

A Task-Technology Fit Theory Approach of Automated Flood Forecasting Systems for Emergency Responders

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ABSTRACT

Predictive capabilities of technological systems, successful disaster preparedness and disaster response rely on how well response capabilities match the operational needs of disaster responders. This study integrated Task-Technology Fit (TTF) Evaluation Framework for the assessment of automated flood forecasting system in the Nigeria context of emergency management. The framework focused on under-researched aspect of flood forecasting, which often focused on the predictive quality of the forecast, but comparatively less attention has been paid to the operational, infrastructure, institutional and user conditions of where the forecast was used. The proposed framework further incorporated eight dimensions of the Task-Technology Fit theory of Goodhue and Thompson (1995) that related to the operational needs of emergency response agencies. A diagnostic scoring model was suggested for comparison of the technical capacity of an automated forecasting system with operational task requirements, in a multidimensional manner. The framework highlighted task-technology mismatches and serves as a structure for further technical, organizational, infrastructural and training interventions. The study is conceptual in nature and is not validated or empirically derived from the field for TTF scores. The numerical examples given in the framework are only illustrative and hypothetical and are provided to serve the purpose of giving an indication of how the proposed scoring process might work. The study thus theorized an extension of TTF to automated flood forecasting in Nigeria and laid a foundation for the empirical testing of the model in other emergency management contexts.

Keywords: Task-Technology Fit; Automated Flood Forecasting; Emergency Response; Disaster Management; Nigeria; Socio-Technical Systems; Early Warning Systems.

INTRODUCTION

Disaster preparedness is of critical importance to households, businesses, communities and countries alike, but most times less attention is given to it. Disaster preparedness involves measures taken to make life and property safer in the event of disaster, including measures taken when it comes to hazardous materials spills, floods or terrorist attacks. With the emergence of technologies such as Augmented Reality (a computer technology that merges a view of the real world environment upon a digital image) the possibility of better training for disaster management has increased to a great extent (Eleonu et al., 2020). The present studies have not satisfactorily covered the issue of incorporating artificial intelligence in disaster management for

better decision making and security. However, to build the disaster resilience, (Hammoudeh, 2024) proposed an architecture for DRM response for disaster risk and emergency management that increases the effectiveness and interoperability in the DRR process. With the support of Artificial Intelligence (AI) models, one could expect to manage disasters in much a more efficient manner and minimize all kinds of losses. The disaster management process is divided into four parts: pre-disaster plans, pre-disaster preparations, application of prediction and early-warning systems, and disaster evaluation, disaster relief. However, several AI models have been developed that can assist in the effective management of natural disasters, and to reduce the risk of disaster to individuals, as Chandra and Lakshmi (2024) outline. When it comes to catastrophe preparedness, response, and recovery, several different types of AI such as Natural language processing, predictive modeling, computer vision, and machine learning are being utilized. Harika et al. (2024) examined the possible avenues through which artificial intelligence (AI) might transform the management of crisis and resource allocation after disasters.

Government and non-governmental organisations (NGOs) are working together in an effective manner to coordinate the relief effort and respond to humanitarian needs from a first hand perspective during post-disaster situations. The application of existing data, such as satellite imagery, sensor data and social media data, with data mining and big data analytics are significantly enhancing the disaster management. However, availability of these data often poses problems of fragmentation and incompleteness (Gupta and Roy, 2024). The application of different AI technologies in disaster management involves four stages: prevention and mitigation, preparedness, response, and recovery, as well as on disaster technology and ethical issues, through bibliometric analysis and knowledge graph analysis. From this perspective, (Xu et al., 2025) discussed the main problems and issues in the disaster management field that have not yet been sufficiently solved by AI, such as disaster pre-disaster and post-disaster resilience enhancement, reinforcement of critical infrastructure, planning and design of evacuation network, long-term post-disaster sustainable recovery and disaster management ethics. The results presented by (Muthukumar et al., 2026) clearly suggest the adoption of simpler rules-based approaches to more advanced deep learning approaches. It offers a reflection of the methodology, and emphasizes the outcome of the performance, as well as directions for research, reflecting existing gaps and recent developments. As far as social and ethical implications of using AI during crises including privacy and effective distribution of resources (Ajaj et al., 2024) noted that the most important trust should be placed not just in AI's ability to enhance disaster management and overall preparedness, but also in its capacity to ensure swift recovery after a disaster.

In combination with utilization, Task-Technology Fit (TTF) proven to be a major predictor of reports of better job performance and effectiveness that could be attributed to their use of the system studied by (Goodhue and Thompson, 1995). The model presented by (Goodhue and Thompson 1995) is a first-order, individual level model; but (Zigurs and Buckland 1998) offer a similar model at the group level of analysis. Since the first one, TTF has been used in the context of different information systems like electronic commerce systems, used together with, or as an extension of other models related to IS outcomes like the technology acceptance model (TAM). Many changes have been made to the TTF measure developed by (Goodhue and Thompson 1995) to fit the specific needs of the specific study. The task-technology fit (TTF) theory suggests that if the capabilities of the IT are a good match to the task(s) that the user is required to perform, then the IT will be more likely to have a positive impact on the individual's performance, and will be used. (Goodhue and Thompson, 1995). Goodhue and Thompson (1995) have created a measure of task-technology fit with eight factors: quality, locatability, authorization, compatibility, ease of use/training, production timeliness, systems reliability, and relationship with users. In Tanzania, Mambile et al. (2026) used the Task-Technology Fit (TTF) model to assess the task and the capability of Deep Learning (DL) models to make forest fire prediction. It measured the readiness of the technologies being developed by stakeholders, and the implementation requirements to enhance early warning and climate risk management in ecologically sensitive areas. The results showed that there was a big difference between the technical capacity and the feasibility of deployment in the field. The study also provided the first empirical evidence on the application of the TTF theory to climate-induced fire risk in Sub Saharan Africa, and emphasized the critical preparedness gaps and enabling conditions that need to be addressed in future efforts to integrate predictive AI tools into EWS in resource constrained and climate vulnerable regions. TFs evaluated the

matching of DL capabilities to the Forest fire prediction tasks, using a structured scoring matrix, with a set of criteria for each of the TTF dimensions.

