
| RESEARCH ARTICLE

Integrated AI-Based Decision Support Systems for Emergency Supply Chain Management in the United States During Natural Disasters

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| ABSTRACT

The more natural disasters increase in frequency and severity in the United States (such as hurricanes, wildfires, floods, and pandemics), the more it illustrates the vulnerability of emergency supply chain systems. These incidents typically result in the general gridlock of transportation systems, prolonged delays in the deployment of resources, and a lack of coordination among federal, state, and local actors, as well as those in the non-governmental sector. The effects are not just logistical; they have a direct impact on the safety, health, and survival of the populations affected. Even at the current stages of development of logistics technologies, the majority of traditional emergency management systems are reactionary, using stale data pipelines, manually planned, and lock-step processes that have little capacity to adapt to the dynamic situation in disasters. To counter these repeated failures, this paper will suggest a connected Artificial Intelligence (AI) based Decision Support System (DSS) framework that will reset how emergency supply chains work in the case of a natural disaster. AI solutions. The possibilities of better disaster readiness, a faster decision-making process, and logistics coordination based on more intelligent, more flexible decisions lie in AI technologies, especially machine learning techniques, predictive analytics, and real-time optimization. The infrastructure introduced here is interoperable, data-composed, and provides real-time situational awareness as it addresses latency, decreases the imbalance between the supply and demand, and assures equal access to resources of the region affected by the disaster. In reviewing the current challenges, the paper proposes a modular AI-based DSS architecture and a broad roadmap of strategic implementation, also covering technical, institutional, and policy aspects. Using historical case examples and simulation-based lessons, the present study provides useful tips to the audience of emergency managers, policymakers, and technology developers. This ends with a future concern about the national resilience problem and the necessity of intelligent, integrated systems in the disaster response segment of infrastructure.

| KEYWORDS

Artificial Intelligence in Emergency Management, Disaster Response Decision Support Systems, Supply Chain Resilience in Natural Disasters, AI-Based Logistics Optimization, Real-Time Emergency Supply Chain Coordination

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1. Introduction

The problem of natural disasters is presently a very frequent and serious threat to the United States, which is aggravated by the

impact of global warming, the growth of cities, and population changes. Hurricane Katrina (2005), Superstorm Sandy (2012), and the COVID-19 pandemic (2020-2022) have shown that the systems of emergency preparedness and response are weak in their structure. As indicated by the Federal Emergency Management Agency (FEMA), billion-dollar disasters have increased more than twice the number in the last decade, characterizing the increasing complexity and uncertainty of the national risk picture. The effectiveness and dependability of emergency supply chain management is a life and death issue in case of such high-stakes situations.

The U.S. emergency supply chains face a variety of operational and strategic threats even in spite of the attempts to ensure the modernization of logistics infrastructure. Among them are a slow response of important supplies like food, water, and medical equipment, incomplete communication among federal, state, and local governments, and a lack of situational awareness in real-time. The results are extreme: affected communities will typically spend a long time bearing misplaced support, and responders will have to contend with a lack of visibility into where the supplies are and where they are needed. The response effort in most cases turns out to be reactive instead of proactive, leading to avoidable inefficiencies and human expenses.

It is on this background that the presence of Artificial Intelligence (AI) as a transformational force has emerged. Allowing one to examine massive data, identify trends, and prescribe the best course of action, the AI-based Decision Support Systems (DSS) promise an unprecedented opportunity to optimize the logistics of disasters. Predictive modeling may be used to predict the courses of storms, mobilization requirements; optimization algorithms can re-route materials dynamically around blocked infrastructure; machine learning models can automatically update themselves on the basis of past events to improve response to subsequent events. Such smart systems can transform the practice of emergency management to a predictive and synchronized paradigm.

The article offers an overall structure of an integrated AI-based DSS concerning a unique proposal within the emergency supply chain management in the United States. The architectural vision is where the focus on data fusion, inter-agency interoperability, and real-time decisions will be made, unlike the system in use currently, which is siloed or ad hoc. It is aimed at building a powerful system that could foresee interruptions, resource distribution, and multi-level coordination in time-compression contexts. The article focuses on challenges, technological possibilities, and limits, all architectural elements, implementation plans, and use prerequisites as an attempt to develop a strategic blueprint in modernizing national disaster response infrastructure.

2. Challenges in U.S. Emergency Supply Chain Management

The supply chain operations' resilience, flexibility, and speed determine such factors as the efficiency of emergency response during natural disasters. In the U.S., regardless of the presence of well-endowed federal organizations such as FEMA and liaisons with state and local governments, there still exist system-related inefficiencies. These are frivolous wastes that can easily increase in the case of enormous natural disasters, causing unnecessary delays, redundant work, and improper allocation of essential resources. The next subsections extend an analysis of the key issues that weaken U.S. emergency supply chain performance.

2.1 Fragmentation Across Agencies

Distribution of power and roles between different stakeholders is one of the problems that remains very persistent in the work of the emergency supply chain logistics. The response to emergencies in the U.S. is associated with a complicated system of players: federal government (e.g., FEMA, Department of Homeland Security), state emergency operation centers, local responders, non-governmental organizations (NGOs), and privately owned logistics partners. Although this multi-strata structure is supposed to increase the level of coordination, it usually leads to protocol clashes, communication failures, and duplication of duties.

