

The Current State of Artificial Intelligence in Disaster Recovery: Challenges, Opportunities, and Future Directions



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The Current State of Artificial Intelligence in Disaster Recovery: Challenges, Opportunities, and Future Directions

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Foreword

The U.S. Environmental Protection Agency (EPA) is charged by Congress with protecting the Nation's land, air, and water resources. Under a mandate of national environmental laws, the Agency strives to formulate and implement actions leading to a compatible balance between human activities and the ability of natural systems to support and nurture life. To meet this mandate, EPA's research program is providing data and technical support for solving environmental problems today and building a science knowledge base necessary to manage our ecological resources wisely, understand how pollutants affect our health, and prevent or reduce environmental risks in the future.

The Center for Environmental Solutions and Emergency Response (CESER) within the Office of Research and Development (ORD) conducts applied, stakeholder-driven research and provides responsive technical support to help solve the Nation's environmental challenges. The Center's research focuses on innovative approaches to address environmental challenges associated with the built environment. We develop technologies and decision-support tools to help safeguard public water systems and groundwater, guide sustainable materials management, remediate sites from traditional contamination sources and emerging environmental stressors, and address potential threats from terrorism and natural disasters. CESER collaborates with both public and private sector partners to foster technologies that improve the effectiveness and reduce the cost of compliance, while anticipating emerging problems. We provide technical support to EPA regions and programs, states, tribal nations, and federal partners, and serve as the interagency liaison for EPA in homeland security research and technology. The Center is a leader in providing scientific solutions to protect human health and the environment.

The study explored the potential of artificial intelligence (AI) in disaster response and environmental remediation by providing a historical overview, conducting a meta-analysis of related literature, identifying natural language processing (NLP) and image analysis as key research areas, and presenting conceptual examples of AI's potential applications. The study emphasized the need for further research and development while addressing barriers and challenges to ensure ethical deployment and data privacy. The findings highlighted the significant potential of AI to revolutionize various sectors, including disaster response and environmental remediation.

Gregory Sayles, Director
Center for Environmental Solutions and Emergency Response

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Acronyms and Abbreviations

AI	artificial intelligence
ANN	artificial neural network
BERT	Bidirectional Encoder Representations from Transformers
CESER	Center for Environmental Solutions and Emergency Response
CNNs	convolutional neural networks
CSV	comma-separated values
CPLM	Transportation Cost per Loaded Mile
EPA	U.S. Environmental Protection Agency
GAN	generative adversarial network
GPT	generative pre-trained transformer
GPU	graphics processing unit
HTML	HyperText Markup Language
LDA	linear discriminant analysis
LSTM	long short-term memory
ML	machine learning
MSW	municipal solid waste
NLG	natural language generation
NLP	natural language processing
NLU	natural language understanding
NMT	neural machine translation
ORD	Office of Research and Development
SME	subject matter expert
UAV	unmanned aerial vehicle
UI	user interface
VAE	variational autoencoder
XAI	explainable AI

Executive Summary

This study explored the potential of artificial intelligence (AI) in disaster response and environmental remediation by conducting a meta-analysis of AI-related literature and providing a historical overview of AI. The study identified natural language processing (NLP) and image analysis as two primary research areas that could greatly benefit from AI integration. Conceptual examples were presented, showcasing the potential of NLP in enhancing communications, code writing, interpreting scientific material, and strategy optimization, while image analysis applications included visualizing training scenarios, debris characterization, and design prototyping.

The study also discussed emerging developments and potential impediments that might influence the adoption of AI in the public sector. It emphasized the importance of establishing policy frameworks and guidelines to ensure ethical applications and data privacy. The report highlighted the significant potential of AI to revolutionize various sectors, particularly disaster response and environmental remediation, while also addressing existing barriers and challenges associated with the deployment and utilization of this technology.

The research demonstrated the transformative potential of AI in disaster response and environmental remediation, but also underscored the need for further exploration and development of AI applications. By addressing the challenges and barriers surrounding AI deployment, AI has the potential to bring about revolutionary changes across various sectors, including disaster response and environmental remediation.

1. Introduction

Artificial intelligence (AI) is a multidisciplinary branch of computer science aimed at developing computational systems that can perform tasks typically requiring human intelligence. The ultimate goal of AI research is to create machines capable of learning, reasoning, perceiving, and interacting autonomously, thereby emulating or even surpassing human cognitive abilities. AI's history can be traced back to Alan Turing's introduction of the Turing Test in 1950 as a criterion for determining machine intelligence indistinguishable from human behavior [1]. The 1956 Dartmouth Conference marked AI's official birth as an independent research field, uniting experts from diverse disciplines to explore the potential of creating machines simulating human intelligence [2]. Subsequent advancements included the development of early AI programs such as the General Problem Solver, the establishment of dedicated AI research centers, and the rise of knowledge representation and rule-based systems in the 1970s [3-5]. The field shifted towards machine learning (ML) in the 1980s with the introduction of the backpropagation algorithm, enabling computers to learn patterns and make predictions based on large amounts of data [6]. Reinforcement learning, a type of ML, emerged in the 1990s, allowing algorithms to make decisions based on interactions with their environment and feedback [7]. The 21st century witnessed significant advancements with the rise of deep learning, a subset of neural networks, leading to breakthroughs in various AI applications such as image classification, natural language processing (NLP), and speech recognition [8].

ML and deep learning form the backbone of AI, enabling machines to learn from data and adapt their behavior accordingly. ML comprises a variety of algorithms for processing and analyzing data, identifying patterns, and making predictions or decisions, with techniques including supervised learning, unsupervised learning, and reinforcement learning. Supervised learning utilizes labeled datasets, unsupervised learning detects inherent structures and patterns without labels, and reinforcement learning involves an agent¹ learning to make decisions through interaction with its environment and feedback in the form of rewards or penalties. Deep learning, a subset of ML, employs artificial neural networks (ANNs) with multiple layers to model complex patterns and relationships in data.

Knowledge representation and reasoning are essential aspects of AI systems, encoding information, facts, and relationships in structured formats that machines can understand and manipulate. Common knowledge representation techniques include semantic networks, frames, and ontologies. AI systems also utilize logic-based reasoning to infer new facts, deduce consequences, and make decisions based on available knowledge. In essence, AI operates through the integration of various techniques and methodologies such as machine learning, deep learning, knowledge representation, and reasoning. This enables AI systems to learn, adapt, and perform tasks typically requiring human intelligence, with applications spanning diverse domains.

Data, algorithms, and computational power form the foundation of AI systems, providing the raw material, rules, and resources necessary for learning patterns and making predictions. In machine learning, data are divided into training, validation, and testing sets for building, fine-tuning, and evaluating software models, respectively, with data quality and quantity directly impacting model accuracy and generalizability [9]. Large-scale datasets, such as ImageNet, have driven significant AI

¹ An agent, in the context of this paper, is a self-directed software entity that can make decisions and take actions to achieve specified goals.

advancements [10]. Algorithms, defining rules and strategies for processing data and decision-making, vary depending on problem and data characteristics. For instance, decision trees suit problems with discrete outputs and few features, while deep neural networks are better for high-dimensional data, such as images or text [11]. Computational power enables complex algorithm execution and large dataset processing, with advancements in technologies like graphics processing units (GPUs) facilitating rapid AI model training and deployment [12, 13]. Cloud-based computing resources further democratize computational power access, allowing researchers and organizations to scale AI systems on demand.

AI offers significant advantages to various sectors, including industry and government. AI utilization enables rapid task execution, automation, and expansion, potentially leading to a transformative phase of innovation that could permanently alter the way humans perceive and conduct work. This report focuses primarily on disaster response, particularly the application of AI in environmental remediation and disaster recovery (herein referred to as simply “disaster recovery”). Historically, the field of disaster response has demonstrated slow adoption of technology, a trend that could persist as AI becomes more prevalent. Despite some preliminary advancements in applying AI to disaster recovery, this domain can greatly benefit from further research, development, and operational applications. To delve deeper into the capabilities of AI in addressing disaster-related challenges, this paper outlines the subsequent objectives:

1. Provide a concise historical overview of AI, its functionality, and its implementation;
2. Conduct a meta-analysis of AI-related literature to identify prevalent patterns, trends, or effects in the context of environmental remediation and disaster recovery;
3. Determine two primary research areas within environmental remediation and disaster recovery that can reap immediate and substantial benefits from AI integration;
4. Illustrate the potential of AI by presenting a series of conceptual examples that address prevalent disaster response tasks and challenges; and
5. Examine emerging developments and potential impediments that might influence the adoption of AI in the public sector.

These objectives will guide the subsequent sections, ultimately offering valuable insights into the potential impact of AI on disaster recovery, as well as opportunities for further research and development in this field.

2. Methodology

The methodology of this study centers on two primary goals, both of which were achieved through a literature search. The first goal is to gain a deeper understanding of AI's background (presented in the introduction of this paper) and applications, while the second goal focuses on identifying common AI applications. By annotating the resulting literature, key research areas and easily achievable innovations can be pinpointed, which can then be applied to aspects of disaster recovery. The literature search was conducted in two stages. The first stage was a quick pass to gain an overview of available literature. Table 1 displays the search strings utilized for this preliminary search. Based on the results and feedback, the search strings were revised to align better with the study objectives, as shown in Table 2.

