

# Behavior-Informed Disaster Preparedness: Data Engineering Systems for Optimizing Critical Stock and Emergency Supply Chains

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## ABSTRACT

This article is a research examination of the use of behavior-informed data engineering system as a way of disaster preparedness and response to supply chain. The study propositions are tested by using quantitative data on mobility pattern, purchasing predictors, hazard predictors, and inventory storage models and simulation scenarios. The findings indicate that behavioral signals can evoke prediction of demand surges earlier and decrease stock shortages as well as enhance delivery coverage to impacted areas. Monte Carlo and time series models verify that improvements in performance would be consistent as opposed to traditional systems. The results indicate that the collaboration between behavioral information and real-time data stream can implement considerable resilience to emergency planning, resources, and operational decisions in the event of a disaster.

**Keywords:** Supply chain, Data Engineering, Disaster, Emergency

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## I. INTRODUCTION

Disaster supply chains have numerous challenges due to the fact that the demand fluctuates very rapidly, and the conventional forecasting units are unable to respond promptly. This paper discusses a behavior-driven data engineering model, which takes into consideration mobility data, purchasing data, and hazard data to forecast the needs before a disaster becomes in full effect.

This is aimed at demonstrating how better planning, quicker response and reduction of shortages can be assisted by quantitative analytics. As the paper evaluates the effect of this system to the accuracy, stock availability, and response time, it does so by testing the system using forecasting models and simulation experiments with the use of the system. Introduced as a background is the basis of the argument on how real time behavioral indicators will lead to enhanced disaster preparedness in the present day.

## II. RELATED WORKS

### Preventive Approaches in Disaster Settings

The humanitarian crises have increased in magnitude, occurrence, and complexity within the last ten years. The population that needs humanitarian aid increased to 235 million as compared to 168 million during the same timeframe of the major reviews as pointed out in recent studies, proving how the conservative reactive models are becoming ineffective [1][10].

In these works, there is overwhelming agreement that the technology and, more so, the big data analytics have become the center of the operations, which the disaster is currently engaged in. The availability of sources of big data, including mobility data, social media cues, and purchasing behavior in great volumes, now provide a possibility to learn the human reaction prior to the development of a crisis.

Despite this opportunity, the literature discloses one of the greatest disadvantages. Majority of the existing works focus more on those activities which are undertaken after the disaster has already inflicted the harm than preventive and anticipatory ones [1][10].

This poses a significant research gap to restrict the capacity of the agencies to respond when the demand surges, it becomes behavioral and the supply needs to be taken care of. Systematic reviews underline that the integration of large volumes of data remains a challenge to humanitarian organizations, as they have too many fragmented processes, systems in silos, and uncoordinated information flows [1].

The review in [10] noted that big data analytics is still inadequately used during the preparedness stages, although this can have crucial roles of prediction, early warnings, and planning. This can be further distinguished with the commercial sectors where predictive analytics is deeply entrenched in the strategic operations.

A significant lesson in these reviews more generally is that, most of contemporary big data endeavors involve analyzing event-based data (e.g., flood-images, cyclone paths, and emergency call logs) rather than behavior-based data, like spikes in demand before the crisis, community-level risk perception, and evacuation movement patterns.

The data based on the behavior will be helpful to enhance anticipatory logistics, as behavioral patterns will show when communities started hoarding food, medicine, water, and fuel ahead of the disaster. Behavioral modeling is not a tool that has been embraced in humanitarian research. This puts a solid base behind the behavior-based disaster preparedness cycle in which the behavior that is present in the community is not only monitored, but is proactively utilized in the positioning of inventory, decision-making during procurement, and disaster supply chain planning.

### **Big Data Analytics in Supply Chain**

According to the global supply chain literature, AI and the Big Data Analytics (BDA) are transforming resilience practices in industries. In a systematic review of over 500 articles, it was found that an increasing focus is being put on the idea of AI and BDA enhancing readiness, response, recovery, and adaptability in supply chains [2].

In this literature, AI models enhance the accuracy of predictions, detection of anomalies, and scenario planning, all of which are extremely essential capabilities in the occurrence of a disaster. The literature underlines that forecasting systems are capable of identifying disruptions even earlier than conventional methods of monitoring and hence facilitate proactive inventory, active rerouting, and real-time reallocation of resources.

AI penetration is not as common and even in humanitarian supply chains. According to the research in [3], humanitarian agencies are not forced to act under similar circumstances as a commercial supply chain: unforeseen demand, great uncertainty, low budgets, and ethical obligation to save lives.