As an example, in the case of Hurricane Katrina, the lack of clearly defined roles and a lack of interoperable systems caused redundancy in shipments, loss of inventory, and numerous delays in the delivery of aid. Fragmented governance, siloed information systems, and a lack of a greater picture are still threatening the unified response approach even after policy reforms like the Post-Katrina Emergency Management Reform Act.

2.2 Delays in Logistics

Logistic delays associated with disasters during response are quite prevalent. Other infrastructure, like roads, harbors, and airports, is easily destroyed, rendering the delivery of relief goods very difficult in the event of a disaster. There are also bureaucratic obstacles in addition to physical constraints. Requisition and request approvals of emergency supplies are often

slowed by ineffective procedures, inefficient inventory processes, and ineffective monitoring and real-time indicators of demand and supply status.

As another example, the distribution of personal protective equipment (PPE) and ventilators to frontline healthcare professionals during the COVID-19 pandemic was not only discussed in terms of major shortages all over the world, but also of ineffective domestic supply chains. Last-mile delivery, rerouting medical supplies, mobilizing mobile clinics, etc., are time-sensitive services where conventional systems cannot produce the necessary agility of operations.

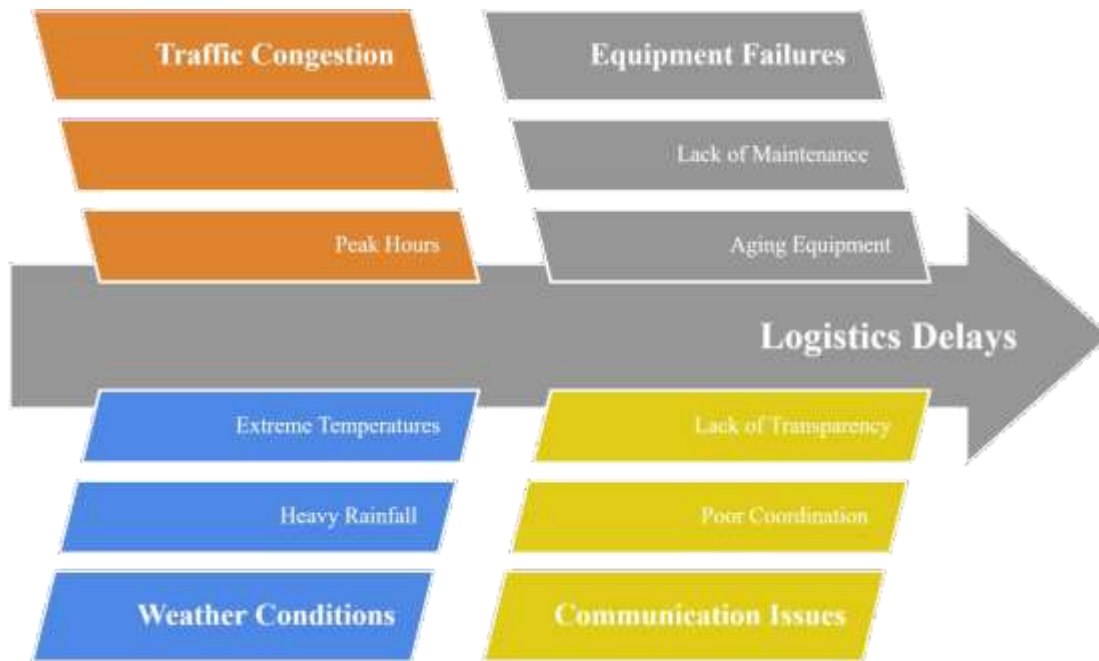


Figure 1: Delays in Logistics

2.3 Inadequate real-time data integration

The second strategic choke point is the nonexistence of real-time, integrated data within the entire supply chain ecosystem. Although private agencies or third-party logistics companies might have embedded tracking mechanisms within them, they are hardly capable of being interoperable or involving multi-agency cooperation. Consequently, decision officers act using fractured information that is old-fashioned, inconsistent, or incomplete.

Failure in sharing input of real-time satellite images, sensor information, forecasted weather conditions, and transportation network with each other undermines situational awareness. Such disjointed intelligence translates to reactive decision-making and suboptimal resource allocation, and the losses against proactive intervention. Moreover, a significant lag in the modern data integration systems is caused by legacy systems of the government agencies.

2.4 Anticipatory Decision-Making Requirement

Probably the most tactical gap of existing emergency supply chain systems is the absence of forethought. The existing strategies are mostly based on static patterns or attempt to make predictions manually, that is not able to predict the dynamic and nonlinear dynamics of disaster situations. There is no way emergency managers could predict a rush of demand, the breaches of routes, or the shortage in supplies until they happened; they would always be in the situation of fighting the last disaster, but not able to prepare for the next.

Simulation-based planning, scenario modelling, and predictive analytics remain underused in public emergency logistics. In times of disasters, time is a limited commodity, as what is decided within minutes might save a life, and what is taken hours may be disastrous. This gap can be reduced with the help of an AI-based DSS that allows forward-looking deals using real-time and historical inputs as a source of data, enhancing responsiveness and efficiency.