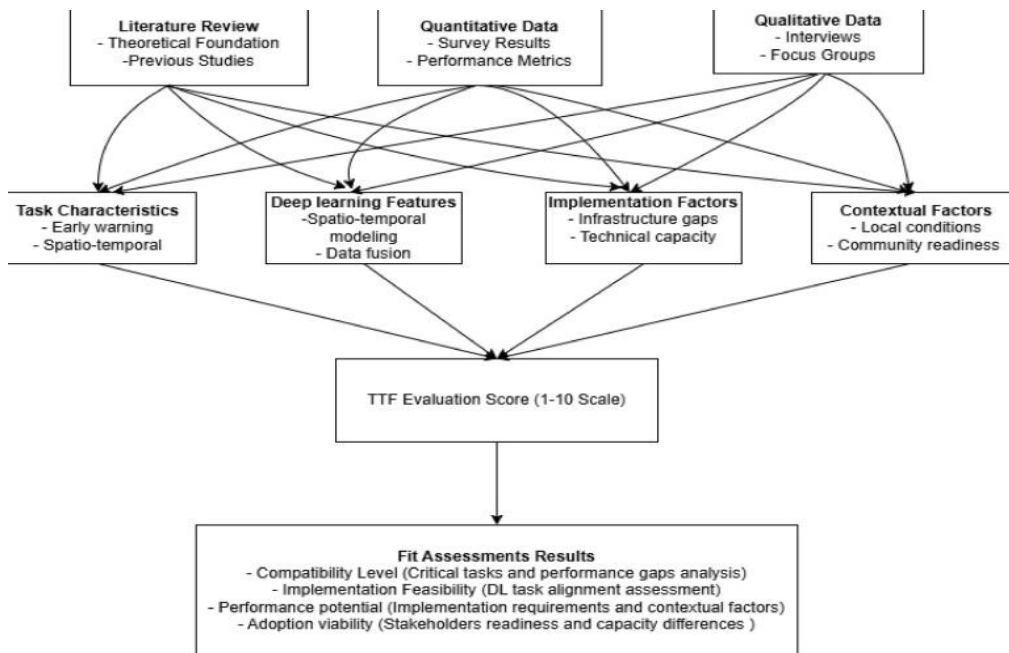


Figure 1: TTF Evaluation Framework for Forest Fire Prediction (Mambile et al., 2026)

To remove the differences between the literature of using digital media in education and its impact on higher education students' learning achievement, (Al-Rahmi et al., 2023) aimed to create a model that would identify the aspects that are predicted to still be significant in TTF and Communication Theory (CT) to increase academic achievement in higher education institutions. The results of this research offered support to the concept that three types of characteristics (technological, task-related, social) would impact academic achievement as they are applied to learning through TTF. Their findings indicated that when there is more contact with digital media in the field of education, communication motivation, communication self-efficacy, and online communication have an impact on academic performance. The use of Smart Manufacturing Technologies (SMTs) greatly enhance productivity, flexibility, and sustainability. However, we are faced with resource limitation and socio technical complexity in adoption, and manufacturers need to strategize and prioritize SMTs. Previous methods mainly focus on outcomes and neglect to consider the users of SMTs in the prioritization. To fill this need, (Liu et al., 2025) presented an idea based on the Task–Technology Fit (TTF) concept. First, the fuzzy Analytic Hierarchy Process (AHP) method was used to quantify the strategic priorities and then, the fuzzy Quality Function Deployment (QFD) method was used to link strategic priorities with the importance of the various manufacturing tasks.

In today's disaster management context, the use of artificial intelligence and automated forecasting models is increasingly moving away from the old paradigm of "disaster response" towards "disaster management," using a wide range of data sources such as satellite images and sensor networks to make disaster management more proactive and climate-proof. While deep learning and automated predictive systems for flood hazards are developing quickly, there is still substantial research that needs to be undertaken to validate and evaluate the technical outputs of these automated flood forecasting systems with regards to the operational tasks and field level constraints of emergency responders in Sub-Saharan Africa, particularly Nigeria. The aim of this study is to suggest an integrated Task-Technology Fit (TTF) Evaluation Framework to evaluate the fit between the automated flood forecasting capabilities and the operational tasks of emergency responders in Nigeria. The framework does not simply assume that the accuracy of forecasting is the only measure of the effectiveness of technology; it is also about the fact that the outputs of forecasting can be accessed, interpreted, communicated and acted upon within the operational context of the emergency management agencies in Nigeria. The study contributes to the body of studies in conceptual terms by augmenting the application of the Goodhue and Thompson's (1995) TTF theory in the context of automated

flood forecasting and emergency response system in Nigeria. The framework describes the eight main TTF dimensions that relate to Data Quality, Locatability, Authorization, Compatibility, Ease of Use and Training, Production Timeliness, Systems Reliability, and Relationship with Users, and correlates them to the activities needed to respond to flooding before, during and after disaster events. The framework is thus to be read as a new theoretical extension and operationalization of TTF rather than a model that can be tested empirically.

MATERIALS AND METHODS

Materials

Task-Technology Fit Theory

In this study, an operationalized version of Task-Technology Fit (TTF) model introduced four different components of the TTF model as shown in figure 2 below to evaluate how the automated flood forecasting systems can support the emergency response in Nigeria:

Task Characteristics: this component deals with the particular needs for running Nigerian agencies in disaster management (NEMA, SEMA) etc. These workflows fall into three major categories: pre-disaster (preparation of a list of vulnerable communities, making proactive evacuations etc.), active response (during the disaster, directing a search and rescue team to a geographic point) and post disaster (rapid mapping of damages of structures, coordinating emergency relief distribution etc.).