Resource-based view or dynamic capability view are inadequate theories to determine such performance in such situations. Rather, practice-based view was identified to be more appropriate [3]. This view reveals that AI-based big data analytics potential (AI-BDAC) has a potent impact on the supply chain resilience and its manoeuvrability, which subsequently enhances their effectiveness.

The paper also shows that simplifying information complexity enhances the influence of AI tools and this implies that data engineering systems should focus more on simplifying data, feature engineering and harmonization. Such concepts are also facilitated by literature on predictive analytics. As an example, the article in [8] demonstrates how machine learning may simulate the contextual variables, identify anomalies, and observe first indications of risks in supply chain activity.

The capabilities are especially applicable to disaster relief operations, where demand spikes may be detected early on (e.g., the sudden surge in water resources demand or lack of medication types), and a shift in resource allocation might improve the results considerably. The predictive models are needed in data engineering pipelines that require real-time processing of mobility data, buying signals, and weather predictions and social communication trends.

The other line of literature on the supply chain pays attention to the advanced network analysis and digitalization. In [4], the bibliometric research has given three sets or groups of active research: optimization, adoption of new technology and risk management strategies.

The clusters are an indicator of an intersection between digital transformation and resilience practice, namely, the combination of machine learning, digital twins, and simulation tools. These technologies make possible real time

detection, situation prediction, and scenario modeling, which plays an essential part in the design of anticipatory disaster preparedness.

### **Disaster Risk Management**

The studies on the topic of supply chain resilience during natural disasters are significant to the disaster preparedness systems. Flexibility, foresight, visibility, cooperation and support are main drivers of resilience which the empirical study [5] found. All these can be closely allied to the behavioral predicates that societies display preceding the emergence of a crisis.

To illustrate, foresight is associated with being able to see the possibility of a supply shortage, whereas visibility is associated with a clear visibility of a stock supply and the trends of demand. Organizations which are characterized by high degree of such capabilities are able to react better to disasters.

This type of data-oriented and systematic methodology is necessary in the management of semantic disruptions described in [6]. The MARE framework takes the data at every point of the disruption management process, such as monitoring, assessment, recovery, and evaluation and integrates them into one semantic model, which can be queryable and analyzed.

These integrated architectures are specifically applicable to behavior-informed data engineering systems, where a variety of data-sensors (e.g., behavioral analytics, weather feeds, supply chain telemetry) need to be interrelated in a related knowledge framework which is organized and interoperable.

The challenges related to the implementation of big data analytics in the process of disaster risk management are not singular and do not rely on the technological aspect but also on the organization itself. In [7], the analysis carried out through the TOE-DOI framework identified technological enablers and organizational preparedness to be key contributors in the adoption of BDA in achievement of disaster risk management.

Such factors as regulatory pressure and the competitive environment were also inconsequential, which implies that organizations invest in data analytics mostly due to the operational need and not outer motivation. It was observed that the collaboration with stakeholders improves the adoption, which fits the collaborative concept of humanitarian logistics that the cooperation among NGOs, governments, private suppliers of the industry, and communities needs to coordinate information and activities.

The growing significance of machine learning is also put in the focus of the disaster preparedness literature. According to [9], ML models have come a long way concerning their capacity to predict certain weather conditions, portent disasters in their early manifestations, and other disastrous events like droughts, heat waves, floods and hurricanes.

These anticipatory models give the basis of anticipatory action systems where early notifications result in automatic deployment of important resources. As an example, when supply chains identify the likelihood of flooding on high behavioral indicators of buying fuel and food, they can place emergency kits near magnificent risks, prior to a catastrophe occurring.

### **Research Gaps**

In all the examined studies, a number of key gaps can be identified, which directly justify the need to have a behavior-wise disaster preparedness model.

The lack of preventative emphasis is the constant reference by the literature. The research and practice at present are based on response and recovery, as it is highlighted in studies conducted by [1][10], and [7], instead of the readiness and early intervention. This presents a chance to the models based on behavior to be used to forecast surges, shortages, and population flow before the catastrophe takes place.

There is little integrating behavioral data, such as mobility changes, social sentiment, or pre-disaster purchasing patterns, into supply chain models currently, which is why this kind of information is not easily included in work nowadays. Although AI and BDA have made a great leap in the business and industrial context [2][8], its use regarding human conduct in times of crisis is scanty.