Table 1: Summary of Critical Bottlenecks in Current Emergency Supply Chains

Challenge Area	Description	Impact on Emergency Response
Fragmentation Across Agencies	Siloed operations, conflicting protocols, lack of interoperability	Duplicated efforts, delays in coordination
Delays in Logistics	Inaccessible infrastructure, bureaucratic approval chains	Slower aid delivery, extended suffering for affected areas
Limited Real-Time Data Integration	Disconnected systems, outdated or partial data	Poor situational awareness, inefficient resource allocation
Lack of Anticipatory Planning	Absence of forecasting tools and AI- driven models	Reactive operations, inability to pre-position critical goods

3. AI-Based Decision Support Systems: Capabilities and Use Cases

Artificial Intelligence (AI) has become an advanced technology that is fast developing in many fields, one of which is the healthcare industry. Intelligent Decision Support Systems (DSS) developed based on AI have been introduced in the field of emergency supply chain management to constitute a flexible data-intensive alternative to traditional planning and supply chain methods. The systems allow the stakeholders to anticipate demand, evaluate the risks, and streamline the supply routes in real-time, which is fundamental in pressure situations associated with disasters. The section contains the description of the fundamentals of using AI-based DSS in the disaster response context with evidence in practice.

3.1 Predictive Analytics: From Storm Paths to Demand Spikes

Among the most useful applications of AI in disaster logistics is predictive analytics. Predictive systems make use of historical data, machine learning algorithms, and real-time feeds to predict the weather patterns, the paths of the storms, and the requirements of supplies long before disaster takes place.

An example is satellites and weather information being fed into AI models to predict the severity of a hurricane and its direction several days before it happens. This has enabled emergency managers to position in advance supplies such as food, fuel, and medical kits that are nearer to areas of estimated impact. In the same manner, demand forecasting models with epidemiology information in the case of health emergencies could forecast the increase of personal protective equipment (PPE), ventilators, or drug demand.

During Hurricane Harvey, which took place in 2017, predictive models created with the help of NASA and the National Weather Service made it possible to more effectively forecast the disaster and evacuate people. But much of the real-time delivery of aid was overtaken by the prediction without the help of integrated AI-driven supply chains. Incorporation of AI into the supply chain decision is another important step.

3.2 Optimization Algorithms for Logistics and Routing

Optimization is another feature that is a key ability of an AI-based DSS. In a disaster, the best channels to deliver aid can shift by the hour depending on road congestions, shortages in fuels or altered weather. These real-time factors are fed into AI-powered optimization algorithms that reroute deliveries, decide how to use available resources in real-time and reduce idle times.

Such technologies as Reinforcement Learning and Genetic Algorithms are used to compare a number of different logistics situations within a short period, determining the most effective routes of transportation. The systems also enable the equilibrium of cost, speed, and the availability of resources, which is particularly valuable in emergency budget cases where

finances are tight.

To take another example, in the age of the COVID-19 pandemic, state health departments, and logistic companies applied the use of AI technologies in route optimization to transport test kits and PPEs in both urban and rural regions, cutting down the time of transportation by up to 30% in comparison to the static route planning.

In case of mass disasters, such as wildfires, or hurricanes, when time really matters, the real-time adaptation driven by the combination of technologies contributes to an efficient rescue and avoidance of a system failure.