Table 1. Preliminary Search Strategy

	QUERY
FIRST STAGE	[AI] AND [(“chemical”) OR (“biological”) OR (“radioactive”) OR (“emergency”) OR (“flood”)] AND (“event”)
	[AI] AND (“disaster”) AND [(“response”) OR (“simulation”)]
	[AI] AND (“natural disaster”)
	[AI] AND [(“planning”) OR (“decision-making”) OR (“decision making”)] AND [(“simulations”) OR (“videogames”) OR (“disaster response”)]
	[Creation]
	[Creation] IN [(“simulations”) OR (“videogames”)]

Table 2. Refined Search Strategy

	QUERY
SECOND STAGE	[AI] AND [(“biological agent”) OR (“chemical agent”) OR (“agent”) OR (“disaster”)] AND (“contamination”)
	[AI] AND (“emergency”) AND (“logistics”)
	[AI] AND (“Haiti earthquake”)
	[AI] AND (“hurricane”) AND (“damage”)
	[AI] AND (“oil spill”)
	[AI] AND (“quarantine”) AND NOT (“COVID”)
	[AI] AND (“radioactivity”) AND (“contamination”)
	[AI] AND (“radiological”) AND (“incident”)
	[AI] AND (“toxic waste”)
[AI] AND (“waste dumping”)	

To conduct the literature search, ReadCube (ReadCube, Cambridge, MA, USA) software was used. ReadCube aggregates scholarly articles and offers querying, cataloging, and annotation capabilities for literature. Credible sources included peer-reviewed journals, scientific manuals, and other scientific

publications, as well as information from nationally and internationally recognized academic, scientific, technical, or response organizations. The search focused on papers published between 2010 and 2021, primarily targeting English-language sources, while making allowances for a few high-impact papers in the field of AI.

A summary of potential research areas and their application to environmental remediation and disaster recovery is discussed in Section 4, while a meta-analysis of the collected literature is presented in Section 4.1.

2.1. Quality Control

The purpose of this study was to synthesize existing knowledge and research as it relates to AI and environmental remediation and disaster recovery. The work and conclusions presented as part of this study were empirical and observational – no scientific experiments were performed. Technical experts in the field of AI evaluated the quality of the information collected by this effort (i.e., secondary data), and based on their expert opinion, determined if the information should be documented within the literature review. All supporting documentation of the secondary data considered worthy for inclusion were cited. However, no experimental confirmation of secondary data (e.g., accuracy, precision, representativeness, completeness, and comparability) was conducted as part of this study.

3. Environmental Remediation and Disaster Recovery

Environmental remediation refers to the process of removing, neutralizing, or containing pollutants and contaminants from indoor and outdoor environments, in order to restore the affected areas to their uncontaminated state. This process typically involves the use of various technologies, methods, and strategies to clean up hazardous waste, manage pollution, and reduce risks to human health and the environment. Disaster recovery, however, is the coordinated set of actions and strategies aimed at restoring, rebuilding, and rehabilitating communities and ecosystems affected by natural or human-caused disasters. These disasters can include events such as hurricanes, floods, earthquakes, fires, or human-caused incidents. Disaster recovery efforts often involve multiple stakeholders, including governments, non-governmental organizations, and local communities, and encompass a range of activities such as infrastructure repair, economic revitalization, and social support systems.

In the context of environmental remediation and disaster recovery, the combined objective is to restore the environment and affected communities, through a series of interconnected processes, expert knowledge, and decision-making efforts. AI, a broad term encompassing various technical capabilities, topics, and industries, holds significant potential for facilitating many decision points within this context. By enhancing decision-making and communication, AI would allow officials to concentrate more effectively on critical aspects of the response. To better understand the application of AI in disaster recovery, the relevant literature needs to be investigated and AI's natural language and image processing components need to be explored.

By providing a series of conceptual examples, this report aims to demonstrate the potential application of AI in this domain, emphasizing its capabilities and the need for further research to fully harness AI's potential in the field of disaster recovery.

3.1. AI Research Trends in Disaster Recovery

Based on the literature search strategy presented in Section 3, the preliminary and refined searches yielded approximately 500 papers. The titles and abstracts of these papers were reviewed to ensure their relevance to the topics of interest. Any irrelevant (e.g., mentioning AI in a broader context but not focusing on AI) or low-quality results (e.g., missing a significant number of metadata fields) were excluded. A small portion of the papers, 16 in total, published before 2010 were retained. Based on the title and abstract review, papers were categorized according to their relevance to environmental remediation and disaster recovery applications. Relevant publications were then retrieved for a full-text review, although the overall number of papers addressing the topic was limited.

To differentiate and group the publications, keywords were extracted from abstracts and categorized into five groups:

- Algorithms – Names of common machine learning algorithms
- Agents – Contamination agents that are the pretext or a component of a disaster event
- Threats – Negative consequences that could be a part of the disaster event
- Environments – Different types of natural environments that are part of the event
- Topics (relevancy) – High-level, topical categories

These categories and their associated keywords are listed in Table 3. In some cases, keywords included multiple variants of spelling or word forms, such as "radioactive," "radiological," and "radiation" all

falling under the keyword "radioactive." Once the categories were fully defined, a Python (version 3.11.3) script was used to read the abstracts, parse the keywords, and generate keyword counts for each category. The keywords within each category are not mutually exclusive, meaning that an abstract could contain multiple keywords or no keywords for a given category, as well as keywords from multiple categories.

Table 3. Abstract Keywords by Category

	<i>Keyword</i>		<i>Keywords</i>
Algorithm	bayes	Agent	radioactive
	clustering		biological
	convolutional neural network		chemical
	decision tree	Threat	
	evolutionary algorithm		contamination
	genetic algorithm		pathogens
	gradient boosting	Environment	
	LDA "linear discriminant analysis"		air
	LSTM "long short-term memory"		earth
	neural network		water
	random forest		
	regression		disaster logistics
	reinforcement learning		environmental research
	support vector machine	Topic	games
			geospatial analytics
	social media research		

Abstracts predominantly contained environment keywords (83% featuring at least one keyword) and topic keywords (79%), while the presence of threat or agent keywords was less frequent (25% and 17%, respectively). Algorithm keywords appeared in 42% of the abstracts. The figures below exclude abstracts without keywords in a specific category, and the number of abstracts with at least one keyword, denoted as n, is displayed for each figure. It is important to note that an abstract might contain multiple keywords; thus, the values on the bars will sum to more than n. One limitation of the keyword analysis is that only the abstracts were searched, meaning a keyword might be present in the main body of a paper but not in its abstract; although, this is unlikely. The counts and plots provided below give a general overview of the abstracts' composition and could be useful in determining the current state of research and the technologies being utilized.

Figure 1 illustrates the prevalence of algorithm keywords. Support vector machines (14% of all abstracts), neural networks (14%), and random forests (10%) were the most frequently mentioned algorithms. To ensure no crucial algorithms were omitted from the keyword list, abstracts without keywords in this category were examined. These abstracts generally did not name any specific algorithms, rather than mentioning algorithms absent from the keyword list.

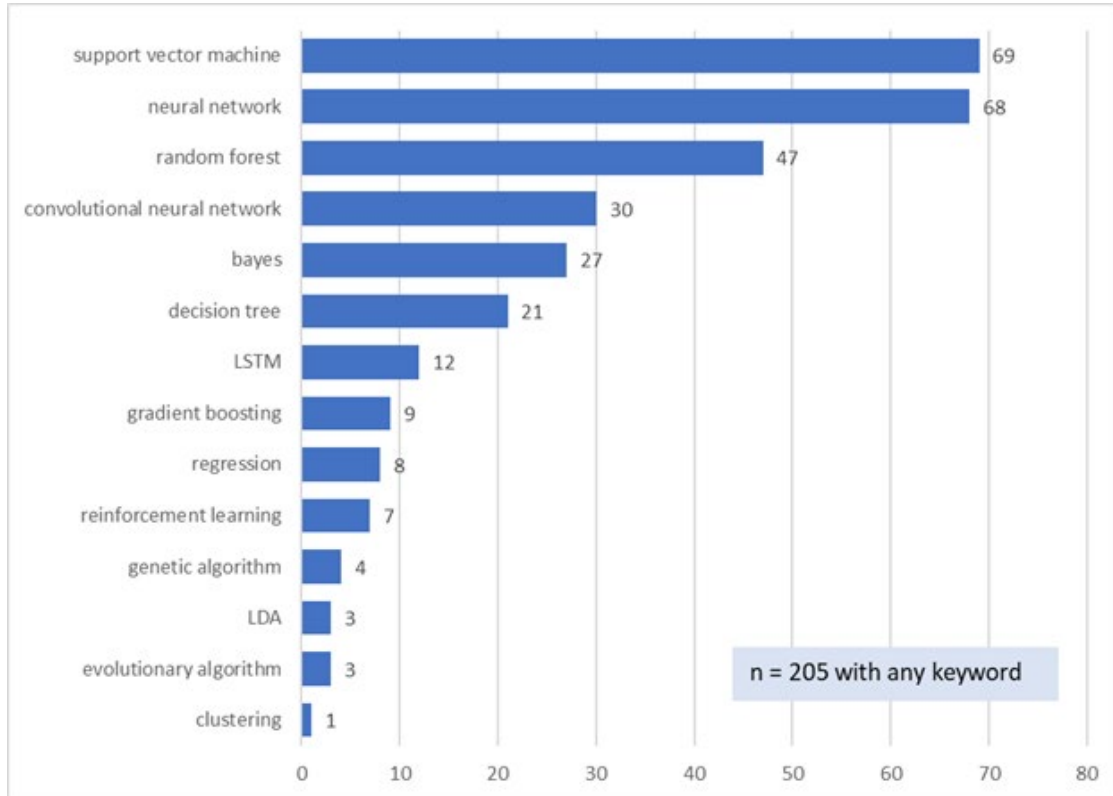


Figure 1. Prevalence of algorithm keywords among abstracts.

Figure 2 displays the prevalence of agent keywords. This category was the least likely to appear in the abstracts, with only 17% of the abstracts containing agent keywords. Among all abstracts, the most frequently mentioned agent was chemical (11%), while radioactive and biological agents were each mentioned in merely 3% of the abstracts. This observation suggested that the majority of the relevant publications identified in this study did not specifically concentrate on a disaster event involving one of these agent types.