- **Technology characteristics:** This component includes inventories of technology characteristics of the automated forecasting infrastructure. It reads the heterogeneous data flows that come in (from satellite, real-time river telemetry sensors, meteorological precipitation data etc.) and processes them, and packages the results that come out (in interactive GIS dashboards, predictive trend graphs, automatic early warning notification triggers etc.) for the user. There is a special taxonomy developed by Goodhue and Thompson (1995), which is specially adapted for flood management scenario in Nigeria, to extensively evaluate the extent of match between the activities of the responders and the automated instruments. **Data Quality:** This refers to the overall accuracy, reliability and spatiotemporal resolution of products generated. Questions whether the automated system has hyper-local risk probabilities (i.e., by a defined neighbourhood or Local Government Area (LGA)) rather than generic (macro level) national trends, which are too coarse-grained to be useful for field operations. One of the indicators for the effectiveness of the system's user interface is how easy and efficient it is for field commanders to use when responding to queries about the system in order to receive information that is important to an active crisis situation. Maps of inundation depth vectors, maps of catchments and evacuation routes can be extracted without any administrative and cognitive delay and with high locatability.
- **Authorization:** Built-in security and data-sharing mechanisms of the platform. It's about whether there's any way for the people closest to the front line of the emergency callers to have prearranged clearances, or whether they need to use the multi-spectral imaging and auto-sensor streams, but run into inflexible bureaucratic hurdles or "from above" institutional hurdles that slow down the action.
- **Compatibility:** is the ease with which the automated forecasting data can be integrated with the current (legacy) communication networks and field equipment used. It is specifically designed to deliver the ability to reduce in size or compress digital hazard alerts to a bandwidth available through analog High-Frequency (HF) radio networks in severe weather when commercial cell phone networks are unavailable, in Nigeria.
- **Easy to Use:** explores the human computer interaction (HCI) design and the way that it lessens the cognitive load during extreme situations. It tests the platform's capability to break down the very complex probabilistic deep learning curves into simple, easy to understand hazard levels, so that the non-

technical emergency personnel can confidently interpret the risk scores, without the need for data science expertise.

- **Production Timeliness:** This is a criteria which defines the advance warning criteria that needs to be fulfilled within a certain time and proactive change in the workflow from reactive to proactive. It can process the input variables quickly and provide and broadcast predictive warnings at least 48-72 hours before a significant flash surge occurs, providing a valuable time period to consider and plan for an evacuation. **System Reliability:** The parameter refers to the system's availability and the robustness of its hardware platform and system under extreme environment. It keeps track of the availability and integrity of the server, and the status of the Hydro-meteorological databases and Emergency backup power cycles -- keeping the forecasting platform available and operational when it is most needed during the actual hydro-meteorological storms.
- **Relationship with users:** This dimension is related to socio-technical feedback and working processes between the software developers of the system and the front end agencies in the disaster management field. It assesses the responsiveness of technical support channels, the frequency of collaborative updates to the system and the ability of the system to be promptly adapted to first-hand experiences of on-the-ground responders.

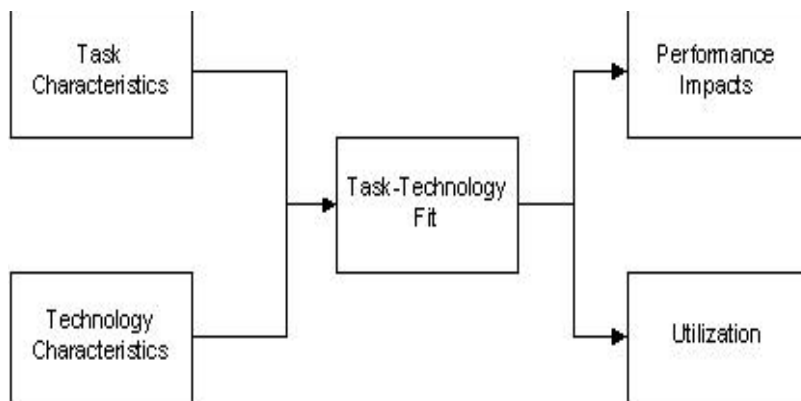


Figure 2: Task-Technology Fit Theory (Goodhue and Thompson, 1995)

Architecture of Proposed System

The architectural design in figure 3 shows how the elements of the tasks, technologies, TTF dimensions, diagnostic evaluation, and decision-support outcomes are interconnected. The socio-technical conception of Goodhue and Thompson's theory of the task technology fit (TTF) places emphasis on the effective use of an information system and stresses that the effectiveness of the system not only depends on the technical features of the system, but also on the fit of the technical features to the requirements of the tasks the system is intended to support. The Task Inputs and Technology Inputs are the upper level components of the architecture. The Task Inputs are the operational activities that the Nigerian emergency responders carry out before, during and after flood events. Pre-disaster activities are: flood-risk assessment, identification of vulnerable communities, preparedness planning, and evacuation planning. During-disaster activities consist of real-time decision making, search and rescue coordination, emergency warning and deployment of field personnel. The Technology Inputs are technological elements that aid in automated flood forecasting. These include satellite imagery, river telemetry sensors, weather data and other relevant environmental data. Artificial Intelligence and deep-learning forecasting models are used to analyze the collected data and produce flood forecasts and information. The technology layer generates products including GIS-based floods risk maps, predictive trends, hazard classifications, and automated early-warning notifications. These outputs are the key technological assets that are available for emergency responders.

The TTF Integration Matrix is the core element in the architecture between the task and technology layers. The matrix compares the eight dimensions of TTF (Data Quality; Locatability; Authorization; Compatibility; Ease of Use and Training; Production Timeliness; Systems Reliability; and Relationship with Users) to the emergency-response requirements. Each dimension concerns a specific component of the forecasting system – operational environment interaction.