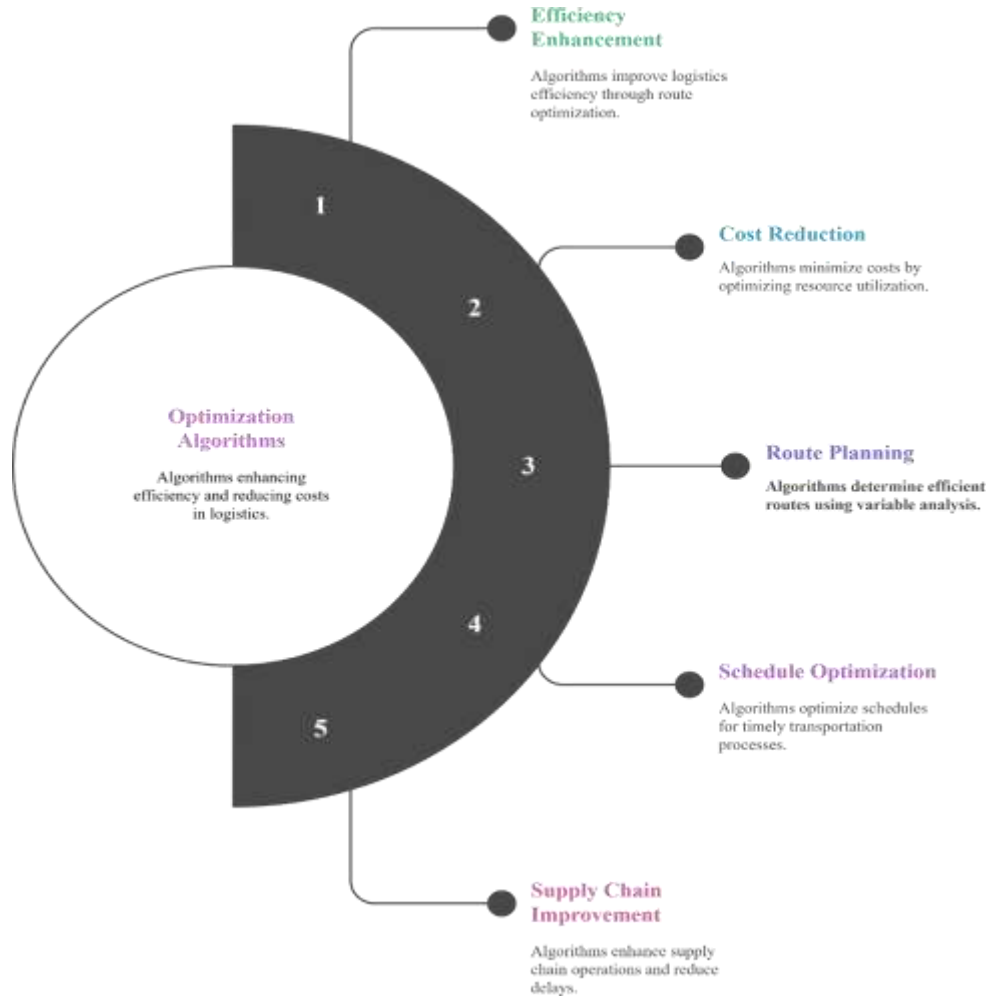


Figure 2: Optimization Algorithms for Logistics and Routing

3.3 Case Examples: Hurricane Harvey and COVID-19 PPE Distribution

Hurricane Harvey in 2017 and the COVID-19 pandemic in 2021 are two recent cases that can be used to teach a lesson the role and possible place of AI-based DSS in the field of emergency logistics.

Hurricane Harvey caused a massive flooding in Texas, forcing more than 13 million people into catastrophe. Although meteorological prediction was comparatively precise, emergency chains of supply failed to handle operations conveniently because of lack of good coordination, and low incorporation of real time data. Weather agencies trained their artificial intelligence systems to predict that the storm would land, but locations had to deal with the crisis because of inefficient logistics systems that failed to respond to the changing crisis. This led to late relief, wastages of shelter and misuse of resources.

COVID-19, in turn, was characterized by the wider use of AI tools, in particular, in the field of healthcare logistics. Corporations, such as BlueDot and IBM Watson Health, employed AI to monitor patterns of virus spreading, whereas Amazon, UPS, and agencies of several states utilized AI-supervised logistics platforms in managing PPE distribution. Nevertheless, in the context of

worldwide supply demands, the systems equipped with AI were better at predicting demands, monitoring inventories, and suggesting dynamic routes as evidence of real-life advantages of combined DSS systems in crisis management in the sphere of public health.

These cases highlight an important lesson that predictive and optimization tools require integration with logistics processes to become worthwhile. Forecasts or data analytics alone are of no value unless they are integrated into an operational DSS that can be used in real-time decision-making.

Table 2: AI Technologies and Their Application in Disaster Management

AI Technology	Application	Disaster Example	Scenario	Impact
Predictive Analytics	Storm trajectory forecasting, demand surge modeling	Hurricane COVID-19 planning	Harvey, PPE	Early resource positioning and accurate forecasting
Machine Learning	Supply-demand pattern recognition, risk scoring	Wildfire deployment	resource	Adaptive response and prioritization
Optimization Algorithms	Real-time routing, resource allocation, inventory management	COVID-19 logistics, earthquake responses		Reduced delivery times, minimized supply waste
Natural Language Processing	Social media analysis for damage assessment and resource need identification	Earthquake aftermath, hurricane tracking		Enhanced situational awareness from public reports
Computer Vision	Damage detection from drone/satellite images	Post-disaster infrastructure assessment		Faster damage evaluation and resource targeting

4. Proposed Framework: Integrated AI-Based DSS for Emergency Logistics

The unified, smart, and adaptable system that could work under the conditions of extreme pressure and uncertainty is urgently needed to address ongoing inefficiencies and fragmentation of the existing emergency supply chains in the U.S. The proposed model of an Integrated AI-Based Decision Support System (DSS) is aimed at establishing a solid architecture that makes it possible through real-time decision-making, predictive modeling, and the smooth interaction of different stakeholders. In this section, the major technological and organizational elements of the framework are described, which jointly lead to the possibility of a proactive, data-powered reaction to natural disasters.