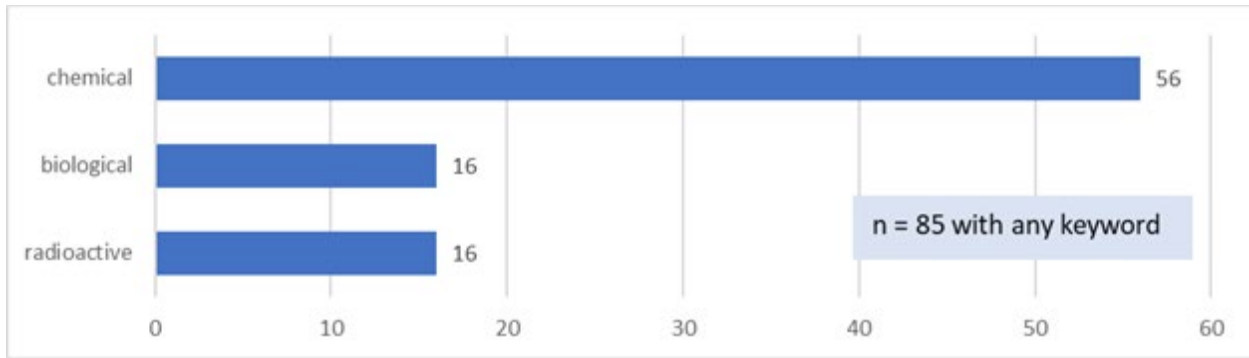


Figure 2. Prevalence of agent keywords among abstracts.

Figure 3 presents the prevalence of threat keywords. Similar to the agent category, a considerable number of abstracts (75%) lacked threat keywords. Among the abstracts that included threat keywords, contamination was mentioned more frequently (17% of all abstracts) compared to pathogens (9%).

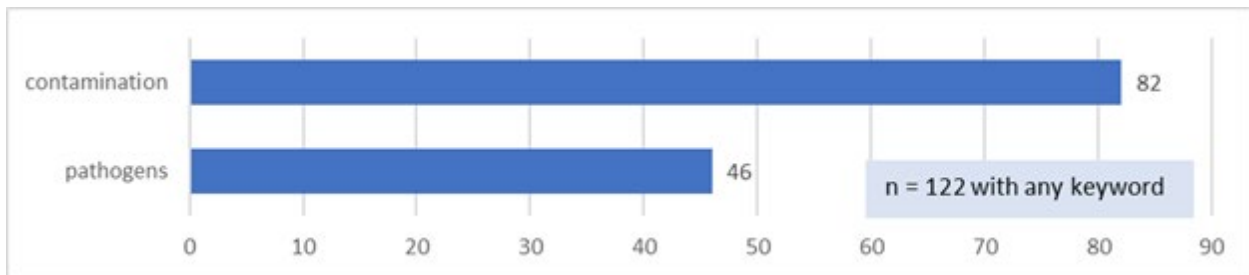


Figure 3. Prevalence of threat keywords among abstracts.

Figure 4 illustrates the prevalence of environment keywords. The most frequently mentioned environment keyword was water (69% of all abstracts), followed by earth (e.g., solid matter or ground surfaces) and air (30% and 15%, respectively). As previously mentioned, environment keywords had the highest likelihood of appearing in the abstracts.

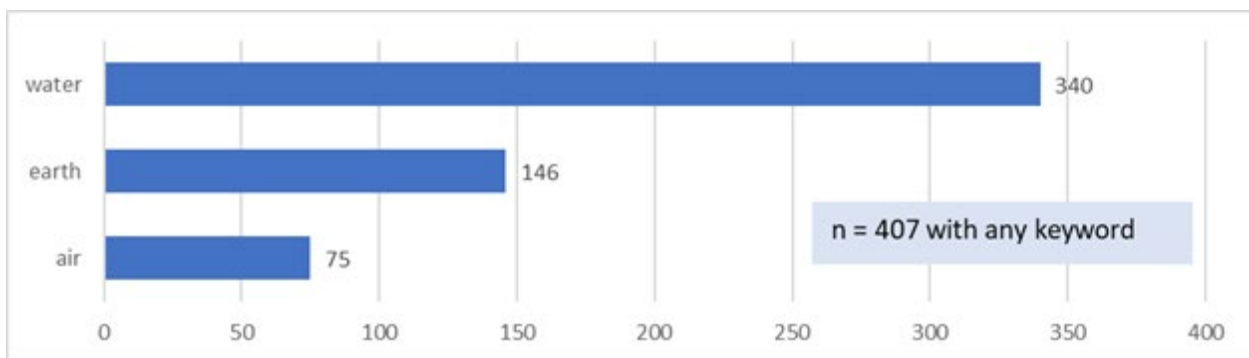


Figure 4. Prevalence of environment keywords among abstracts.

Lastly, Figure 5 presents the prevalence of topic keywords. Environmental research was the most frequently mentioned topic, appearing in 61% of all abstracts. This result was expected, considering the broader theme of this literature review and the queries used in the search process. More notably, 29%

of the abstracts contained keywords related to disaster logistics. This subset of articles might be particularly valuable for identifying tools relevant to disaster debris logistics.

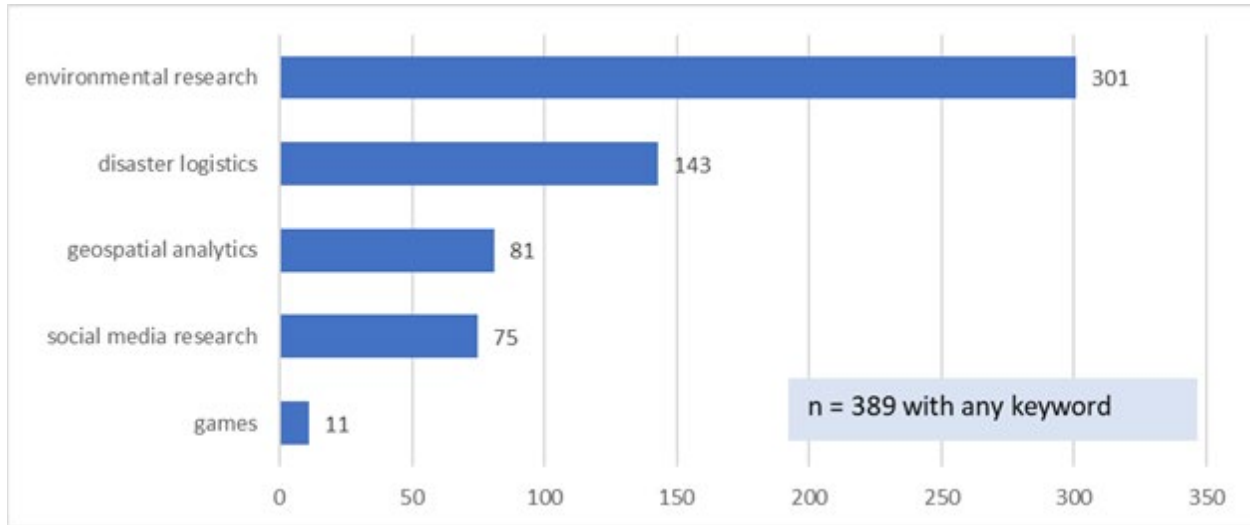


Figure 5. Prevalence of topic keywords among abstracts.

The analysis of approximately 500 papers focusing on the application of AI in the field of environmental remediation and disaster recovery revealed that the literature on this topic is limited, with a majority of relevant publications focusing on environmental research and disaster logistics, evident from the prevalence of environment and topic keywords in the abstracts, while agent and threat keywords were less frequently mentioned. The identified subset of articles related to disaster logistics could be valuable for developing novel disaster event scenarios and tools. Despite the limitations of the keyword analysis, such as only searching abstracts and the possibility of overlooking keywords in the main body of papers, the findings provide a general understanding of the current state of research and the technologies being employed in this field.

3.2. Natural Language Processing and Information Analysis

Natural language processing (NLP) is a subfield of AI that focuses on enabling computers to understand, interpret, and generate human language [14]. The development of NLP techniques has been facilitated by the rapid progress in deep learning, which has allowed researchers to create more sophisticated models for language representation [14]. Key NLP tasks include, but are not limited to, corpus linguistics, named entity recognition, sentiment analysis, and machine translation. The evolution of NLP has led to the emergence of conversational AI, a branch of AI that aims to create natural and effective communication between humans and machines through chatbots and virtual assistants [15].

Conversational AI relies on a combination of NLP techniques and additional components to facilitate human-like interactions. To achieve this, systems typically employ an architecture consisting of three main components: natural language understanding (NLU), dialog management, and natural language generation (NLG)[16]. The NLU module processes and extracts meaning from user input, dialog management maintains the context and flow of the conversation, and the NLG component generates human-readable responses. State-of-the-art conversational AI systems, such as OpenAI's GPT

(Generative Pre-Trained Transformer) series, demonstrate remarkable language understanding and generation capabilities [17].

Through advanced machine learning techniques, particularly deep learning models, NLP has achieved significant progress in various tasks, such as sentiment analysis, machine translation, and text summarization [18]. NLP and AI-driven analysis involve the use of algorithms and models that can process and learn from large amounts of textual data. These models are typically trained on extensive datasets to capture the nuances of human language and are capable of understanding the context and semantics of text. By leveraging techniques such as tokenization, parsing, and vectorization, NLP models can break down and represent text in a format that can be easily processed and analyzed by AI systems.

Despite significant advancements in the field, challenges remain in developing conversational AI systems capable of handling complex, context-dependent interactions. Existing limitations include difficulties in maintaining long-term context, addressing ambiguous queries, AI hallucination, and generating safe and unbiased responses [19]. The following sections provide examples of the application of NLP and conversational AI to four areas of research that are relevant to disaster recovery.