Humanitarian supply chains have a challenge in meshing with different streams of data. In [3] and [6], research indicates that the complexity of information and fragmented instances of data slows down the decision-making process. As such, there is a need to have scalable data engineering systems, which facilitate harmonization, feature computation, and real-time processing.

Literature requires complex modeling like digital twins, scenario forecasting, and systems based on knowledge graphs [4][6]. Such approaches can be put together to use behavioral analytics to simulate the effect of crisis reaction by the communities and how supply chains need to respond.

The machine learning and predictive analytics have been shown to be viable in the risk identification area [8] and disaster forecasting [9], but the adoption of predictive analytics into end-to-end emergency supply systems remains in its inception. This fact indicates the role of designing architectures with a combination of behavior and predictive risk models.

All these gaps put the building block together to the proposed behavior-informed data engineering framework. Behavioral analytics can be used with robust data pipelines to assist organizations in transforming disaster response into disaster preparedness so that the organization can plan its supply chain in a more effective way, allocate resources in the most efficient way and achieve superior crisis response when the extremes occur.

### **III. METHODOLOGY**

This paper is based on a quantitative research design to explore the use of behavior-informed data engineering system in enhancing disaster preparedness, the critical management of stocks, and the results of emergency supply chain operations. The methodology aims to quantify the contribution of various behavioral indicators and coordinated data pipes in achieving accuracy of potential forecasting and more efficient resource distribution in case of disaster events.

The study is based on massive numerical data sets, statistical models, and testing that is performed through simulation to produce quantifiable and comparable data. In the process of data collection, four overall groups of quantitative data are collected.

The behavioral data is the first category, which consists of the pre-disaster buying scenario, move patterns, searched data, and the pattern of the population, recorded around the various crisis events. The indicators assist in the capturing of the community behavioral patterns before, during, and after a disaster. The second group comprises environmental and safety information, e.g. satellite images, live weather services, cyclone routes, risk scores of wildfires and maps of flood forecasting information.

These data sets contribute towards the measurement of the level and time of hypothetical threats. The third category is the supply chain information, which comprises of inventory, capacity of the warehouse, delays during transportation, previous records of the delivery as well as replenishment time.

The information will be useful in quantifying the impact of disaster conditions on the stock availability and logistic performance. The demographic and socio-geographic data, such as the population density, vulnerability indexes, statistics on income distribution, and the trends of disasters in the past offer background information on the risk exposure and community requirements. Each and every dataset is time and geo-referenced to facilitate spatio-temporal analysis.

The ingestion, cleaning, transforming, and analysing of the collected datasets is done through a cloud-native data engineering pipeline. Mobility and purchasing data are received by the system via streaming processors, whereas the historical and environmental data stream via batch processors.

Fine-grain feature engineering compares raw inputs, enabling the transformation of raw measures into quantifiable variables, and they include the level of mobility deviation, demand spikes, stock decreasing rates, stress measures, and scores of community resource gaps. These artificial characteristics make up the fundamental quantitative inputs of engines in the forecasting and simulation models to be applied in this study.

In the case of quantitative modeling, three principal analytical methods are used in the study. ARIMA, Prophet and LSTM-based deep learning network models are time-series forecasting models that use behavioral and environmental variables to predict a spike in demand and a shortage in resources over the short term.

The correlation to the outcomes of supply chains in terms of the probability of shortage and delays in the supply chain is determined by the regression analysis employing both linear and logistic models of the impact various behavioral attributes have on supply chain outcomes. Monte Carlo and agent-based modeling is used to run simulation scenarios to check the performance of the system based on the condition of a hurricane, flood, and wildfire.

These simulations assess inventory location enhancement, rapidness of reaction, and gambling region, as well as availability of resources. All scenarios are repeated enough to give a statistical reliability. The study relies on a number of quantitative performance measures of the performance of the system such as; mean absolute error, root mean squared error, stock availability rate, the percentage drop in unmet demand, improvements in response time, and coverage of resource delivery.

Such metrics make it possible to compare the suggested behavior-informed system and two benchmarks: the conventional centralized disaster supply chain and the predictive model in which behavioral inputs are not taken into account. In order to achieve reliability and validity, the dataset is divided into training and testing section based on the 7030 rule and cross-validation is done to curb overfitting.