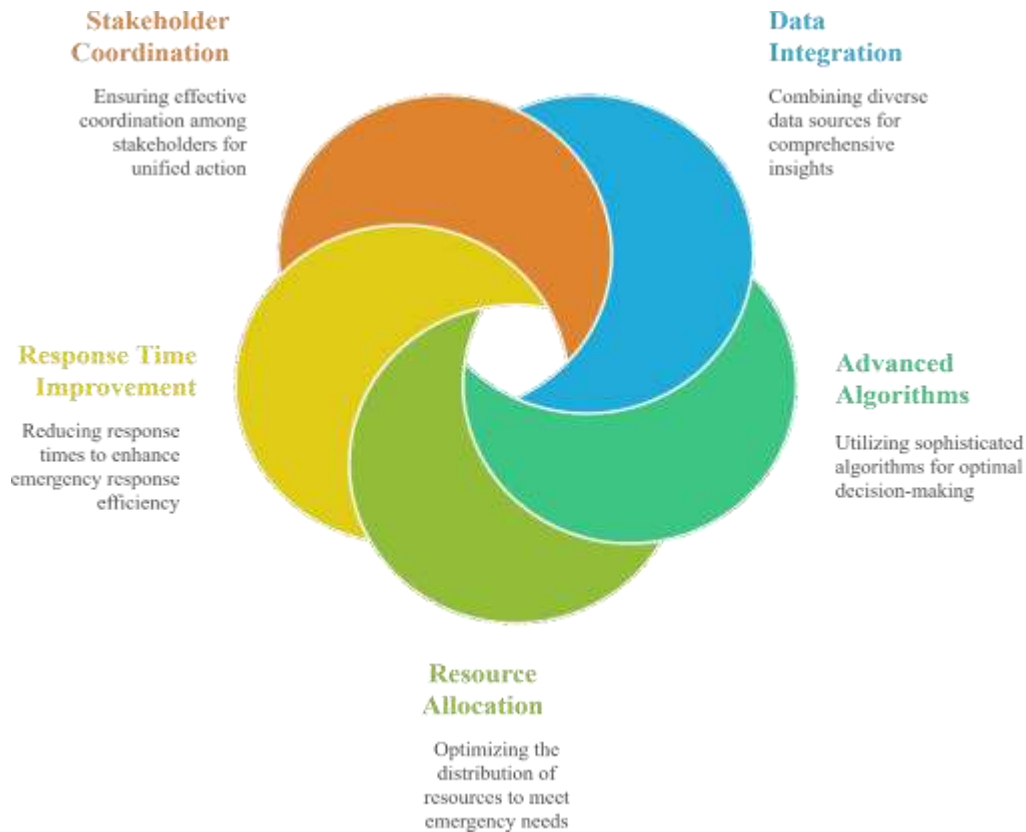


Figure 3: Proposed Framework: Integrated AI-Based DSS for Emergency Logistics

4.1 Situational Awareness: Data Fusion as its Basis

The key to the proposed DSS is a robust data fusion engine that can, in real time, aggregate, filter, and analyze a large amount of heterogeneous data. Such sources of data are:

- The satellite imagery and the remote sensing feeds
- Logistics centres and vehicle sensor data on the Internet of Things (IoT)
- The posts on social media and incident reports that are geotagged
- Seismic info and weather prediction
- Supply-partner metrics (such as real-time inventory and transportation)

Aggregating all these feeds to a centralized data lake and running analysis on them by means of AI-based analytics, the system generates a single operational image of a disaster environment. The combination facilitates the rapid determination of the gravity, geographical dimensions, and logistical requirements in areas hit by any disaster.

In addition to that, the architecture of the system must be able to consume structured as well as unstructured data formats, in case of legacy systems, and in case of data pipelines in the future. Machine-readable actionable incoming data is guaranteed through the application of semantic interoperability standards (e.g., XML, JSON-LD).

4.2 Real-Time Dashboards and Forecasting Engines

The other important one is incorporation of live time dashboards driven by live data feeds with embedded forecasting engines. Emergency managers have in these dashboards visually appealing representations of:

- Statuses and positions of assets (e.g. warehouses, supply trucks)
- Disaster impact areas and hazard heat maps
- Regionally predicted supply demands
- Resource deployment level and shortages

Forecasting engines based on AI use an endless stream of time series data and models of simulations to predict logistical requirements, surges in demand, and changing disaster paths. Dynamic scenario planning can occur because these forecasts are updatable in real-time as new data becomes available.

An example of this is that when the system leads to forecasting of high rates of evacuees in a particular region due to weather conditions and gaps in traffic movements, it is capable of automatically notifying the agencies to either step up supplies of medical resources and provision of temporary shelters. Such prediction capability changes emergency logistics as a response activity to a preemptive action.

4.3 Multi-Agent Systems for Distributed Decision-Making

Since emergency response in the U.S. is decentralized, the framework should have architecture of multi-agent systems. These systems are characterized and compose of the autonomous software agents, where each one is bound to undertake a specific task, including inventory control, route planning, or shelter capacity monitoring among others, running and working together within the wider DSS.

Every agent is able to:

- Localized data analysis
- Create decisions that are domain-specific
- Interact with others agents to discard any conflicts or share information
- Be flexible to receiving feedback and circumstances

Such distributed intelligence makes it scale better, fault tolerate, and responsive. As an illustration, a Florida routing agent can be left on its own to optimize fuel delivery, but at the same time coordinate with federal agents in charge of control the distribution of national supply.

Another advantage of multi-agent systems is that they can offload the cognitive demands on an operator since tedious or compute-intensive processes can be automated so that human operators can concentrate on the strategy and coordination.

4.4 Inter-Agency Data-Sharing Protocols

The first precondition for the successful work of this integrated DSS is inter-agency interoperability, the capability of various organizations to exchange data transparently and operate on the same plane. This is both technical solutions and institutional solutions.

Technically, the system should be based on open APIs, encrypted cloud infrastructures, and permissioned access layers that secure important information and still allow collaboration. Examples of standards included are: National Information Exchange Model (NIEM) and Emergency Data Exchange Language (EDXL), which can bring order and trustworthiness in data streams between:

- Agencies of the federal government (e.g., CDC, FEMA, DoD)
- Local and state emergency operation centers (EOCs)
- Humanitarian organizations and NGOs
- Contractors and providers of commercial logistics

Institutionally, the governing principles of logic and protection of data, such as a memorandum of understanding (MOU), common operating procedures, and legal frameworks, should be put in place.

The group dynamic means that AI generated at one tier (e.g., to predict the PPE needs of the mainland US using the demand data published by the CDC) could be shared to drive the logistics plan at another (i.e., send a truck to a state using the EOC) without the time-consuming delays and the resulting lack of coherence.