3.2.1. Enhancing Communication and Collaboration Among Stakeholders

AI has increasingly been applied to facilitate and enhance communication and collaboration among stakeholders in various domains, ranging from organizational management to software development [20]. AI-driven technologies, such as NLP and machine learning, have been employed to analyze textual data, automate routine tasks, and provide context-aware recommendations, enabling stakeholders to engage in more effective communication and collaboration [21].

One notable application of AI in enhancing stakeholder communication and collaboration is through the use of intelligent chatbots, such as ChatGPT (OpenAI, San Francisco, CA, USA). These chatbots can help organize and streamline communications, provide real-time language translation, offer data-driven insights, and automate tasks, ultimately improving efficiency and fostering a more inclusive and engaged working environment [22]. Additionally, AI-driven analysis tools can be employed to gauge stakeholder sentiment and identify areas of concern or disagreement, allowing organizations to address potential issues proactively [23]. Despite the potential benefits of AI in enhancing stakeholder communication and collaboration, certain challenges remain, such as ensuring data privacy, addressing the potential for algorithmic bias, and managing the integration of AI systems within existing workflows [24].

Communication is one of the most critical aspects of disaster response. Poor communication can have consequences on operations, decision making, and public sentiment often associated with the challenge of communicating information in a timely manner and communicating technical details to audiences with varying cultural and educational backgrounds. Throughout history there have been numerous examples of information not being communicated in a clear and consistent manner, which resulted in the loss of life and property. This problem is further shared with subject matter experts and scientists who translate highly detailed technical data from models and software tools. These tools are used to communicate important information such as evacuation zones or technical guidance to operational experts. The application of AI-driven technologies like NLP can help bridge the communication gap, enabling a more effective and accurate transmission of critical information during disaster response situations.

3.2.1.1. Conceptual Example - Enhancing Communication

In the following conceptual example, GPT-4, an advanced NLP model, is applied to process and communicate a technical spreadsheet generated by one of U.S. Environmental Protection Agency’s (EPA’s) waste management tools. This tool supports waste logistics planning and provides information regarding total waste amounts, transportation costs, and time. The NLP model (otherwise known as the “agent”²) was tasked with translating the technical data into an easily readable format for two distinct stakeholder groups: 1) decision-makers, and 2) community members. Table 4 represents the spreadsheet that was passed to the agent (GPT-4), containing information primarily related to waste amounts and the associated cost and time for transporting waste to disposal facilities.

Table 4. Example Waste Logistics Modeling Result

Type	Result
Waste Type	Municipal Solid Waste (MSW)
Waste Medium	Volume Solid
Total Waste Amount	150,000,000
Allocated Amount	150,000,000
Unallocated Amount	0%
Waste Unit	m ³
Condition ID	Default
Factor ID	Default
Facility Attributes ID	Default
Road Transporter Attrs ID	Average Truck Hauling
Rail Transporter Attrs ID	Average Train Hauling
Total Number of Facilities	5
Total Number of Road Shipments	12995
Total Number of Rail Shipments	115
Total Transportation Cost per Loaded Mile (CPLM) Cost (\$)	\$0
Total Fixed Cost Per Contr (\$)	\$4,106,617
Total Fixed Cost Per Hour (\$)	\$280,656
Total Fixed Cost By Volume (\$)	\$0
Total Tolls (\$)	\$0
Total Misc Trans Costs (\$)	\$0
Total Transportation Cost (\$)	\$4,387,273
Total Staging Site Cost (\$)	\$0
Total Disposal Cost (\$)	\$14,072,896
Total Labor Cost (\$)	\$123,095
Total Vehicle Decon Cost (\$)	\$0
Total Cost Multiplier (\$)	\$4,645,816
Total Cost (\$)	\$23,229,082
Vehicle Time to Complete (days)	10
Destination Time to Complete (days)	188

² The term "agent" in AI is borrowed from the fields of multiagent systems and artificial intelligence, where it is used to describe entities that possess a certain level of intelligence, autonomy, and decision-making capabilities.

Total Time Days (days)	23200%
------------------------	--------

The subsequent passages were generated by the AI agent, specifically tailored for two distinct audiences: decision-makers and the community. These adaptations were based on a simple prompt designed to consider the specific need of each stakeholder (e.g., “Explain this table as if you were talking to a [insert audience type]”).

Decision-maker:

The Municipal Solid Waste (MSW) generated in the given scenario amounts to 1,500,000 cubic meters, with no unallocated waste. It is crucial for decision-makers to consider the fact that the waste management process involves a total of five waste handling facilities. The transportation of this waste is handled by both road and rail, with 12,995 road shipments and 115 rail shipments, respectively. Given the number of facilities and transportation methods, it is important to assess the overall efficiency and cost-effectiveness of the waste management process.

When it comes to the financial aspect of waste management, the total transportation cost amounts to \$4,387,273.64. In addition to this, the disposal cost is significant, reaching \$14,072,896.28. Labor costs contribute another \$123,095.75 to the total expenses. It is important for decision-makers to evaluate these costs in relation to the potential benefits of the waste management process, as well as to explore opportunities for optimizing and reducing expenses.

Another important factor to consider is the time it takes to complete the waste management process. In this scenario, vehicles require 10 days to complete their transportation tasks, while it takes 188 days for waste disposal at the destination sites. The entire process spans a total of 232 days. Decision-makers should take these timeframes into account when planning and implementing waste management strategies, aiming to minimize the time it takes to handle the waste effectively and safely.

In summary, the given scenario presents a waste management process that involves 1,500,000 cubic meters of Municipal Solid Waste, transportation by road and rail, and a total of five facilities. The costs associated with this process are substantial, including transportation, disposal, labor, and other miscellaneous expenses, totaling \$23,229,082.09. The entire process takes 232 days to complete. Decision-makers should use this information to evaluate the efficiency and effectiveness of the current waste management process, seeking opportunities to optimize and reduce both time and costs.

Community:

In the aftermath of the recent disaster, our community is faced with a significant challenge in managing the debris generated by the event. To ensure the safety, health, and well-being of our residents, it is crucial to properly address the large volume of waste that has accumulated. The waste in question is classified as

Municipal Solid Waste (MSW) and amounts to 1,500,000 cubic meters. To manage this waste, a well-planned and executed waste management process is necessary, which involves the use of five dedicated waste handling facilities. The transportation of this waste will be carried out using both road and rail services, ensuring that it is efficiently moved and disposed of in the most suitable locations.

The process of handling and disposing of the debris involves several costs, which are necessary to ensure that our community can return to normalcy as quickly and safely as possible. The transportation of waste is one of the key expenses, which includes the cost of shipping the waste by truck and train to the appropriate facilities. Alongside transportation, there is a significant cost involved in properly disposing of the waste in a manner that is both environmentally responsible and compliant with regulations. Additionally, the wages of the workers who are responsible for handling and managing the waste must be accounted for, as their hard work and dedication are essential to the cleanup efforts.

In addition to the financial aspects, the time it takes to complete the waste management process is also an important consideration. The transportation of the debris by vehicles takes 10 days, while the waste disposal process at the designated sites requires 188 days. The entire cleanup process is expected to span a total of 232 days. This timeframe is essential to understand, as it helps our community plan for the recovery and rebuilding process while ensuring the safety and well-being of all residents.

In summary, the recent disaster has left our community with a significant amount of debris, requiring a comprehensive waste management process. The costs associated with this process, including transportation, disposal, and labor, are necessary investments to ensure a safe and efficient cleanup. The time it takes to complete this process is also an important factor to consider, as it helps our community plan for the future. By working together and supporting the waste management efforts, we can overcome this challenge and restore our community to its former state.

In this conceptual example, an NLP agent, such as GPT-4, was tasked with consuming a spreadsheet containing a range of values and text, inferring the content, and presenting the information in a contextually relevant manner for two separate audiences: decision-makers and the community. The agent (GPT-4) successfully transcribed the text and presented accurate factual information while adapting its tone specific to each audience (e.g., promoting alternate options for decision-makers, and emphasizing simplified explanations for the community).

Additionally, the agent (GPT-4) effectively summarized the main points in the conclusion of each summary. However, there are certain limitations to consider. Although not directly emphasized in this example, the agent could lack knowledge of or sensitivity to the local community, which could result in text that comes across as impersonal or detached. Moreover, some technical aspects associated with waste transportation, such as implications of transporting waste across state lines or opportunities for improving the plan to reduce cost or time, were not identified in the agent's response. The agent would instead tell the decision maker to broadly consider the effectiveness and overall cost of the plan. However, the prompt could potentially be modified to address these specific needs.

Despite these limitations, this conceptual example demonstrates the potential of NLP agents like GPT-4 in processing complex data and generating contextually relevant summaries for different audiences. The generated text can create a starting point that can be improved upon by the user, allowing for even more tailored content. By refining the prompt and incorporating additional domain-specific knowledge, the agent's capabilities can be further enhanced, ensuring that the generated summaries are both informative and attuned to the unique needs of each stakeholder group.

3.2.2. Software or Code Writing

AI has demonstrated considerable potential in the realm of software development, particularly in automating aspects of code writing and generating high-quality, maintainable code [25]. Machine learning, specifically deep learning techniques, have been applied to analyze, understand, and generate source code, improving the efficiency of software development processes and reducing the likelihood of introducing errors [26].

One prominent application of AI in code writing is through the use of neural machine translation (NMT) models, which have been adapted for code generation. These models can translate natural language descriptions of a problem or algorithm into source code [27]. For example, OpenAI's Codex, built on the GPT architecture, is capable of generating complex code snippets based on natural language prompts, demonstrating the potential of AI-assisted code writing [28]. Despite the advancements in AI-assisted code writing, challenges remain, such as ensuring the generated code is secure, maintainable, and adheres to best practices. Moreover, AI-generated code could still require human intervention and validation to ensure it meets the desired functionality and performance criteria [25].

