# AI Alignment of Disaster Resilience Management Support Systems

Andrzej M. J. Skulimowski[1,2](✉) and Victor A. Bañuls[3]

[1] Chair of Automatic Control and Robotics, AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Kraków, Poland
ams@agh.edu.pl

[2] International Centre for Decision Sciences and Forecasting, Progress & Business Foundation, ul. Lea 12B, 30-048 Kraków, Poland

[3] Universidad Pablo de Olavide, Ctra. de Utrera, 1, 41013 Seville, Spain
vabansil@upo.es

**Abstract.** This paper presents an application of Artificial Intelligence (AI) prospective studies to determine the most suitable AI technologies for implementation in Disaster Resilience Management Support Systems (DRMSSs). The pivotal role in our approach is played by the security needs analysis in the context of most common natural disasters and their co-occurrence with other threats. The AI trends and scenarios to align with are derived according to foresight principles. We apply expert knowledge elicitation and fusion techniques as well as a control model of technology dynamics. The pre-assessments of security needs and technological evolution prospects are combined to rank and select the most prospective AI methods and tools. Long-term ex-ante impact assessment of future disaster resilience improvements resulting from different DRMSS implementations, allows for the identification of the most suitable AI deployment variant. The target market of the DRMSSs under study includes industrial corporations and urban critical infrastructures, to become part of their Industry 4.0 ecosystems. The models of protected area and its environment are continually updated with visual monitoring and other sensors embedded in the Industrial Internet-of-Things infrastructure. The software architecture of DRMSS focuses on model-based decision support that applies fuzzy-stochastic uncertainty and multicriteria optimization. The business processes behind the AI alignment follow these goals. In the conclusion, we will show that DRMSS allows stakeholders to reach social, technological, and economic objectives simultaneously.

**Keywords:** Decision Support Systems · Disasters resilience management · AI alignment · Technological evolution · Security process modelling

## 1 Introduction

The progress in AI provides opportunities to implement new powerful methods for autonomously processing big and vulnerable data in disaster resilience management


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support systems (DRMSSs). These systems are a relatively new class of advanced software [22] that support decision makers in public administration and corporations not only in case of emergency, as common crisis management systems do, but also in allowing them to build resilience of their organizations in a systematic way. To achieve anticipated results of enhanced disaster resilience, the DRMSS developers must also take into account any potential social and technological AI threats. To overcome this challenge, we propose to analyze the AI forecasts and potential future hazards in the strategic alignment framework. This analysis allows us to derive optimal models of AI deployment, while indicating prior best practices in applying AI tools and methods in DRMSS. According to recent research trends on natural threats and AI, both constitute a major challenge to mankind in upcoming decades. Threats include hazards of purely natural origin, such as volcanoes, as well as mixed-origin threats such as climate change and pandemics. When investigating the synergies between these threats, the benefits of AI are clear since a great deal of AI-based technologies may be deployed to prevent or mitigate the impact of natural disasters. However, little is known about other incidences of AI/disaster interdependence, specifically those that might become relevant in the middle- or long-term future.

On the one hand, developers of specialized information systems such as DRMSSs or intelligent Decision Support Systems (DSSs) to be used for crisis management anticipate that AI will predominantly contribute to the growth in overall system quality. AI techniques are also expected to make autonomous robotic systems, such as search and rescue robots (SRR), a powerful tool that assists first responder teams in case of emergency. However, the increasing share of autonomous decision making processes required from AI-based systems creates a diversified spectrum of new problems that need to be solved. These range from operational security assurance to global impact modelling and universal AI ethics related to autonomous systems deployment. The ever-growing sophistication and scope of AI-based systems, devices, and software agents make the problems of explainable AI [2] and human-computer understanding increasingly relevant, especially in cases of resilience building activities.

## 1.1 The Resilience Management Support System Aims and Functionalities

The characteristic feature of prevention and resilience assurance measures, to be recommended or automatically controlled by DRMSS, is a high share of decisions that should be implemented immediately with specialized actuators, humans as first responders, as well as human-robot and robot teams. This, in turn, creates a need for endowing the DRMSSs with learning modules that process feedback information, gathered as observations of consequences of prior decisions. The efficiency of such learning schemes is ensured by the fusion of large amounts of information on similar operations collected from global databases and data streams and processed by state-of-the-art machine learning algorithms. Processing big data coming from environmental observations, such as satellite images, meteorological radar measurement, distributed precipitation data and precipitation-dependent soil porosity is another challenge.

While AI research will feed decision making, pattern recognition, and machine learning algorithm updates into the DRMSS evolution control module, current decision planning and implementation will strongly depend on the capabilities of rescue teams, sensor networks, and robotic systems. Motivated by real-life applications, this article is focused on industrial threat monitoring, alerting, and mitigation with DRMSS endowed with evolving AI tools. The system should also provide AI-supported coordination of mixed teams, composed of humans, and autonomous unmanned aerial and ground vehicles. For brevity's sake we refer to all of them as 'first responders'. The other key functionality of DRMSS is to provide decision support to enterprise managers who should be capable of quickly finding trade-off decisions with – communication dependent - restricted information exchange with regional crisis authorities. The DRMSS recommendations are simultaneously presented to all actors, taking into account the anticipated consequences of planned decisions.