Table 3: Components of the Proposed DSS Architecture

Component	Description	Function
Data Fusion Engine	Aggregates structured and unstructured data from multiple sources	Builds a unified operational picture in real time
Real-Time Dashboards	Interactive interfaces powered by live data and visualizations	Provides situational awareness for decision-makers
AI Forecasting Engine	Uses machine learning to model future scenarios and demand patterns	Enables anticipatory decision-making and resource planning
Multi-Agent System	Decentralized agents handling logistics, planning, and monitoring	Distributes computation and enhances system scalability
Inter-Agency Data Protocols	Technical and legal standards for data sharing across organizations	Facilitates seamless coordination and information exchange

5. Implementation Strategy and Best Practices

Deployment of an Integrated AI-Based Decision Support System (DSS) in the U.S. emergency supply chain management must not only present technological innovation but also need diligent execution plans backed by alignment on organizational levels, coverage by policies, and long-term investments. This part describes best practices and strategic planning needed to make the proposed DSS work in real life, including the need to collaborate across industries, workforce readiness, and the ability to deal with emerging cyber threats.



Figure 4: Implementation Strategy and Best Practices

5.1 Public-Private Partnerships

Public-private partnerships (PPPs) prove to be one of the most effective forms of setting up complicated AI-based systems in emergency logistics. Although complexity in the coordination of a disaster response is usually the role of federal agencies, companies in the private sector boast the latest technologies, the know-how of logistics, and the ability to stretch their infrastructure when needed. The DSS model can only be implemented successfully when the advantages of the two sectors are capitalized on.

Companies like Amazon, UPS, and Palantir have already helped; they are making a major contribution to the problem of integrating logistics and data in the conditions of major crises like the COVID-19 pandemic. Such companies provide useful assets such as AI platforms, cloud computing services, and real-time tracking. In their turn, government agencies introduce regulatory responsibility, territorial reach, and access to important information.

PPPs have to be institutionalized to prevent such duplication and enhance synergy by using formal agreements, which clearly explain roles, responsibilities, data-sharing, and escalation modes. There should also be joint emergency preparedness drills and simulation exercises with the private partners so as to make them operationally ready.

5.2 Training and Scalability

The performance of any AI-based DSS will largely depend on the ability of human operators to learn and trust a system. This renders the training and workforce development as an essential pillar of the implementation strategy. The personnel involved in emergency measures, including emergency managers, logistics coordinators, and IT personnel, must be trained on:

- Processing AI-created predictions and risk evaluation
- Knowledge of the shortcomings and confidence of predictive models
- Multitasking, real-time dashboards, and multi-agent interfaces
- The ability to adapt to dynamic processes in workflow is made possible by automation.

The training needs to be standardized, and it should become a part of the National Incident Management System (NIMS), where knowledge acquired should be consistent across jurisdictions. Besides the centralized training, on-the-ground drills and tabletop exercises will establish local competence and help in cross-agency cooperation.

The other critical requirement is scalability. The DSS should be constructed in a way that it can be used in a wide range of disaster situations, such as local floods and national pandemics, without making any significant structural changes. Those include construction of modular units, cloud-based design, and elastic computing power that will be expanded or reduced depending on the scale of the event.

5.3 Funding and Cybersecurity Considerations

An important enabler is the financial sustainability of the DSS initiative. Although start-up funding can be obtained through federal grants, like those offered by the Department of Homeland Security or National Science Foundation, the funding needs to be on an ongoing basis when it comes to maintenance and updating. A possible funding arrangement is a shared services funding system, with the federal, state, and private sectors contributing according to the proportionality of use and jurisdiction.

In addition, as the information on disasters and current intelligence on operations is confidential, cybersecurity should be a fundamental aspect of the DSS system. It will administer real-time data sets regarding infrastructural vulnerability, bottlenecks within the chains of supply, and population dynamics, which can be made use of by the malevolent actors if you do not secure it.

Cybersecurity best practices must consist of:

- Secure cloud storage and multiple-layer encryption
- Active monitoring and intrusion surveillance
- Role-based access controls (RBAC)
- Duplication and disaster recovery plans
- Adherence to the federal guidelines, such as FedRAMP, NIST, and CISA directives

Also, an AI ethics committee must be developed that will be in charge of the responsible use of algorithms, especially data privacy, bias mitigation, and decision-making transparency.

Table 4: Policy and Technical Enablers for DSS Adoption

Category	Enabler	Implementation Insight
Public-Private Partnership	Formal MOUs, collaborative training, joint simulations	Establish trust and clear roles among federal, state, and private stakeholders
Workforce Readiness	Standardized training modules, NIMS integration, local capacity building	Equip operators with the skills needed to manage AI-based systems
Scalability	Modular system design,	Ensure adaptability across different disaster types and geographic scales
Funding	Multi-source financing, federal grants, shared services models	Provide consistent funding for implementation and maintenance
Cybersecurity	Encrypted communication, RBAC, compliance with federal IT standards	Protect sensitive operational and infrastructure data from cyber threats
Ethical Oversight	AI transparency, bias audits, ethical governance frameworks	Ensure fairness, accountability, and public trust in AI-driven decisions

6. Case Scenario Simulation: DSS in Action During a Category 4 Hurricane

In a bid to provide a demonstration of the functional value of the proposed AI-based Decision Support System (DSS), this section uses a simulated case scenario that involves a Category 4 hurricane hitting the southeastern United States. It will aim at comparing the performance of emergency supply chains both in the situation before the implementation of the proposed DSS framework and after its implementation, with the dimensions of coordination level, decision-making velocity, optimization of logistics, and effectiveness of outcomes.