In the context of disaster recovery, decision-makers and subject matter experts (SMEs) use models and decision support tools to facilitate decision-making and predict outcomes. Maintaining the associated code repositories requires significant resources, and compatibility issues can compel developers to quickly shift projects to address problems that would otherwise prevent the code from running. Furthermore, the application of AI-assisted software or code writing can be used to generate or bug-check code that would otherwise take a substantial amount of time or resources to develop. This would allow developers and scientists to focus more on critical code areas or on the technical application of the code to achieve a desired effect.

3.2.2.1. Conceptual Example – Code Writing

In the following conceptual example, GPT-4 was applied to conduct code writing. The agent (GPT-4) was provided with a technical problem and instructions (e.g., prompt) on the desired code functionality. Based on the provided prompt, the agent generated code that was compatible with Python 3. In this particular use case, the agent was asked to generate code capable of visually describing the waste logistics table (referenced as Table 4 earlier in the text). Specifically, the agent's task involved writing Python code to read in the comma-separated values (CSV) file and its associated data and generate a HyperText Markup Language (HTML) file that could be locally opened to view the results of the CSV file, including bar charts that visually described the data. The agent was instructed to avoid using libraries or solutions that would require the user to download or connect to special software. The emphasis of this use case was to create custom code that could convert CSV files generated by models into a format that was easily shareable and could be opened using a simple web browser, rather than relying on proprietary spreadsheet software.

By generating code tailored to these specific requirements, the NLP agent demonstrated its potential in facilitating software development processes and addressing unique challenges within the disaster recovery domain. This use case further highlighted how AI-driven NLP models could be leveraged to automate code generation, improve the efficiency of software development, and create versatile solutions that cater to the needs of different stakeholders.

Prompt: "Design a Python 3 script that generates a locally hosted HTML5 webpage displaying a table with data from a supplied CSV file. The page should not require any special libraries or services to run and should use pure HTML5. The script should be capable of inputting a CSV with the schema provided in the example. Create two bar charts on the page: one displaying total costs with the following variables: Total Transportation Cost, Total Staging Site Cost, Total Disposal Cost, Total Labor Cost, Total Vehicle Decon Cost, Total Cost Multiplier, and Total Cost; and another chart displaying the following variables: Vehicle Time to Complete, Destination Time to Complete, and Total Time Days. Label the bars on each chart, display the values to the right of each bar, and use different colors for each bar."

In this conceptual example, the agent (GPT-4) was assigned the task of creating a Python script based on the previously described prompt. The agent successfully generated viable Python 3 code (refer to Appendix A for the source code). When executed, the code generated an HTML page compatible with any modern browser. Figure 6A displays an example of the table created using the CSV inputs as a reference, while Figure 6B presents a bar chart based on the prescribed values. The key emphasis in this conceptual example was the agent's ability to traverse multiple languages (e.g., Python and HTML5), ultimately resulting in successful code generation. This example demonstrated the effect NLP models can have on software development, as code can be dynamically generated based on a specified need or outcome. However, the importance of developers interpreting the generated code for security and efficiency purposes should not be underestimated. Simply generating and executing code without understanding its implications can lead to serious consequences. The role of developers remains essential in validating the code for safety, efficiency, functionality, and compliance with best practices.

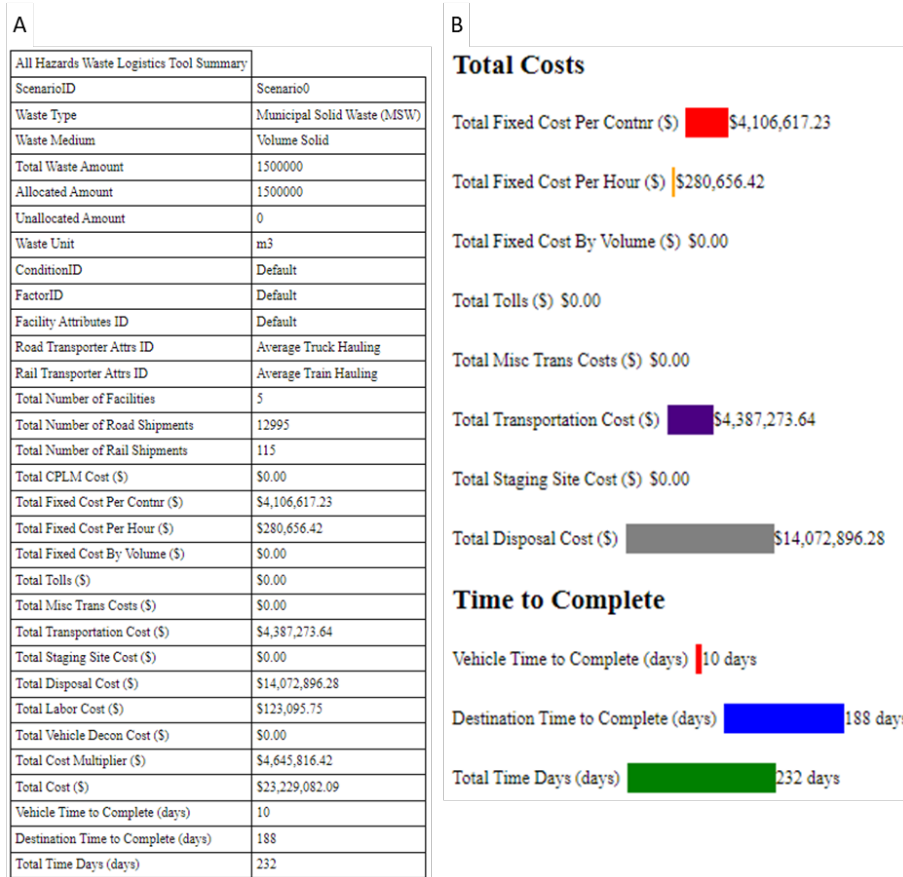


Figure 6. Webpage generated by GPT code.

3.2.3. Analyzing and Summarizing Scientific Research for Decision-Making

The rapid growth of scientific research and the increasing volume of published articles present a significant challenge for decision-makers who should stay up-to-date with the latest findings in their field. AI has emerged as a powerful tool for analyzing and summarizing scientific research, enabling decision-makers to quickly access relevant information and make well-informed choices. AI-driven techniques, such as NLP and machine learning, have been employed to develop models capable of understanding complex scientific texts, extracting key information, and generating concise summaries [29].

One example of an AI model that has demonstrated exceptional performance in understanding and summarizing textual information is BERT (Bidirectional Encoder Representations from Transformers) (Google, Mountain View, CA, USA) [29]. BERT, and its variants, such as RoBERTa [30], have been widely used for a variety of NLP tasks, including question answering, named entity recognition, and sentiment analysis. By fine-tuning models such as these on domain-specific datasets, researchers can develop highly accurate summarization systems that can condense large volumes of scientific research into easily digestible summaries. In addition, AI-driven literature search engines, such as Semantic Scholar [31], employ advanced NLP techniques to index and retrieve relevant research articles, further aiding decision-makers in accessing pertinent information. However, AI is known to occasionally generate false

responses or hallucinations. Given that NLP models are extremely efficient at generating convincing text, users could inadvertently interpret data as truthful and potentially act on erroneous information.

Using AI to analyze and summarize scientific research could have significant implications for decision-making and research across various domains. In the context of disaster recovery, for instance, AI-driven summarization systems could help digest and summarize relevant technical information to quickly identify efficient solutions to support cleanup. These potentials could include identifying optimal environmental sampling approaches, generating sampling designs, determining appropriate decontamination options, and optimizing waste minimization outcomes.

3.2.3.1. Conceptual Example – Summarizing Scientific Reports

In this conceptual example, the agent (GPT-4) was tasked with summarizing a technical report titled "A Review of Biological Agent Sampling Methods and Application to a Wide-Area Incident Scenario to Characterize Time and Resource Demands" [32]. The goals of this example were twofold: 1) to determine if the agent could recall the text by merely mentioning the report title and author (GPT-4's knowledge cutoff date is September 2021), and 2) to determine if the agent could successfully recall quantitative values embedded within the report. The result of the first prompt, which asked the agent to summarize the publication by merely providing the agent with the associated title and author name, is presented below:

Title: A Review of Biological Agent Sampling Methods and Application to a Wide-Area Incident Scenario to Characterize Time and Resource Demands

This EPA report provides a comprehensive review of biological agent sampling methods and their application to a wide-area incident scenario. The aim of the study is to understand the time and resource demands associated with different sampling techniques when dealing with a large-scale biological contamination event.

The report begins by outlining various sampling methods, including air, surface, and bulk sampling, as well as the advantages and limitations of each method. It also discusses the importance of determining appropriate sample sizes, locations, and collection frequencies to ensure accurate characterization of the contaminated area.

The study then applies these sampling techniques to a hypothetical wide-area incident scenario involving the release of Bacillus anthracis spores. By assessing the time and resource demands of different sampling strategies, the report highlights the challenges of collecting, processing, and analyzing a large number of samples in a timely manner.

The report concludes by emphasizing the need for improved sampling methods, streamlined laboratory processes, and better integration of sampling strategies with risk assessment and decision-making processes. This would allow for more efficient and effective response efforts in the event of a large-scale biological contamination incident.

The agent (GPT-4) successfully summarized the document, but the summary lacked technical details. When asked to provide more detail related to sampling metrics, the agent acknowledged that it could

not find the requested information. For instance, when asked to provide more information on the time and cost metrics discussed in the aforementioned report, the agent acknowledged it could not locate this information. However, when the agent was supplied with the text directly (the methodology section (Section 4) of the report was made available to GPT-4), it successfully recalled the requested values, as shown below:

This information presents the results of a hypothetical large-scale contamination scenario involving different environments: outdoor, indoor, and underground transit systems. The tables show the total number of samples, sample types, and estimated costs and time required for sampling and analysis in each environment.

For the outdoor area (Tables 23 and 24), approximately 3,630,000 samples would need to be collected, costing about \$1.9 billion and taking around 1.4 years to characterize.