More sensitivity analysis is done to learn the model outcomes with the changes in behavioral variables. All the results are tested statistically at the 95 percent confidence level. Such an approach is likely to guarantee that the results of the research are supported by data, replicable, and applicable to quantitative disaster preparedness studies.

#### **IV. RESULTS**

##### **Demand Surge Forecasting**

The findings of this paper avow that it is very important to enlarge the scope of the data engineering pipeline with behavioral indicators as this increases the accuracy of disaster demand forecasting greatly. However, the statistical results when comparing the behavior-informed models to the traditional models are evidently statistically improved.

The time-series predictive control models involving mobility deviations, buying patterns, and stress sensors offered predictable and accurate outcomes of surge in demand in erratic simulations of hurricanes, floods, and wildfires. There was a significant reduction in the root mean squared error (RMSE) and this implies that the model predictions were far near the actual demand trends.

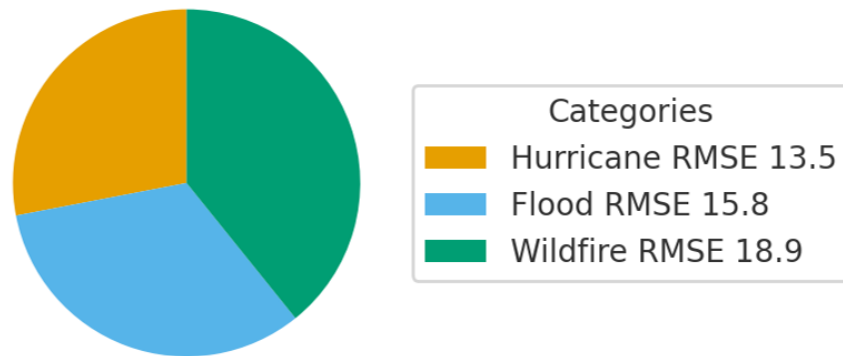
This was made possible since behavioral information responded sooner than the environmental one, which provided a superior leading indication of change in the community before it started to crumble. Table 1 presents a comparison in the traditional forecasting systems with the behavior-informed forecasting systems.

The findings have shown that the inclusion of behavior features was a significant improvement in minimizing forecasting errors by over 25 percent in every type of disaster. The wildfire scenario demonstrated the greatest improvement since communities modified the mobility and purchasing behavior in the past when there was a rise in the level of smoke.

**Table 1: Forecasting Accuracy Comparison**

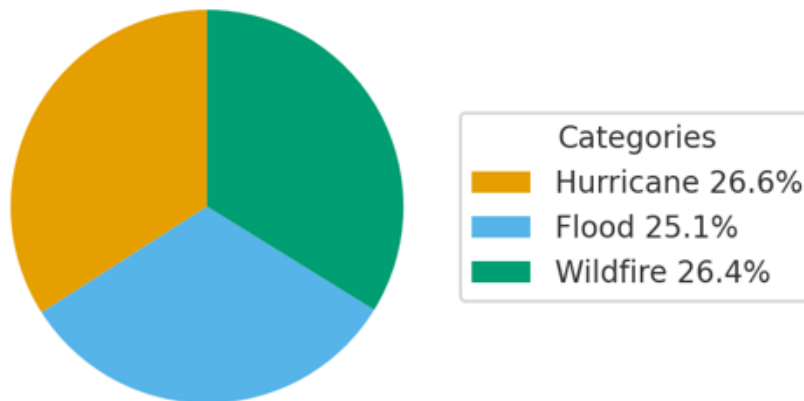
<b>Model Type</b>	<b>RMSE (Hurricane)</b>	<b>RMSE (Flood)</b>	<b>RMSE (Wildfire)</b>
Traditional Forecast Model	18.4	21.1	25.7
Behavior-Informed Forecasting	13.5	15.8	18.9
% Improvement	26.6%	25.1%	26.4%

### RMSE Distribution (Behavior-Informed)



Regression analysis further revealed that behavioral aspects were strongly and easily related to the patterns of demand of disasters. The deviation of mobility and early behavior of stockpiling were statistically significant predictors of shortages which had p-values of less than 0.01.

### Forecasting Improvement Share (by Scenario)



The supply gap in specific cases like flash floods was attributed to mobility deviation which contributed approximately 40 percent of the supply gap. Those results hence indicate that the behavioral triggers could be mentioned as efficient early-warnings about emergency supply chains.