6.1 Scenario Context: Hurricane Phoebe

In this scenario, Hurricane Phoebe is generated in the Atlantic and it is expected to hit the Florida and Georgia shores. The Sustained winds of 140 mph mean that the hurricane will cause massive flooding, block roads, and cause power cuts to affect more than 10 million people who live in the area. The emergency response is coordinated by various stakeholders, which include FEMA, state emergency operations centers (EOCs), National Guard, non-governmental organizations (NGOs), and commercial partners in logistics.

Emergency needs are:

- Ventilators and medical kits
- Shelf-stable food and bottled water
- Generators and fuel
- Shelter items (Tents, blankets, and cots)
- Home, personal hygiene, and infant products

6.2 Before DSS Integration: Fragmentation and Delays

In a pre-DSS situation, there is a problem of no real-time data available, disparate coordination, and reactive decision-making in response to a scenario:

- **Late Requirement Evaluation:** The state departments depend on outdated demographic charts and paper-based evaluation of needs. This means that the supply estimations become inaccurate, causing the oversupply of some regions and acute undersupply of others.
- **Fragmented Logistics:** Each database and information sharing facility maintained by FEMA and state EOCs leads to duplication of efforts. There are cases of relief supplies going to the same shelter, yet there are other served areas that are undernourished.
- **Ineffective Routing:** Emergency supplies carried by convoys are unable to avoid unforeseen road congestions and flooded roads because of real-time traffic and infrastructure information. The alternative routes are not found until there are major delays.
- **Wastage of resources:** Mobile health clinics and water tanks are sent in view of the movement of people. Some of them end up in areas that have a scarcity of people, whilst leaving the high-demand areas unattended.

The result is low responsiveness in hosting distribution, and a lack of visibility of the overall work, which means that thousands of affected inhabitants lack sufficient supplies after 4872 hours.

6.3 After DSS Integration: Intelligent, Coordinated Response

Under the post-DSS conditions, the suggested AI-powered framework will be implemented at all the agencies involved in a cloud-based form:

- **Forecasting and Pre-positioning:** Weather data used in the weather models is combined with the DSS through predictive analytics to find the most likely landfall and impact areas. Prior positioning of supplies in warehouses occurs within 150 miles of anticipated hotspots so that it does not require long transport distances after the disaster.
- **Unified Operational Picture:** A centralized dashboard with live information provided by IoT sensors, satellite images, social media, and agency stocks. It allows decision-makers to visualize the occupancy in shelters, road conditions, and supply flow in real time.
- **Multi-agent routing algorithms** adjust delivery routes dynamically according to flooding, traffic jams, and fuel availability in optimized logistics. Convoys are diverted on the fly so that bottlenecks can be avoided, and the high need zones can be accessed faster.
- **Demand Matching:** AI models predict the demands depending on the real-time data about the population flow (e.g., density of mobile devices, the patterns of traffic during evacuation), so the busiest shelters will first be supplied with the goods. The inventory will automatically be reallocated to meet current needs.

Consequently, life-saving resources cover over ninety-five percent of the affected individuals within 24 hours of the landfall. In the case that there are duplicates made in delivery, then this is dropped by 80%, whereas the overall supply chain performance jumps by 45%, using delivery time and fulfillment accuracy as the metric.

Table 5: Comparative Summary: Before vs. After DSS

Metric	Before DSS Integration	After DSS Integration
Demand Forecasting Accuracy	Low – based on outdated models	High – AI-driven predictive models with real-time updates
Delivery Time to Affected Areas	48–72 hours	Within 24 hours for 95% of affected population
Resource Utilization	Poor – oversupply and undersupply across regions	Optimized – matched supply based on population movement
Inter-Agency Coordination	Fragmented – siloed systems and delayed communication	Unified – shared dashboards and real-time data exchange

Route Optimization	Manual – no live adjustment for road closures	AI-powered – dynamic rerouting based on live data
Outcome for Affected Population	Prolonged exposure to unsafe conditions	Rapid aid delivery and reduced human suffering

7. Discussion and Strategic Implications

There is a profound technological and strategic choice within the sphere of emergency logistics, represented by the implementation of AI-based Decision Support Systems, which are bound to become a nationwide and even worldwide pillar of resilience. With increasing intensity and frequency of occurrence of natural disasters owing to climatic changes, population increase, and the excessive spread of cities, the response systems require intelligent, scalable, and adaptive systems of response more than ever before. This part addresses broader ramifications of the proposed framework to the United States, addresses risks and ethical issues, and considers how it can be applied to global disasters.

7.1 Enhancing U.S. National Resilience Through AI

The fundamental aspect of the proposed system is the evolutionary change in the process of preparing the U.S., responding, and recovering with regard to natural disasters. The effectiveness of traditional emergency logistics systems is based on a fragmented, linear, and reactive system that cannot keep up with the complexity of contemporary disaster events. The decision intelligence and computational resources that AI DSSs can produce are the requirements to be able to work in an environment characterized by uncertainty, time pressure, and multi-actor coordination.