For the indoor area (Tables 25 and 26), around 26,300,000 samples would be required, with an estimated cost of \$13.4 billion and a time requirement of 8.7 years for characterization.

Finally, for the underground transit system (Tables 27 and 28), about 121,000 samples would need to be collected. The cost for characterization is estimated at \$1.4 million, and the process would take roughly 34 days.

The information highlights the time, labor, and financial demands of sampling and analyzing large-scale contamination events in various environments, emphasizing the need for efficient and effective response strategies.

This conceptual example demonstrated that AI can successfully summarize and recall technical reports. However, specific details that could inform operational or research efforts might be lacking. When provided with the report directly, the agent (GPT-4) was able to describe the information in greater detail. For this process to function optimally, GPT-4 would likely benefit from direct internet access (currently, GPT-4 lacks access to the internet). As of the date of writing this report, there are indications that GPT-4 may soon allow for direct links that will enable access to documents, and therefore the summarization of entire documents. The agent GPT is not the only NLP capable of consuming and interpreting technical information; other models, such as BERT, also allow for large-scale interpretation of data from scientific documents.

3.2.4. Optimizing Remediation Strategies and Resource Allocation

The application of AI in optimizing remediation strategies and resource allocation has become increasingly relevant as environmental challenges continue to escalate. By leveraging advanced machine learning algorithms, AI models can analyze vast amounts of data to predict the potential effects of different remediation approaches and optimize the allocation of resources for improved environmental management [32]. The ability of AI to process complex information and generate robust solutions has led to enhanced decision-making in various environmental domains, such as contaminated site remediation, water resource management, and waste management.

In the field of disaster recovery, AI techniques such as symbolic regression have been utilized to identify efficient and cost-effective sampling strategies [32]. These methods can help determine optimal remediation sampling solutions by considering various factors associated with surface sampling and affected environments. Furthermore, in the context of waste management, AI has the potential to optimize collection and transportation routes, estimate waste generation rates, and predict the performance of waste treatment facilities, ultimately leading to reduced environmental effects and cost savings. The optimization of strategies and approaches using AI likely offers the greatest potential in the field of disaster recovery, as these decision points require rapid interpretation of large datasets within a short period of time, while identifying optimal outcomes.

3.2.4.1. Conceptual Example – Optimizing Remediation Strategies

In this conceptual example, an NLP (GPT-4) was applied to a model-derived dataset to determine the optimal outcome when comparing two separate sampling scenarios. Tables 5 and 6 present the technical details associated with two proposed environmental sampling plans, referred to as Sampling Plan 1 and Sampling Plan 2. The primary difference between these plans is the number of samples (i.e., the extent of the sampling area is consistent for both plans), with an increase in samples in Sampling Plan 2 resulting in a tenfold increase in cost and time outcomes. The data contained within Tables 5 and 6 were provided to the agent (GPT-4) as input.

Table 5. Sampling Plan 1 and 2 Summary

Plan	Number of Samples	Total Cost (USD - \$)	Total Time (days)	Sampling Team Hours	Days to Complete Sampling	Sampling Labor Cost (USD - \$)	Sampling Material Cost (USD - \$)	Analysis Lab Hours
100 Samples Plan	100	49207	4.2	21	4.2	8820	4687	70
1000 Samples Plan	1000	492070	42	210	42	88200	46870	700

Table 6. Sampling Plan 1 and 2 Summary Continued

Plan	Days to Complete Analysis	Analysis Labor Cost (USD - \$)	Analysis Material Cost (USD - \$)	Total Sampled Area (ft ²)	Time to Prepare Kits (person hours)	Time to Collect Samples (person hours)	Total Waste Volume (L)	Total Waste Weight (lb)
100 Samples Plan	2.917	11800	23900	69443	12	9	10	430
1000 Samples Plan	29.167	118000	239000	694442	120	90	100	4300

The summary provided by the agent (GPT-4) is displayed below. The agent successfully interpreted the given tables and offered valid considerations for enhancing the sampling plan. Although this scenario seems straightforward, it is important to note that the agent might not have encountered an extensive library of similar examples, yet it still successfully identified critical decision points such as confidence considerations and solutions for accelerating sample collection and analysis. However, the agent did not mention any specific considerations related to the level of confidence and its effect on the sampling design or the potential application of targeted sampling, which could potentially be achieved through refined prompting.

The 100 Samples Plan has the advantages of lower costs, shorter time frames, and less waste generation. However, it may result in lower confidence and limited scope due to its smaller coverage of the area of interest. To improve this plan, consider optimizing sampling locations, using more efficient sampling techniques or equipment, and focusing on specific areas of interest. On the other hand, the 1000 Samples Plan offers higher confidence and more comprehensive data by covering a larger area, but it comes with higher costs, longer time frames, and increased waste generation. To enhance this plan, consider increasing the sampling team size, negotiating bulk discounts on materials, implementing automated or semi-automated sampling equipment, and exploring alternative cost-effective analysis methods.

If high confidence is the primary goal, the 1000 Samples Plan is likely the more suitable choice due to its larger sample size and more extensive coverage. However, it is crucial to consider factors such as budget, time constraints, and environmental impact when selecting a plan. Implementing the suggested improvements for the chosen plan may help optimize the outcomes while addressing its limitations.

3.3. Image Recognition and Generation

Image recognition, also known as computer vision, is a field within AI that aims to enable computers to interpret and understand visual information from the surrounding world. This area encompasses techniques such as object detection, image segmentation, and facial recognition, among others [33]. AI-driven image recognition techniques have been developed using deep learning models, particularly convolutional neural networks (CNNs), which have demonstrated exceptional performance in tasks such as object recognition and classification [34].

However, AI-based image generation refers to the process of creating new images or modifying existing ones using machine learning techniques. Generative models, like generative adversarial networks (GANs) and variational autoencoders (VAEs) have become increasingly popular for image generation tasks [9, 35]. These models can produce high-quality, diverse, and contextually relevant images, making them invaluable tools for various applications, including design and prototyping. More recently, AI models like DALL-E (OpenAI, San Francisco, CA, USA) have emerged, leveraging GPT-based architectures to generate images from textual descriptions [36]. An evolving risk linked to AI-generated visuals lies in their capacity to produce fabricated or altered images, unethically or improperly depicting individuals or scenarios. Cutting-edge image generation models are capable of creating highly realistic visuals, which could prove difficult to identify even when utilizing specialized detection software.

3.3.1. Improving Safety and Efficiency of Response Activities

In recent years, AI has made significant advancements, especially in the realm of image generation. Machine learning models like DALL-E and stable diffusion have become increasingly capable of producing high-quality images suitable for diverse applications, such as supporting training and demonstrations. Employing AI-powered image generation tools would enable instructors and trainers to craft highly efficient, immersive learning experiences that reduce manual effort, promote innovative problem-solving techniques, and potentially yield more captivating and successful educational outcomes.

Stable diffusion, another generative modeling technique, uses a noise model and denoising score matching³ to create intricate and realistic images. Both technologies can be used to support training and demonstrations by generating a wide range of visual concepts based on text inputs, making the development of training materials more efficient and streamlined [36]. In training and demonstration contexts, the generated images can function as interactive routes, tailored to particular decisions or outcomes, akin to a "Choose Your Own Adventure" learning approach.

3.3.1.1. Conceptual Example – Image Generation

In the following conceptual example, image generation using DALL-E was applied to create distinct environments that target common scenarios associated with disaster recovery, such as pollution and contamination. The agent in this scenario (DALL-E) was tasked with rendering two separate environments: (1) a well-organized indoor environment for storing chemicals, and (2) a pristine small body of water. The agent was also tasked with rendering the inverse of these environments: (1) a cluttered and poorly maintained indoor environment for storing chemicals, and (2) a polluted small body of water. Each of the four prompts was fed separately into DALL-E (e.g., create a realistic image showing [environment description]).

Figure 7 presents the outcome of these prompts. Specifically, Figure 7A and 7C depict clean and well-maintained environments that could be considered optimal. In contrast, Figure 7B and 7D display the inverse of both environments, with clear signs of disorganization or pollution, respectively. Through this example, DALL-E demonstrated its capability to generate diverse and contextually relevant images for various environmental contamination-related scenarios.

³ A noise model represents data variations, while denoising score matching trains models to distinguish clean data from distorted versions.



Figure 7. DALL-E generated images: (A) a well-organized indoor environment for storing chemicals, (B) a cluttered and poorly maintained indoor environment for storing chemicals, (C) a pristine small body of water, and (D) a polluted small body of water.

The conceptual example showcased the level of detail that image generation models can produce. Specifically, Figure 7A shows a clean, shiny floor reflecting light, as well as a well-organized arrangement of chemicals, and in some cases, protective bars preventing containers from toppling over. A similar level of detail can be seen in Figure 7B, in which poor lighting contributes to the decrepit conditions of the storage area. Barrels appear poorly maintained, with some lying on their side, and a pool of unknown liquid is on the floor to indicate potential contamination. Overall, this test generated realistic results that can be utilized to support training or data visualization in the context of environmental contamination scenarios.

3.3.2. Image Recognition for Disaster Debris Characterization and Management

The application of AI image recognition in characterizing disaster debris is an emerging area of research, driven by the increasing frequency and severity of natural and human-made disasters worldwide. This process involves using advanced machine learning techniques, such as CNNs and deep learning algorithms, to automatically analyze and classify various types of disaster debris captured in images, including building rubble, infrastructure components, and hazardous materials [37]. Implementing AI-

based techniques in this field has the potential to significantly improve the accuracy and efficiency of disaster debris characterization, thereby enabling more effective disaster response and recovery efforts.