The AI research screening will identify new technologies that are suitable for implementation into the decision support engine. Of particular interest are information fusion and multicriteria decision support methods as well as carefully selected machine learning and data mining techniques. Coordination of multi-robot and human-robot teams will require optimization of cyber-physical system activities, path planning, and simultaneous location and mapping (SLAM) of inspection and rescue robots. These aforementioned AI and robotics areas will be further focal points of the AI evolution model. This modelling tool will evolve itself, based on technology screening and reinforcement learning procedures. The overall DRMSS will use its sensors to detect and manage varying natural threats, such as landslides, falling rocks, and floods. The DRMSS will also monitor and prevent malicious human activities, including intrusions, violation of security rules by employees, etc.

### 1.2 The Aims and the Structure of this Paper

AI development trends observed over the past decades, when coupled with natural disaster and anthropogenic threat models, and confronted with real-life security needs should make it possible to create intelligent technology solutions to enhance disaster resilience. The primary aim of this paper is to provide a systematic approach to the design, implementation and deployment of intelligent DRMSSs endowed with a sufficient flexibility to align with AI development and capable of handling new emergency situations. The AI alignment problem to be solved differs from both, the heretofore general formulations relating AI to human values and ethics [10] as well as from the classical AI [21] or information technology (IT) business alignment [11]. Instead, we focus on an informed selection of the best AI tools and techniques to enhance DRMSSs as complex information systems to achieve best disaster resilience. The implemented methods should also make the system competitive and resilient against any adversarial AI support that can be used by intruders. We propose a general principle of aligning the DRMSSs to state-of-the-art AI solutions. Consequently, most of the background research is contained within intelligent decision support systems and autonomous decision making areas, both applied to the design of DRMSSs.

The structure of presentation follows the above formulated aim, starting from a survey of recent AI methods and tools applicable in DRMSSs, which is contained in Sect. 2. Section 3 formulates the technological AI alignment problem to be solved when designing a DRMSS that is continually updated according to the progress in AI. Section 4 presents the AI evolution modelling tool (AIEM), which supplies information about AI trends and scenarios to DRMSS developers. Then we outline the AIEM implementation, the DRMSS architecture and its links to the AI evolution model. The summary of our research findings is discussed in the final Sect. 5, together with general conclusions and future research plans.

## 2 Related Work

One of the first design proposals for emergency management DSS can be found in [6]. An overview of early developments in emergency response information systems and their future development prospects is provided in [22]. Multicriteria optimization and preference modelling approaches are commonly used in DRMSSs to include different resilience-related goals. An example of using them for location planning in disaster areas was given in [7]. Fundamental for the DRMSS implementation is research on decision support, with collaborative scenario modeling, to protect critical infrastructures. This group of methods can be used in DRMSS for project management [4].

The above background research, together with urgent real-life needs met a number of DRMSS implementations, both research prototypes and commercial systems. The THEMIS prototype applies an AI-based decision support system to be used by disaster managers and first responders. The architectures of DSS tailored to optimizing aid distribution during natural disasters are discussed in [15] and [9], including the assurance of supply chains and vehicle routing problems.

A great challenge posed to our research involves the integration of human and robot rescue teams under one coordination support system, a component of the DRMSS. Meanwhile, Search & Rescue is one of the leitmotivs and drivers of the autonomous mobile robotics development. The research includes a combination of advanced AI methods used predominantly to plan the search, identify the surrounding with pattern recognition and scene understanding approaches, assess the emergency situation and prioritize actions. Cyber–physical aspects of SRR are of utmost importance, including assistance to victims, cooperation with human rescue and repair teams, and communication with the management team that controls or supervises disaster mitigation activities. Rescue vehicle and repair crew scheduling was optimized with a combination of Mixed Integer Linear Programming and Ant Colony Optimization algorithms in [16]. Non-linear optimization for the solution of swarm SRR is described in [3]. An implementation of the simulation of an Industrial Internet-of-Things (IIoT) environment in a salt mine, where several mining inspection robots seek optimal anticipatory strategies to mitigate water and gas leaks, is presented in [20].

The problem of explainable AI, within the context of communicating robot action plans during S&R activities and human-robot interactions is discussed e.g. in [2]. The DRMSS design, based on AI alignment, proposed in this paper is aimed to bridge this gap, focusing on rescue action efficiency and on minimizing risks for the enterprise's personnel. To sum up, optimal embedding of robotic teams into overall disaster resilience building processes coordinated with a DRMSS remains an important research problem [9] to solve utilizing the knowledge on rapidly changing AI and robotics technologies. As we will show in Sect. 3, this knowledge can be gained from foresight exercises, specifically from Delphi surveys.

