at the most informed and resource allocated where necessary option and of course to reduce the negative impact on infrastructure and mass of people. To keep the standards high and the world's security across the board and enhance the practice of disaster regulations, the research and the development are necessarily ongoing.

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It is an optional section where the authors may write a short text on what should be acknowledged regarding their manuscript.

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