One of the key applications of AI image recognition in disaster response and recovery lies in assessing structural damage following earthquakes, hurricanes, and other natural disasters. By analyzing high-resolution aerial or satellite imagery, AI algorithms can identify and quantify the extent of damage to buildings and infrastructure, facilitating rapid damage assessment, and helping prioritize response efforts [38]. In addition to assessing damage and hazards, AI image recognition could be expanded to optimize debris removal and management efforts in the aftermath of disasters. For instance, AI algorithms could analyze images captured by unmanned aerial vehicles (UAVs) or ground-based cameras to estimate the volume, composition, and spatial distribution of disaster debris. This information could be used to inform debris management strategies, such as identifying suitable locations for temporary storage and processing facilities. Ultimately, the integration of AI image recognition in disaster debris characterization has the potential to greatly improve the process of managing and segregating debris.

3.3.2.1. Conceptual Example – Object Identification

The following conceptual example applied Google's Vision AI to identify objects in imagery, with a range of environments and varying levels of difficulty. Figure 8A depicts a water's edge littered with plastic, wood, and other waste. Figure 8B illustrates a trailer house impacted by a large wind event. Figure 8C presents a pile of debris primarily consisting of bricks. Figure 8D features a picture of a dog against a white background. These images are assorted according to the level of detail, which ultimately infers the level of difficulty (with Figure 8A being the most difficult and Figure 8D being the least difficult). Table 7 displays the results of the analysis, including the identified objects and their relevant scores (otherwise known as levels of confidence). Objects are sequenced according to the confidence in their identification.



Figure 8. Assortment of images showing various objects and environments: (A) waste at the edge of a water body, (B) a trailer house with debris, (C) a pile of bricks, and (D) a dog against a white background.

Table 7. Image Analysis Results

Figure (F) A Label	FA Score	FB Label	FB Score	FC Label	FC Score	FD Label	FD Score
Water	97%	Plant	94%	Brown	98%	Dog	92%
Mountain	92%	Sky	89%	Wood	84%	Carnivore	85%
Blue	89%	Wood	88%	Brick	83%	Companion dog	78%
Sky	89%	Branch	87%	Building material	80%	Dog breed	75%
Pollution	85%	Land lot	85%	Event	72%	Terrier	72%

The conceptual example highlighted the ability and accuracy of AI, specifically in image recognition, for identifying objects within pictures. In this example, the agent correctly identified the primary objects in these images, with a few exceptions. Notably, in the FC label and score, the primary object was identified as "Brown," and the secondary object as "Wood," while the bricks shown in the image appear red (the "bricks" label is shown in the third row down), and no wood is visible in the image. Overall, this

test yielded accurate results and illustrated the capability of AI to rapidly (i.e., in a matter of seconds) identify objects or classify imagery appropriately.

3.3.3. Image Synthesis in Design and Prototyping

The fusion of OpenAI's DALL-E and GPT models has created a tool for generating imagery and detailed descriptions simultaneously. DALL-E has demonstrated potential in providing visual representations for prototyping visual designs. By using natural language prompts, scientists and engineers could quickly generate an array of visual concepts that can be easily refined and iterated upon. This approach could reduce the time and effort required in traditional design processes, allowing for greater exploration of design alternatives.

The integration of GPT further enhances the design prototyping process. GPT can generate coherent, contextually relevant, and detailed descriptions, which DALL-E can transform into visual concepts. This combination of text description and image generation would enable designers to effectively communicate their design concepts and ideas, simplifying the collaborative process and ensuring that all potential design elements are fully considered. By using AI-generated descriptions, scientists and engineers could reduce ambiguities and ensure that the design intent is accurately conveyed to other stakeholders, such as emergency response personnel. However, similar to other aspects of AI, this design process could be affected by error propagation or hallucinations, as described in earlier sections, which could result in designs that are inconceivable from an engineering or materials perspective.

The application of this capability is twofold: 1) it presents a method for operational experts to visually communicate designs or ideas by using an NLP to transform basic descriptions into well-engineered concepts; 2) from the research and development perspective, this approach allows for designs to be iterated based on a range of stakeholder needs (e.g., the NLP can be prompted based on an inventory of keywords and needs), resulting in hundreds of potential designs in a relatively short period of time. This approach holds significant potential in prototyping designs and technologies in realms that require quick turnaround and limited research budgets.

3.3.3.1. Conceptual Example – Design Prototyping

In the following conceptual example, GPT-4 was asked to generate a detailed image prompt using specific design parameters. The text below presents the prompt employed to create the targeted design, as well as the response generated by GPT-4:

Prompt: Create an AI image prompt for developing a 3D prototype that adheres to the following characteristics. The description should be approximately 400 characters long. A plastic handheld scoopula that has rigid sides for cutting and a deep *reservoir* for collecting liquid.

Response: *Create a 3D prototype of a versatile plastic handheld scoopula, featuring rigid sides for precise cutting and a deep reservoir for efficient liquid collection. The design should be ergonomic, ensuring comfortable use, and incorporate a unique blend of aesthetics and functionality. The scoopula should be durable and easy to clean, catering to various applications in laboratories, kitchens, and other settings.*

The agent (GPT-4) was asked to modify the response, as the initial images showed a lack of raised edges necessary for cutting materials. Consequently, the revised response placed a greater emphasis on "cutting capabilities."

Prompt: Recreate this, but emphasize the saw-like appearance of the scoopula for cutting

Response: *Design a 3D prototype of a plastic handheld scoopula, showcasing a distinct saw-like ridge on its sides for effective cutting capabilities. The scoopula should have a deep reservoir for effortless liquid collection, while maintaining an ergonomic and visually appealing design. With its unique, saw-like appearance and versatile functionality, this scoopula is perfect for diverse environments such as laboratories, kitchens, and more, offering both durability and ease of cleaning.*

The prompts were inputted into DALL-E, resulting in a series of images shown in Figure 9. Figures 9A-B display different iterations of the first prompt, featuring a deep reservoir and curved tip that would enable liquid grab samples. However, neither design included any features suitable for cutting. Figures 9C-D depict the outcomes of the second prompt iteration, clearly exhibiting razor or rigid edges that could be used for sampling. In particular, Figure 9C shows promise as it incorporates both a reservoir and a cutting apparatus.

All four results demonstrated the ability of image generation tools like DALL-E to create highly detailed 3D imagery that reflects specific design elements. Furthermore, the demonstration highlighted the ability of GPT-4 to enhance the prompt to allow for improved design and engineering considerations. Overall, this example resulted in viable designs; however, it might take multiple iterations of prompts or image generation to identify a suitable prototype that meets the design requirements.



Figure 9. Grab sampling scooper prototypes: (A) first iteration of rounded edge scoop from first prompt, (B) second iteration of rounded edge scoop from first prompt, (C) first iteration of saw-edge scoop from second prompt, and (D) second iteration of saw-edge scoop from second prompt.

4. Discussion

AI could greatly benefit the field of disaster recovery, which encompass complex interrelated processes requiring specialized expertise and intricate decision-making strategies. In this study, the role of AI in disaster recovery was explored by reviewing pertinent literature and employing key AI components, such as NLP and image processing techniques, to prevalent scenarios. An analysis of approximately 500 papers revealed limited literature on this topic, with most publications focusing on environmental research and disaster logistics. The findings provide a general understanding of the current research state and the technologies being used. The literature review introduced key aspects of NLP and image analysis (e.g., image recognition and generation). Four potential NLP capabilities were highlighted: enhancing communications, code writing, interpreting scientific material, and strategy optimization. As an example of enhancing communications, GPT-4 was applied to a debris management scenario. The conceptual example demonstrated AI's ability to process complex data and generate contextually relevant summaries for different audiences. However, it is important to recognize NLP agents' limitations pertaining to public communications, such as lack of regional understanding or cultural sensitivities.

The study also showcased the effect NLP models could have on software development, with AI-assisted code writing providing dynamic code generation based on specific needs or outcomes. Developers' role in interpreting and validating the generated code for security, efficiency, and best practices compliance remains crucial. AI-driven summarization systems can identify efficient solutions for cleanup, waste minimization, and other aspects of environmental management quickly. While NLP agents like GPT-4 can summarize and recall technical reports, they might lack specific details that inform operational or research efforts. Specialized access to the Web or by accessing reports directly could enhance the agent's capabilities.

The image analysis section highlighted three potential AI capabilities: visualizing training scenarios, debris recognition, and design prototyping. In each example, a combination of DALL-E and GPT-4 were applied to relevant disaster recovery applications. The study provided a conceptual example of AI-generated images, showcasing their potential use in creating immersive learning experiences. Furthermore, AI image recognition demonstrated the ability to characterize debris from static imagery that has the potential to optimize future debris characterization efforts. Lastly, AI could help engineers and operational experts communicate designs and iterate based on stakeholder needs, generating numerous potential designs quickly. Advanced image generation tools, such as DALL-E, are capable of producing intricate 3D visuals that accurately represent specific design elements. Nevertheless, it might be necessary to undergo several iterations to pinpoint an optimal prototype that fulfills the desired design criteria.

Building on the successful integration of AI in the aforementioned conceptual examples and considering the growing potential for AI to be further incorporated into a wide range of sectors and workflows, it becomes crucial to comprehend emerging advancements, their implications, as well as the obstacles and challenges that organizations and the workforce might encounter due to AI adoption. The subsequent sections offer an overview of these topics.

4.1. Emerging Developments and Impacts

The advent of AI as a useful and widely available technology has undeniably become a transformative force in various industries [39]. Although still in the early stages of development, the potential effect of AI on creativity, writing, and technical capacities of individuals cannot be understated. With the rapid pace of advancements, AI tools are expected to proliferate, eventually becoming central to business and mission strategies for organizations worldwide [40]. For instance, a surge in AI-related repositories on GitHub was observed. As of April 2023, all trending GitHub repositories were related to AI, which demonstrated the increasing interest and investment in this technology by the development community [41]. However, the widespread adoption of AI as an integral part of various sectors also raises concerns about potential ethical and societal implications. Organizations should establish robust systems for maintaining and updating guidance to ensure transparency and privacy in AI applications. Furthermore, as AI applications become more embedded in the daily lives of individuals and organizations, education and upskilling in AI-related fields might be needed. Ensuring that individuals have access to the necessary resources and training to harness the benefits of AI might be needed to mitigate potential skill gaps and foster a workforce that can adapt to the rapidly evolving technological landscape.