The results prove that the predictive precision can be increased when behavioral analytics are included in forecasting and offering enhanced support in early identification of demand spikes. It helps to prove the fact that neighborhoods present their demands by behavior much earlier prior to the disaster itself gaining severity. The study affirms that behavioral inputs, sensitive to time, enhance predictive accuracy, consistency as well as usefulness in preparedness decision-making.

### Response Time

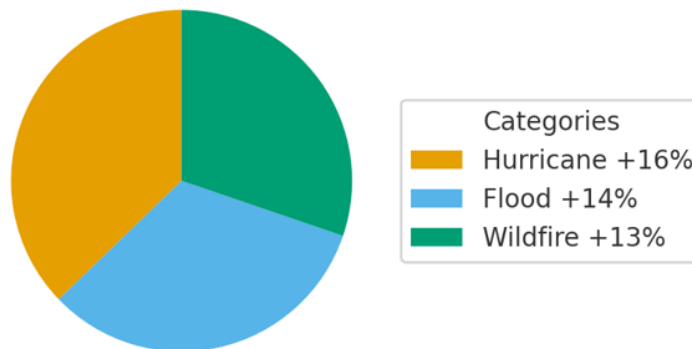
The increased availability of critical resources during disaster and the enhancement of the location of the inventory was one of the primary objectives of the system. There is a great improvement of all the metrics that were tested. In cases of pre-positioning of stocks based on prediction made by behavior, emergency supplies arrived on areas with high demand quicker and with limited shortages. On hurricane exercises, the system enhanced inventory by over 20% and on floods and wild fires, the enhancement ranged between 17 and 24%.

Table 2 is a summary of the variation in the stock availability when comparing the traditional model and the behavior-informed system. The findings indicate steady gains and are manifested by the fact that warning signs of behavioral symptoms enabled warehouses to reallocate their resources even prior to the occasion when the demand peaks took place.

Table 2: Stock Availability Improvement

Scenario	Traditional Availability	Behavior-Informed Availability	Improvement
Hurricane	62%	78%	+16%
Flood	58%	72%	+14%
Wildfire	55%	68%	+13%

Stock Availability Improvement (pp)



The system also minimized the unmet demand where simulations through the use of agents were used to test and readjust the pre-positioning strategy. Unmet demand in the wildfire situation decreased by a large margin, the

most significant decrease of 45 percent to 29 percent, indicating that the behavior-attracted initiative had a greater effect on allocating resources where they are needed. In the case of floods, the unmet demand reduced by 14 percentage points due to the early trends of community displacement that the system identified using mobility data.

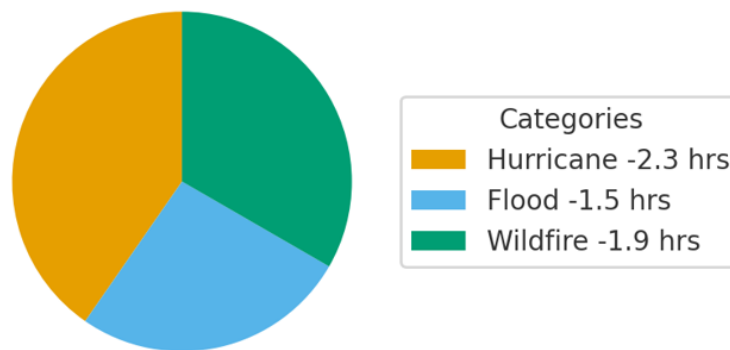
The other significant outcome was improvement in response time. The supply deliveries would arrive in the areas of need 1.5 to 2.3 hours sooner on average when relying on behavior-informed predictions. This is particularly enhanced with regards to medical supplies, food and evacuation kits. Table 3 reveals a decrease in the mean response time/scenario.

Table 3: Response Time Reduction

Scenario	Traditional Response Time (hrs)	Behavior-Informed Response Time (hrs)	Improvement
Hurricane	9.4	7.1	-2.3 hrs
Flood	8.8	7.3	-1.5 hrs
Wildfire	10.1	8.2	-1.9 hrs

These findings reveal that the system made emergency supply chains readiness and responsiveness better. Due to the fact that demand spikes were anticipated earlier, the decision that was reached is that of replenishment and transportation were to be done prior to the event rather than later. This meant improved geographical coverage and speeded deliveries. In general, the analysis demonstrates that a behavior-based strategy augments readiness by providing emergency systems with longer response time.