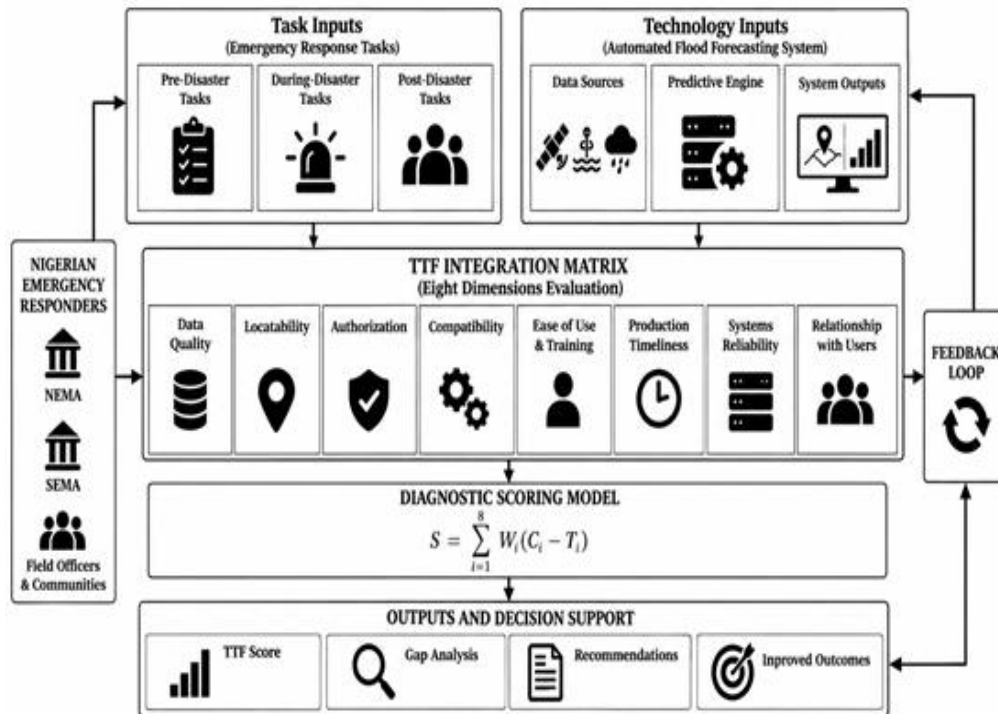


Figure 3: Architectural Design of Proposed System

Methods

Variables Descriptions for TTF Evaluation Framework

Table 1 illustrates the key variables that were used to define the proposed Task-Technology Fit (TTF) Evaluation Framework for automated flood forecasting systems. The eight TTF dimensions are the core areas for considering the suitability of the technology, and Operational Task Requirement is what the emergency responders need, and Technical Capacity is what the forecasting system can provide. Priority Weight indicates the importance of each dimension, and the TTF Score represents the overall measure of task–technology alignment. The variables can be evaluated by using a 5-point likert scale that will have a structured basis for technological gaps and areas for improvement.

Table 1: Variables Descriptions

TTF Dimension / Variable	Variable Code	Operational Definition	Measurement Indicator	Measurement Scale
Data Quality	DQ	Extent to which flood forecasting data are accurate, reliable, complete, and sufficiently detailed for emergency decisions	Accuracy, completeness, reliability, spatial and temporal resolution	1–5 Likert
Locatability	LOC	Ease with which responders can	Ease of locating risk maps, affected	1–5 Likert

		locate and retrieve relevant flood information	locations, inundation information, and evacuation routes	
Authorization	AUTH	Extent to which authorized responders can access and share required forecasting information during emergencies	Access rights, data-sharing permissions, approval delays, emergency access	1–5 Likert
Compatibility	COMP	Degree to which the forecasting system can operate with existing communication networks and field equipment	Integration with existing systems, mobile networks, HF radio, and low-bandwidth infrastructure	1–5 Likert
Ease of Use and Training	EUT	Degree to which the system is understandable and usable by emergency personnel	Interface simplicity, interpretability of risk levels, training requirements	1–5 Likert
Production Timeliness	PT	Ability of the system to generate and communicate forecasts within the required warning period	Processing speed, warning lead time, timeliness of alerts	1–5 Likert
Systems Reliability	SR	Ability of the forecasting infrastructure to remain available and functional during flood emergencies	System availability, connectivity, backup power, hardware/software stability	1–5 Likert
Relationship with Users	RWU	Degree of interaction and feedback between system developers and emergency-response personnel	Technical support, user feedback, system updates, customization	1–5 Likert
Operational Task Requirement	Ti	Level of capability required by emergency responders to perform their flood-management tasks effectively	Required performance for each TTF dimension	1–5 Likert
Technical Capacity	Ci	Level of capability actually delivered by the automated flood forecasting system	Measured system capability for each TTF dimension	1–5 Likert
Priority Weight	Wi	Relative importance	Importance of	0–1

		assigned to each emergency-response task or TTF dimension	dimension to emergency operations	
TTF Score	S	Overall degree of alignment between technical capability and operational requirements	Weighted difference between C_i and T_i	Continuous
Structural/Operational Misfit	SOM	Degree to which technological capability fails to satisfy operational requirements	Negative difference between C_i and T_i	Categorical/Continuous
User Feedback	UF	Information obtained from emergency responders regarding system performance and field usability	Satisfaction, usability issues, infrastructure constraints, recommendations	1–5 Likert

Flowchart of Proposed System

The proposed flowchart for the Integrated Task-Technology Fit (TTF) Evaluation Framework for Automated Flood Forecasting Systems is shown in figure 4. It depicts a sequence of the system operations to be undertaken. It starts with identifying emergency-response tasks and operational requirements of NEMA, SEMA and field officers during pre-disaster, during disaster and post disaster activities. Data preprocessing and quality check are then performed on relevant hydro-meteorological data obtained from sources like satellite images, river sensors and meteorological systems.

The processed data is further provided to the automated flood forecasting part which uses AI and deep-learning algorithms to produce flood forecasts, GIS risk maps, and early-warning products. A decision stage is then used to validate the forecasting model and outputs. If the model is not valid, it is retrained and/or reconfigured before the forecasting process can proceed, and if it is valid, the outputs go to the TTF integration evaluation process.