Having evaluated the current state and potential applications of AI within the domain of disaster recovery, the subsequent section delves into the broader near-term and long-term applications of AI. By evaluating both immediate and future use cases, a deeper understanding of the potential outcomes can be gained, along with the development of strategies for effectively harnessing the benefits of AI across various applications.

Near-Term Applications (1-2 years):

- Document editing: enhance document editing by automatically detecting grammar and spelling errors, suggesting improved phrasing, and ensuring coherent structure and flow. AI would likely adapt writing styles to target specific audiences or meet predefined guidelines, streamlining the editing process and improving overall document quality.
- Digital assistants: employ AI to understand natural language queries, perform tasks, and provide personalized recommendations. AI could enable digital assistants to learn user preferences and habits over time, allowing for proactive assistance and increasingly accurate and relevant responses.
- Image and video generation: create realistic visual content based on textual descriptions, user inputs, or existing images and videos. Generative models like GANs and VAEs could produce high-quality visuals for applications such as advertising, entertainment, and design, enabling rapid prototyping and creative exploration.
- Assisted programming: leverage AI to provide code suggestions, error detection, and automatic code generation based on specific needs or outcomes, which could result in increased efficiency, fewer bugs, and a more streamlined development process, allowing developers to focus on higher-level tasks and problem-solving.
- Internet searching: search engines could become synonymous with AI as they leverage the technology to enhance their capabilities. As AI-powered search engines become more prevalent, the need for traditional keyword-based search methods might diminish, paving the way for more contextually aware and personalized search experiences.

- Literature review: efficiently analyze vast amounts of data, extract relevant information, and summarize findings. Assisted searches could enable rapid identification of key resources, while AI-generated reviews could provide an accessible overview of existing research, streamlining the knowledge acquisition process.
- System integration: integration of AI platforms with various online services through application programming interfaces (APIs) could enhance communication and facilitate seamless interactions between diverse systems. Such integration between AI platforms and other online services could lead to greater automation. For example, AI could be tasked with performing a search using a specific keyword, subsequently generating a list of related keywords based on the initial results. The system could then retrieve pertinent information and efficiently summarize the findings, streamlining the entire process that spans multiple systems and services.

Long-Term Applications (5-10 years):

- Human/AI integration: AI might be used to augment human capabilities and improve decision-making by providing insights and recommendations based on real-time data analysis. AI could also be integrated into wearable technologies to enhance physical abilities and health monitoring. AI-driven brain-computer interfaces could allow direct communication between the human brain and machines, opening up new possibilities for interaction and control.
- User interface (UI) and system interactions: AI could be applied to create more intuitive and personalized user interfaces, enabling systems to understand and predict user preferences and needs. Natural language processing would allow users to interact with systems through speech or text, making it more accessible for a wider range of people. AI could also learn from user behavior to improve system performance and usability over time.
- Fully autonomous agents: AI could be employed to develop intelligent agents that operate independently, making decisions and taking actions without human intervention. These autonomous agents could be used in a wide range of applications, such as self-driving vehicles, autonomous drones, and robotic assistants. They could revolutionize industries by increasing efficiency, safety, and reducing the need for human labor in repetitive or hazardous tasks.

4.2. Barriers and Challenges

Despite the myriad of promising opportunities outlined here, several persistent challenges and barriers remain. The accumulation and utilization of extensive data sets raises questions about user privacy and security. Simultaneously, ethical dilemmas, such as the potential misuse of AI for nefarious purposes, necessitate thorough deliberation. These barriers and challenges might limit the application of AI and would likely require policy frameworks and guidelines to establish acceptable use. Therefore, the following impediments should be considered:

- Data privacy: protection of personal information used to train and operate AI systems. Ensuring data privacy involves addressing concerns related to the collection, storage, and usage of personal data, as well as potential breaches that might compromise user privacy. Responsible AI development should incorporate privacy-preserving techniques, such as differential privacy and federated learning, to minimize the risks of unauthorized access, data misuse, and potential harm to individuals.

- **Algorithmic bias:** presence of unfair or discriminatory outcomes generated by AI systems, often as a result of biased training data or flawed algorithm design. Such biases can perpetuate and exacerbate existing social inequalities, leading to unfair treatment of specific groups or individuals. Addressing algorithmic bias involves developing methods for identifying, measuring, and mitigating these biases to ensure that AI systems produce fair and equitable outcomes.
- **Transparency:** ability to understand and interpret the decision-making processes of AI systems. Achieving transparency would be crucial for fostering trust, enabling users to comprehend AI-generated outcomes, and facilitating the identification of potential biases or errors. Techniques such as explainable AI (XAI) and interpretable machine learning models aim to enhance transparency by providing insights into the inner workings of AI systems and the rationale behind their decisions [42].
- **Accountability:** establishing mechanisms to hold AI developers, operators, and users responsible for the consequences of AI system decisions and actions. Ensuring accountability would be essential for promoting ethical AI use, preventing potential harm, and addressing any negative consequences that arise from AI deployment. Establishing clear guidelines, regulatory frameworks, and monitoring mechanisms would help attribute responsibility and enforce accountability in AI systems.
- **Weaponization of AI:** development and use of AI technology in military and offensive applications, such as autonomous weapons or surveillance systems. The weaponization of AI raises ethical, legal, and security concerns, as it can lead to unintended consequences, increased risk of conflict, or misuse by malicious actors. Addressing these concerns involves developing international norms, policies, and agreements that regulate the use of AI in military and policing contexts and promote responsible AI development for the benefit of humanity.
- **Hallucinations:** instances where the model generates outputs that are not grounded in the input data or real-world knowledge [19]. These outputs might seem plausible but are, in fact, erroneous or nonsensical. Hallucinations can occur due to limitations in the AI model's understanding, training data biases, or the model's tendency to create outputs that seem contextually appropriate [19]. Addressing hallucinations in AI systems would be necessary to improve their reliability and fact checking across various domains.
- **Ethics:** moral implications and responsible practices associated with the development and deployment of artificial intelligence. Key concerns in this area encompass issues such as biases and discrimination, which could arise due to unfair algorithms, transparency and interpretability for accountable AI systems, privacy, and surveillance as they relate to the protection of individual rights, job displacement stemming from AI-driven automation, and the concentration of power, which explores the risks of misuse and manipulation by influential entities.
- **Workforce:** AI is poised to have significant effects on the workforce, transforming various industries and job roles. According to recent research, fields that will experience the most significant effects include legal services, office and administrative support, social sciences, art design and entertainment, engineering, and business finances [40]. As AI systems become more advanced and integrated into these sectors, they would likely reshape job roles, creating new opportunities, potentially displacing some workers. Navigating these changes might require a

focus on reskilling, continuous learning, and adapting to an evolving job market to ensure a sustainable and equitable future for the workforce.

5. Conclusion

In conclusion, this report aimed to explore the potential of AI in disaster recovery and environmental remediation by addressing five main objectives. First, a historical overview of AI was provided, illustrating its potential to revolutionize various sectors, including disaster recovery. Second, a meta-analysis of AI-related literature was conducted, revealing a limited number of studies in the context of environmental remediation and disaster recovery. Third, two primary research areas, NLP and image analysis, were identified as having the potential to greatly benefit from AI integration. Fourth, a series of conceptual examples were presented to demonstrate the potential of AI in addressing common disaster recovery tasks and challenges. These examples showcased the capabilities of NLP in enhancing communications, code writing, interpreting scientific material, and strategy optimization, as well as image analysis in visualizing training scenarios, debris characterization, and design prototyping. Finally, the report examined emerging developments and potential impediments that could influence the adoption of AI in the public sector, emphasizing the importance of establishing policy frameworks and guidelines to ensure ethical applications and data privacy.

This study highlighted the potential of AI to revolutionize the work environment and complex undertakings such as disaster recovery and environmental remediation. While research in this domain is still limited, the conceptual examples and identified research areas underscore the need for further exploration and development of AI applications. By addressing the existing barriers and challenges associated with the deployment and utilization of this technology, AI has the potential to bring about revolutionary changes across various sectors, including disaster recovery and environmental remediation.

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7. Glossary

Adversarial networks: Neural networks designed to compete against each other, typically involving a generator and a discriminator, used frequently in generative models.

Artificial intelligence (AI): The capability of machines to imitate human intelligence and perform tasks that typically require human intelligence.

Artificial neural networks: Computational models inspired by the structure and functions of biological neural networks, designed to recognize patterns.

Corpus linguistics: The study of language as expressed in corpora (large and structured sets of texts) to identify linguistic patterns.

Hallucination: In AI, it refers to the generation of data or patterns that were not in the training data, often seen as a form of over-interpretation.

Machine learning: A subset of AI that allows computers to learn from and make predictions or decisions based on data without being explicitly programmed for the task.

Natural language generation (NLG): The process of producing meaningful phrases and sentences in the form of natural language from some internal representation.

Natural language processing (NLP): A field of AI that focuses on the interaction between computers and humans through natural language.

Natural language understanding: A subfield of NLP that focuses on the comprehension and interpretation of human languages by machines.

Neural machine translation: The use of deep learning models, particularly neural networks, to translate between different languages.

Sentiment analysis: The use of NLP to determine and extract subjective information, such as the sentiment or emotion of a piece of text.

Tokenization: The process of converting a sequence of text into individual tokens, typically words, phrases, or other meaningful elements.

Vectorization: The process of converting non-numeric data, especially text, into a numerical format or vector to facilitate computational processing.

Variational autoencoders: A type of generative model that learns a probabilistic mapping between data and a latent space, often used in unsupervised learning scenarios.