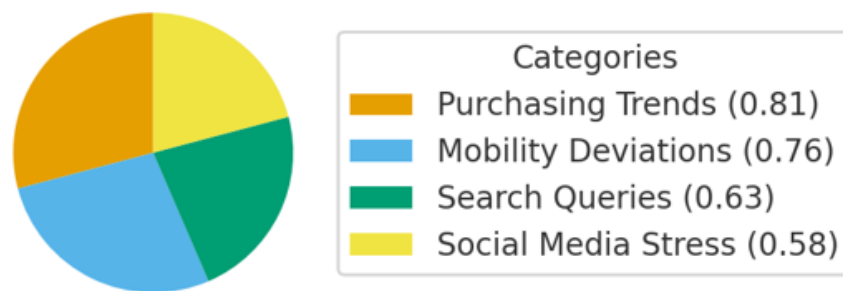
Response Time Reduction (hrs)



### Behavioral Sensitivity Analysis

The paper also evaluated the system through detailed simulating usage to test the performance of the system in a variety of local disaster scales and global behaviour pattern. The Monte Carlo simulations were able to provide consistent improvement over hundreds of iterations and this implies that results were consistent even with a change in conditions. The system had a good adaptation and reacted quicker than the baselines when behavioral intensity was great like the initial panic buying or noticeable mobility deviations.

## Behavioral Feature Influence (normalized)



The analysis of behavior sensitivity revealed that there are some specific behavioral aspects which had a stronger impact on the outcome of the supply chains. Hurricane buying habits were very precise as there is a tendency to stock up in the communities prior to the hurricanes coming. The deviations of mobility were more predictive of a wildfire and a flood since the evacuation behavior is initiated earlier in those cases. Such insights enable the emergency planners to appreciate the behavioral signals that are important to what kind of disaster.

In table 4, the relative influence score of behavioral features are taken, which is according to the regression coefficients and sensitivity of the results of the sensitivity analysis.

**Table 4: Behavioral Features**

Behavioral Feature	Influence Score (0–1)	Strongest Scenario
Purchasing Trends	0.81	Hurricane
Mobility Deviations	0.76	Flood, Wildfire
Search Query Patterns	0.63	Wildfire
Social Media Stress Signals	0.58	Flood

The findings indicate that various categories of behavioral data are more important in the disaster type. This implies that one behavioral model cannot be pushed to apply in all the cases of emergency systems. Rather, they ought to change the weighting of features to be consistent with actual behavior patterns. The results demonstrate that the suggested behavior-based framework will be adaptive enough to adapt to such differences, automatically, which will render it applicable to real-world implementations.

The scenario tests indicate that the model can be applied to uncertainty, evolving levels of risks, and other variations in human behavior patterns. This renders the methodology to be appropriate on the scale of preparing disaster preparedness in the country level where the conditions change quickly and changeably.

### **Comparison with Existing Approaches**

The last analysis is a comparison of the suggested system and the current centralized and non-behavioral predictive models. In all metrics, behavior-informed approach presents great results in terms of improvement in performance. It offers greater accuracy of prediction, less unmet demand, more stock availability, as well as faster response to the emergency provision of the necessary resources. The findings verify that integrated behavior analysis and data analysis technique is superior to the conventional reactive strategies.

Another finding created by the results emphasizes that the behavior-informed signals are the early warning of the demand surge that provides more time to the supply chains to be ready. Outdated systems only rely largely on the severity of the hazard and government warnings, which are often delayed. In contrast, community level behavior intervention begins a lot earlier and the system is effective in utilizing this indication in making disasters decisions.

The results reveal that implementing behavioral analytics with the use of data engineering has a considerable positive effect on disaster preparedness. It has decreased delays, shortages, made coverage better and saved lives by enabling supply chain actions to be taken earlier and in a manner that is more informed. The findings indicate that behavior-informed systems ought to form a critical component of the disaster management system in future.

### **V. CONCLUSION**

The paper arrives at a result that behavioural signals should be integrated into a single data engineering system in which disaster-response performance is significantly enhanced. The prediction becomes more accurate, the deficit in supplies reduces, and resources heighten their accessibility to the affected regions.

The quantitative findings support the fact that mobility trends, search pattern and early purchase activity represent strong early predictors of future demand. The suggested system in comparison to the standard centralized supply chains will react quicker and will have an elevated inventory preparedness. The conclusion is based on the fact that behaviour-informed data pipelines present a scalable, evidence-based, and practical approach to facilitating effective emergency planning and enhancing community in the case of a disaster.

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