The second segment of the flowchart emphasizes whether the forecasting technology meets the real needs of emergency response. The system assesses eight TTF dimensions: Data Quality, Locatability, Authorization, Compatibility, Ease of Use and Training, Production Timeliness, Systems Reliability and Relationship with Users. These dimensions are part of the diagnostic TTF scoring model to detect possible mismatches between technological capabilities and field requirement in the structure and/or operation.

Gap analysis results in suitable technical, organizational or training enhancements where mismatch is found. If a major mismatch is not detected, the system moves into the dissemination of early warnings and the implementation of emergency responses, and then impact assessment and ongoing monitoring. Feedback from users and experience in the field is fed into the adaptation of the system or framework, leading to an iterative improvement cycle that will ultimately contribute to an operationally aligned, proactive and climate-resilient flood disaster management in Nigeria.

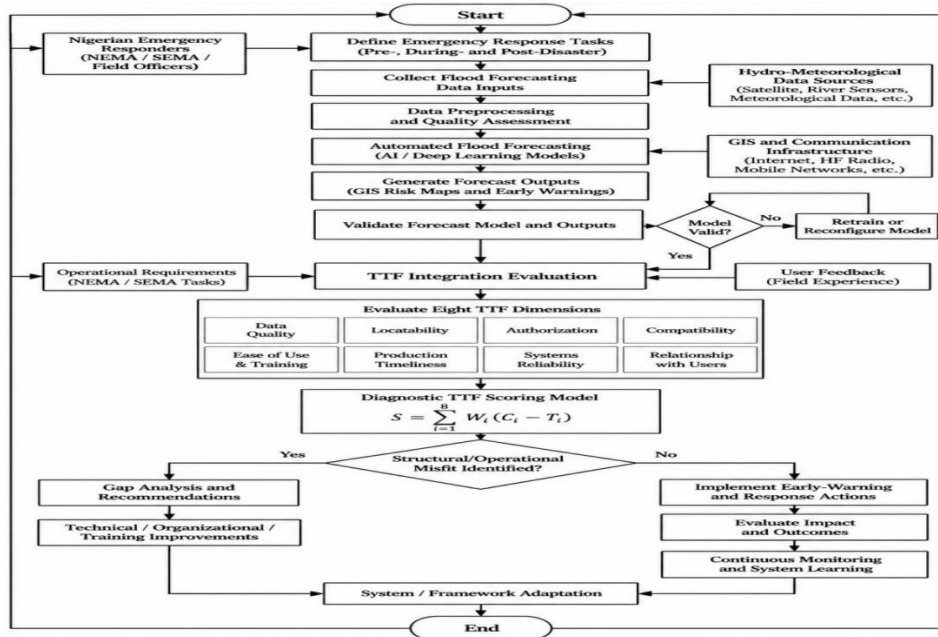


Figure 4: Flowchart of the Proposed System

Operational Task Requirements and Technical Capacity across the Eight TTF Dimensions

Table 2 illustrates the comparison of Operational Task Requirements (T_i) and Technical Capacity (C_i) across the eight dimensions of the proposed Task-Technology Fit (TTF) framework. Because the study is conceptual and no field survey or system-performance data were collected, the values in the table were not obtained from NEMA, SEMA, emergency responders, or empirical system measurements. Instead, they were hypothetically assigned on a 5-point scale to demonstrate how the proposed framework could be operationalized and applied in a future empirical study. The T_i values were assigned by conceptually estimating the level of capability that would be required for each dimension to support effective flood emergency operations. For example, Systems Reliability was assigned 4.9 because continuous availability of the forecasting system would conceptually be highly important during flood emergencies, while Production Timeliness was assigned 4.8 because timely forecasting and warning dissemination are essential for preparedness and response. Similarly, Compatibility was assigned 4.7 to represent the high operational requirement for integration with existing communication networks and field equipment. The remaining T_i values were assigned within the 1–5 scale according to their assumed operational importance. The C_i values were assigned to represent hypothetical levels of technical capability that an automated flood forecasting system might provide for each dimension. For example, Production Timeliness was assigned 4.5, representing a relatively high hypothetical capability to generate forecasts and warnings within the required period, whereas Compatibility was assigned 3.2 to illustrate a potential limitation in integrating advanced forecasting outputs with legacy, low-bandwidth or alternative communication infrastructure. Systems Reliability was assigned 3.7, while Relationship with Users was assigned 3.5, to demonstrate how technical and socio-technical capabilities could potentially fall below operational requirements.

Table 2: TTF Scores across the Eight Task-Technology Fit Dimensions

TTF Dimension	T_i	C_i
Data Quality	4.6	4.3
Locatability	4.4	4.1
Authorization	4.2	3.6

Compatibility	4.7	3.2
Ease of Use	4.3	3.9
Production Timeliness	4.8	4.5
Systems Reliability	4.9	3.7
Relationship with Users	4.1	3.5

RESULTS

Proposed Framework

This study is expected to deliver a conceptual design of the integrated Task-Technology Fit (TTF) Evaluation Framework as shown in figure 3, optimized for an automated Flood Forecasting System in the Nigerian emergency management system. The socio-technical logic of (Goodhue and Thompson, 1995) forms the basis for the structural architecture, which expands that same logic from a general corporate information systems tool to a tool that is highly useful during disaster response. The line graph shows the conceptual connections between Operational Task Requirements (T_i) and Technical Capacity (C_i) for the eight dimensions of the proposed Task-Technology Fit framework. The Operational Task Requirement line is relatively high in all dimensions (4.1 to 4.9) reflecting high operational tasks requirements for an effective automated flood forecasting system. The Technical Capacity line shows a wider range of variation, and a greater similarity in Data Quality, Locatability, Ease of Use and Production Timeliness, but larger gaps are seen in Authorization, Compatibility, Systems Reliability, and Relationship with Users. The biggest gap is in the technical capacity of Compatibility, which is much lower than the operational requirement, indicating that there may be integration issues with the current communication and field infrastructure.