The wider strategic advantages to the U.S. national resilience are:

- **Quicker Response Rate:** Forecasting models that AI facilitates and real-time dashboards may accelerate response rate by hours or even days, which can be reflected directly in saved lives.
- **Informed Decision-Making:** Decision-making on the allocation of resources is more accurate and timely as the federal and local leaders have data-driven insights that increase efficiency in the operation of any organization, as well as public confidence.
- **Systemic Integration:** AI-based DSSs reduce the siloing of data between different agencies and promote a unified and adaptable emergency management infrastructure due to interagency information-sharing and following consistent rules of communication.
- **Scalability:** Modular system architecture facilitates being deployed over multiple urban and rural geographies in hurricane-prone regions of Florida to wildfire-prone regions of California.
- **Learning and preparedness:** Machine learning elements enable ongoing development based on previous data and results of the events accumulated in time, so the future state of preparation is enhanced.

7.2 Ethical Considerations and Systemic Risks

Although the potential of AI in this technology is enormous, it is crucial to mitigate the risks and the ethical implications of using AI in the critical infrastructure and public safety.

7.2.1 Algorithmic Bias and Equity

The quality of AI models is at least as high as the quality of the data that is trained. In crises, prejudiced or deficient data may result in inappropriate allocation of assets, e.g., under-servicing of marginal communities and rural communities. As an example, a model that operates on urban data mostly may neglect the assistance of the sparsely populated regions. It should be an essential system design principle that DSS based on AI is transparent and fair.

7.2.2 Data Privacy and Security

Emergency DSSs can store and receive so much sensitive information, such as health records, geo data, and real-time

surveillance feeds. Although this kind of data is critical when it comes to operational efficiency, it has serious privacy risks. Improper permission or exploitation of such information without authority, particularly at times of Mayhem, may give rise to transgression of civil liberty. Sound encryption, limited access, and adherence to data protection systems (i.e., HIPAA, CISA guidelines) are necessary protective measures.

7.2.3 Technological Dependence and Systemic Fragility

Dependence on AI systems may create another type of systemic vulnerability. In case of a disaster, failing to deliver, say, on cyberattacks, a caesura in infrastructure, or a malfunction in software, emergency operations could be drastically maligned. So, they will have to allow redundancy, manual override features, and architectures that prevail in disasters.

7.3 Global Relevance and Adaptability

Even though the discussed framework in the article is focused on the United States, the core concepts of the AI-driven DSSs are easily transferable to any other region across the world. Earthquakes in the Japanese region, typhoons over the Philippines, floods in Bangladesh, wildfires in Australia, etc, have so much in common when it comes to logistical and coordination issues.

All the main aspects contributing to international flexibility are:

- **Modular Design:** The system architecture may be tailored to the nationally specific type of structures, whether centralized (e.g., China) or decentralized (e.g., EU countries).
- **Language and Localization:** One can find language and localization techniques through natural language Processing and translation algorithms.
- **Cloud Accessibility:** Infrastructures in the cloud can be implemented quickly and within developing regions where IT resources may be scant.
- **NGO and International Partnerships:** Global organizations like the Red Cross, UN OCHA, and WHO might implement AI-based DSSs in order to organize more streamlined international aid delivery and coordination.

Nevertheless, low-resource regime deployment should take into account such limitations as unfavorable access to the internet, the absence of digitisation of infrastructure, and governance capacity. Global scalability will require international cooperation, capacity building, and the transfer of technology programs.

The argument presented above highlights the fact that although AI-powered DSS models are highly favorable to emergency logistics, their use should be supported with a robust governance, a set of ethical norms, and a custom-tuning to the context. With nations everywhere gearing up to face the future that beckons with more disasters in terms of both their frequency and complexity, intelligent decision support systems will become not only a technical modification but also a moral and combative requirement.

8. Conclusion and Policy Recommendations

There is a significant build-up of natural disaster rates all over the United States that have put a serious strain on the current emergency civilian supply chain environments. Darden has yet to find effective checks on fragmented communication, delays in logistical support, restricted situational awareness, and the inability to make proactive decisions in the form of disaster response. Such institutional limitations highlight a compelling necessity to pursue a paradigm shift towards smarter, approachable, and flexible solutions, which can be utilized by dealing with a high-stakes and fast-changing emergency.

The paper has introduced a detailed structure of an integrated AI-based Decision Support System (DSS) to support the peculiarities of the situation in emergency logistics in the case of natural disasters. The proposed system is a revolutionary move by integrating predictive analytics, sensor fusion, optimization algorithms, and distributed decision-making processes. Compared to the traditional systems, the AI-based system can, in addition to effectively reacting to the disasters, also anticipate the disruption and therefore the resources can be allocated before their occurrence becomes critical. The advantages, which include better speed, coordination, transparency, and equity, are enormous and extensive.

A multi-actor initiative is needed to accomplish this potential. The national and state-level resilience agendas should prioritize AI-based emergency infrastructure, followed by sustained funding, cross-agency integration, and good governance structures. The technology developers should pay attention to the development of ethical, transparent, and solid AI models that do not violate data privacy and reduce bias. LSP and emergency management professionals should be able to undergo continuous training, simulation, and system feedback to be ready and versatile.

The need to act is obvious: in the days of more chaotic disaster environments, integrated AI-based decision support is no longer a luxury; it is a necessity. It is high time to invest in smart, hardy systems.

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