In the same way, the difference between Systems Reliability shows the need for maintaining the availability of systems during extreme flooding conditions. The overall graph illustrates that the comparison of C_i and the T_i can be useful to identify possible task technology mismatches and aspects that need to be improved technically, organizationally, at the infrastructure level or through training. The numbers are framework numbers and need to be replaced by field numbers before conclusions can be drawn statistically.

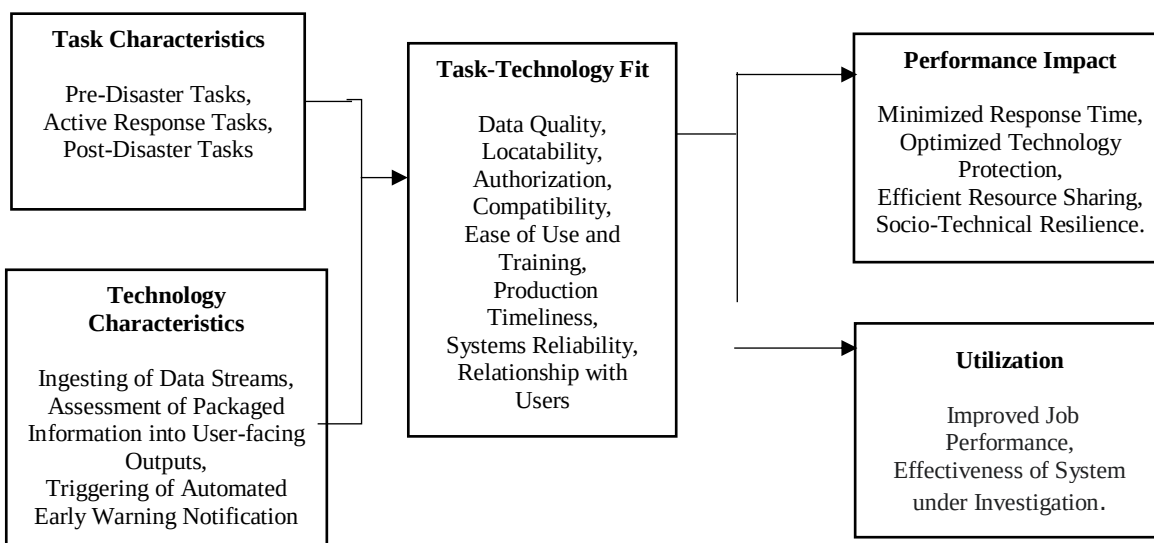


Figure 4: Proposed Task-Technology Fit Framework for Automated Flood Forecasting Systems (Authors)

Figure 5 presents a hypothetical illustration of the relationship between Operational Task Requirements (Ti) and Technical Capacity (Ci) across the eight dimensions of the proposed Task-Technology Fit framework. The figure is not an empirical result and should not be interpreted as evidence of the actual performance of automated flood forecasting systems or the actual requirements of Nigerian emergency response agencies. The illustrative values are assigned solely to demonstrate the analytical logic of the proposed framework. Higher hypothetical values of Ti represent dimensions in which emergency response activities would require greater technological capability, while the corresponding Ci values represent hypothetical levels of capability that a forecasting system could provide. Differences between the two values are used to demonstrate how potential task–technology gaps could be identified. For example, if Compatibility were assigned a hypothetical operational requirement of 4.8 and a hypothetical technical capacity of 3.0 on a five-point scale, the resulting difference would indicate a potential compatibility gap of -1.8. This does not mean that Nigerian emergency response agencies currently experience a compatibility gap of -1.8; rather, it demonstrates how such a gap would be calculated if these values were obtained through future empirical assessment. The purpose of Figure 5 is therefore methodological rather than evidentiary. It demonstrates how the proposed framework could distinguish between dimensions where technical capacity satisfies operational requirements and dimensions where further technical, organizational, infrastructural or training interventions may be required. Actual values should be obtained through field surveys, interviews, system-performance measurements, observational studies, operational records and other appropriate empirical methods before substantive conclusions are drawn.

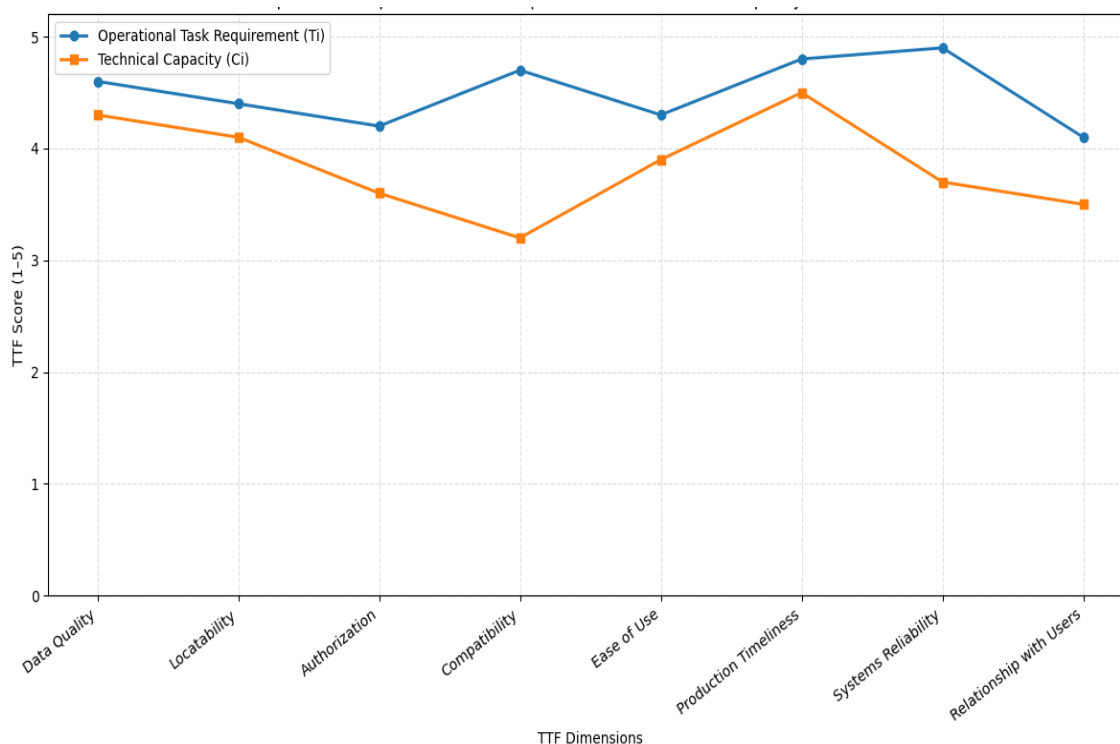


Figure 5: Line Graph of Proposed Framework

The proposed framework operationalized the dimensions of Task-Technology Fit by associating each of them with certain requirements which may come up in the process of automated flood forecasting and emergency response. Conceptual operationalisation as a basis for future empirical measurement.

- **Data Quality:** Data Quality is the degree of accuracy, reliability, completeness of forecasting information, and its level of detail, needed to make emergency decisions. For the proposed framework, this includes spatial and temporal resolution of the satellite pictures, river telemetry, rainfall observations and other hydro-meteorological inputs. A forecasting system that can make accurate national level forecasts but cannot make predictions for individual Local Government Areas (LGAs), communities or

watersheds may not be of much use to field responders. The framework hence takes account of the accuracy in addition to completeness, reliability, spatial resolution, and temporal resolution.

- **Locatability:** This is related to how easily emergency services can access and access information that is needed during flooding. The proposed framework will also take into account the ability of responders to easily identify communities affected, inundation areas, river locations, evacuation routes and vulnerable areas on maps, dashboards or other interfaces. In time-critical response tasks, it is especially critical that the locatability is high, since users may waste time in navigating through complex interfaces.
- **Authorization:** Authorization is the level of access and access to sharing forecasting information that is allowed to be accessed and shared by emergency personnel as appropriate. For the Nigerian emergency-management scenario, authorization can be granted more than traditional username and password logon. Potential barriers could be the time needed to gain access to limited datasets, centralization of data for the satellites or sensors, institutional factors that limit how quickly response agencies can share data among themselves, confusion regarding who is responsible for issuing warnings, and lag time in transmitting data between federal, state and local response organizations. For instance, in a flash flood event, a field officer might need to access watershed telemetry, satellite imagery and/or forecast data, but have to go to a higher administrative level for approval to access it and share it with another response agency. This may diminish the utility of the timely information for forecasting purposes. Finally, the proposed framework takes into account if emergency authorization will allow suitable staff to gain access to and share information in a timely manner, while also ensuring security and accountability.
- **Compatibility:** How well the automated forecasting system can integrate with the current communication network, field equipment and institutional information systems. This is especially important if the responders could have low bandwidth or electricity outages, or unreliable mobile connectivity. The proposed framework therefore takes into account the possibility of transforming forecast products to a format that could be acceptable in current communication means, such as low bandwidth/low power, or legacy High-Frequency (HF) radio infrastructure. An example of this is a complex GIS product, which must be converted to a shorter warning, coded location data or another low bandwidth representation for the conventional cellular communication case
- **Ease of use and training:** This dimension relates to how easily emergency personnel can interpret and use the forecasting system without undue technical and/or cognitive burden. The framework takes into account the simplicity of interfaces, clear hazard classification, training needs and interpretation of probabilistic outputs. The system could provide output in the form of easily interpreted categories, for instance low, moderate and high risk, with the associated operational guidance rather than having to assess the complex probability model directly.
- **Production Timeliness:** The effectiveness of the system to provide warning from available data within the time allowed for emergency response. The proposed framework takes into account processing speed and warning lead time and communication delays. The usefulness of a forecast for flood preparedness also depends on the time available for evacuation planning, deployment of personnel, movement of equipment and communication with vulnerable communities, as well as forecast accuracy. This 48 to 72 hour period is thus not considered a performance result but an operational concept.
- **Systems Reliability:** Systems Reliability relates to the availability and functionality of the forecasting system in environmental and infrastructural conditions during flood emergency. The framework reflects the availability of the server, network connectivity, backup power, hardware stability, software reliability and continuity of access to hydro-meteorological data. A system with good operational fit would be limited if it failed during severe weather when it was needed. Failure recovery, redundancy and continuity mechanisms should be part of the reliability assessment.

- **Relationship with Users:** Socio-technical interaction between the development team of the technology and emergency personnel using the system. The proposed format should be facilitated via formal processes, including regular feedback with users, formal incident reporting, the help-desk, post event review, field usability assessments, review of system updates, and requests for new features and changes. For instance, during a flood, field responders might record challenges they faced with understanding a warning or obtaining a specific map. The development team will then be able to use that observation to tweak the interface, warning format, or how people are informed. This forms a feedback loop in which the experience gained in operations feeds into the development and refinement of the system in later operations. As such, Relationship with Users is not confined to user satisfaction, it is a continuous process of keeping the forecasting technology in tune with the evolution of operational needs.

The Diagnostic Scoring Matrix Model.

A multi-dimensional diagnostic scoring matrix was developed as part of the framework to make it more actionable in the field in the future. The evaluation approach to mathematics that demonstrated by Mambile et al. (2026) was applied and the 8 dimensions of the TTF were correlated with the structured qualitative index sheet to quantitative mathematics index sheet of the specific task blocks in the flood response as presented in the equation below.

$$TTF_{score} = \sum (W_i * (C_i - T_i)) \quad (1)$$

here

W_i = Priority weight of the specific emergency task

C_i = Technical capacity value delivered by the automated system

T_i = Operational baseline task requirement of the responder

When this scoring model is deployed, any negative outcome will mathematically flag a "Structural Systemic Misfit." For instance, if a flood forecasting engine possesses superior predictive speed $C_i = 5$ but cannot transfer data over low-bandwidth field radios $T_i = 5$, yielding a compatibility misfit, the overall framework score will drop. This will allow public health and disaster administrators to pinpoint exactly why an advanced tool is failing on the ground.

DISCUSSION

The proposed Integrated Task-Technology Fit (TTF) Evaluation Framework provides a conceptual basis for examining the relationship between automated flood forecasting technologies and the operational requirements of emergency responders in Nigeria. Its central proposition is that the usefulness of an automated forecasting system should not be evaluated exclusively through predictive performance indicators. Instead, technical capability should also be considered in relation to the conditions under which emergency personnel must access, interpret, communicate and act upon forecasting information.

Addressing the Algorithmic–Operational Disconnect

One of the key concepts the framework makes is the consideration of the difference between what algorithms can do and how they can be practically applied in a real environment. While effective during controlled evaluation, automated flood forecasting systems can have challenges in practice due to issues of connectivity, power supply, bandwidth, legacy communication systems, or technical skill. It is important to note that there is no empirical field data to confirm the magnitude of such mismatches now taking place in Nigeria because of the proposed framework. Rather, it highlights these conditions as potential task–technology misfits that need to be examined empirically. For instance, a system can deliver accurate predictions of flooding and warnings in time, but if the outcome of the system is disconnected from the hands of the systems' responders during a communications failure, it is not of much value. Likewise, an extremely sophisticated GIS interface can deliver a wealth of information, but place unnecessary cognitive demands on operators at risk due to time constraints. Compatibility is, therefore, placed in a prominent position and needs a specific evaluation. The framework suggests that future assessments should research

whether forecasting information can be conveyed via communication channels available to field responders such as low-bandwidth and legacy systems as needed. This is especially true in emergency situations where traditional communications networks could be cut off or compromised.

Administrative and Institutional Considerations

The proposed Authorization dimension broadens the traditional notion of access control beyond that of granting or denying access to information by incorporating the institutional processes that could affect the availability of and dissemination of emergency information. When multiple agencies are involved in disaster management, the access to forecasting information might include data-sharing agreements, administrative approval, institutional responsibilities and communication protocols. The framework therefore implies that future empirical studies should examine whether the authorisation procedures help to ensure timely access to key information. Indicators can include the time taken to get access, inter-agency responsibilities, emergency access procedures, authorized access personnel being able to pass relevant information to other response agencies. This is not to say that all Nigeria's existing emergency agencies are not challenged with these barriers, only that they may be challenged with these barriers at a particular level. The framework, on the other hand, considers them operational variables that require onsite measurement and investigation in order to be validated.

The Importance of User Interaction and Continuous Adaptation of the System

Relationship with Users offers a way to bring operational experience into subsequent development of forecasting systems. The model suggests a shift in the paradigm: emergency responders are not just end-users but also contributors of operational knowledge for the improvement and refinement of the system. Structured Post-Event reviews, Periodic Stakeholder workshops, Digital Feedback forms, Technical support, Usability assessments, Incident reporting, Direct consultation between Software developers and Emergency response teams are possible mechanisms being applied. The data created with these mechanisms can be utilized for updating warning formats, for adding to interface improvements, and for data visualization and communication issues. This feedback process is especially important given the potential for evolving emergency-response needs due to the emergence of new technologies, communication systems, hazards and institutional processes.

Climate Resilience and Technology Design

The framework also suggests moving away from technology procurement that is mostly on technical specifications to technology assessment that takes into account operational fit. For this reason, factors like interoperability, reliability, communication resilience, usability, training needs and institutional compatibility may also be taken into account when making procurement decisions, in addition to predictive performance. The diagnostic scoring model is a conceptual approach that can be used to determine dimensions of technical capability that may be insufficient to meet operational requirements. The framework does not specify what technology should be purchased or a set score for the TTF dimension. The importance of the dimensions should be decided empirically based on consultation with relevant stakeholders.

CONCLUSION

Based on this, this study developed Task-Technology Fit (TTF) Evaluation Framework for evaluating the congruence between automated flood forecasting systems and the operational needs of the emergency responders in Nigeria. Based on Goodhue and Thompson's (1995) TTF theory, the framework situates eight dimensions, which include Data Quality, Locatability, Authorization, Compatibility, Ease of Use and Training, Production Timeliness, Systems Reliability, and Relationship with Users into the socio-technical conditions of flood disaster management. The framework being proposed is not just an evaluation of the performance of the algorithm used by the automated forecasting system, but also the ability of the forecasting information to be accessed, understood, communicated and used by the emergency responders in their operational environment. This looks at communication compatibility, institutional authorization,

system reliability and ongoing interactions with users in particular conceptual terms as these factors can affect the success of technically capable forecasting systems in supporting field-level decision-making. A diagnostic scoring model, which generates scores according to the dimension specific priority weights W_i , was also suggested to compare the Operational Task Requirements T_i with the Technical Capacity C_i , by which, dimension-specific scores are generated. The model is designed to serve as a framework for recognizing possible task–technology mismatches, and prioritizing areas for additional technical, organizational, infrastructural or training intervention. The numerical examples given in the study are used only for illustrative purposes and are not actual data, but are provided to illustrate how the proposed model could be applied once empirical data is available. This study does not provide empirical validation of the framework nor give an actual measure of task–technology fit in NEMA, SEMA or other emergency response organizations in Nigeria. This framework should instead be considered as a conceptual and theoretical piece of work that gives the basis for further empirical study. Further research is needed to test the eight dimensions by conducting field surveys, expert interviews, system-performance metrics, and usability tests, as well as multi-state evaluations of emergency response personnel. Future studies should also look at differences between the six geopolitical zones of Nigeria, account for variations in communication/crisis management infrastructure and consider self-reporting bias, and periodically review to reflect changes in AI, RS, IoTs, communication and emergency-management infrastructure. Longitudinal field studies over several flood seasons would be helpful to see if the suggested size of the TTF correlates with a measurable increase in effective dissemination of warnings, effective decision making and response.

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