More information on the relationship between AI and disaster resilience management can be found in the survey [14] of related technological challenges such as early warning systems, navigation, geographic information systems (GIS), and diverse heuristics. Two real-life examples of DSS applications, including the real-time water quality management are also given. An attempt to provide taxonomy of disaster management support with AI methods, based on nine cases, is presented in [1]. The authors claim that about 60% of disaster management tools use AI methods, which coincides with our estimations. A survey on the AI-related methods of systems analysis and control with hints regarding future trends is presented in [13]. Another survey on the relations between AI and business models is contained in [8]. Finally, [23] studies quantitative disaster resilience indicators, which may be employed in DRMSSs.

## 3 AI Alignment and the Software Architecture of DRMSS

Progress in technology, specifically AI, provides a chance to win the race between growing disaster threats and the decreasing will to accept disaster-related losses. Hence, the design of disaster management support system architecture and its implementation should be aligned to state-of-the-art AI solutions, while taking into account a prior needs analysis, and the availability of suitable AI technologies. The resulting alignment problem to be solved can be formulated as follows.

**Problem 1 (technological AI alignment in the DRMSS context)**
Keep the AI implementation level in an enterprise information system (EIS) to standards ensuring at least an equally strong response of this EIS to the challenges and threats created by external agents with adversarial AI.

AI alignment in an enterprise with integrated information systems or a situation where all EISs will be aligned can be referred to as *enterprise AI alignment*.

**Problem 2 (enterprise AI alignment in the DRMSS context)**
Identify the best AI technologies to be used in an enterprise as a remedy to any external threats, caused by adversarial AI or not, and implement them in the enterprise.

Problems 1 and 2 can be resolved with the following iterative and continual system design procedure involving in-the-loop AI technology implementation.

**Procedure 1**
Start point: A digital innovation-aware enterprise is committed to use AI for its business security advantage. To achieve this goal, it will design and implement a DRMSS based on an AI technology assessment process.

Step 1. Determine the goals, use cases, key features, and DRMSS success factors in the context of a class of specific applications (DRMSS pre-design).
Step 2 Perform a technological needs analysis addressing the relevant risks and threats and relate them to the system pre-design categories.
Step 3. Scan the market of AI technologies, links to prototype solutions, and ongoing applied AI research. Retrieve those fitting the identified needs of the DRMSS related to the relevant problem to be solved (Problem 1 or 2 or both).

Step 4. Rank the technologies in each needs category according to the price, compatibility with other key technologies, forecasted outcomes of the updated system, and other DRMSS or user performance criteria suitable for the real-life situations concerned.
Step 5. Select the best technology portfolio and build the implementation plan.
Step 6. Assess ex-ante the resulting system architecture and performance with impact prediction and multicriteria analysis methods, taking into account the additional preference information coming from the simulation of the system performance and expert judgments.
Step 7. Implement the final technology selection in the DRMSS architecture.
Step 8. Repeat Steps 1–7 during the system lifetime or until the stop condition holds.

The overall procedure can be assessed with aggregated performance criteria evaluated in Step 6. The procedure ends when a disruptive change in system goals or architecture occurs so that the subsequent changes cannot be regarded incremental.

In contrast to typical strategic IT alignment [11], Problems 1 and 2 touch upon the alignment of information systems to be built with state-of-the-art AI methods, and of their users to learn these methods. Moreover, the rapid progress in AI hinders a traditional system design approach, where the methods and tools are selected just once, at the inception stage of system planning, and then are incrementally updated during the system lifetime. Instead, AI-driven systems of strategic relevance, such as DRMSS, require a continual re-design process.

## 4 AI Evolution Modelling Tool

The solution to above AI alignment problems can be supported with a dedicated technological foresight tool, termed the AI evolution model (AIEM). A general scheme of AIEM deployment, conforming to the Procedure 1, may be presented as follows:

- The AI evolution model will be established to provide clues regarding the development of selected AI technologies, relevant to DRMSSs for the next 10–15 years. The technology development modelling may use methods of various degrees of sophistication, from judgmental forecasts [18] to sophisticated system dynamics.
- The AIEM is a scalable tool that may align just one class of DRMSSs or even a single system as well as a broad class of enterprise IS. It can scan progress in a specific AI technology, e.g. photogrammetric drones, or an AI technology portfolio.
- AIEM can be self-contained and provided as software as a service (SaaS) by a specialist company or it may be coupled with other DRMSS modules. The latter case is more likely when it scans a single technology or a bulk of related technologies. On the other hand, a built-in AIEM can evolve itself towards a self-contained foresight support system, capable of modelling the development of a variety of AI and related technologies while serving multiple DRMSSs. Its owner can create a specialist spin-out company and the first of the above business models will apply.
- Needs assessments are to be performed prior to system implementation and updated every year. The assessments deliver the requirements for AI technologies and IT to be

implemented in the DRMSS. In case of large industrial plant resilience, the relevant AI techniques may include information fusion, autonomous inspection robotics, or sensor networks within industrial internet of things.

- Needs confronted with technology forecasts make it possible to select most viable and robust software architectures, AI techniques, and an implementation time plan.
- Finally, the subsequent versions of DRMSS, aligned to state-of-the-art AI methods, will be implemented and validated during the system's lifetime.

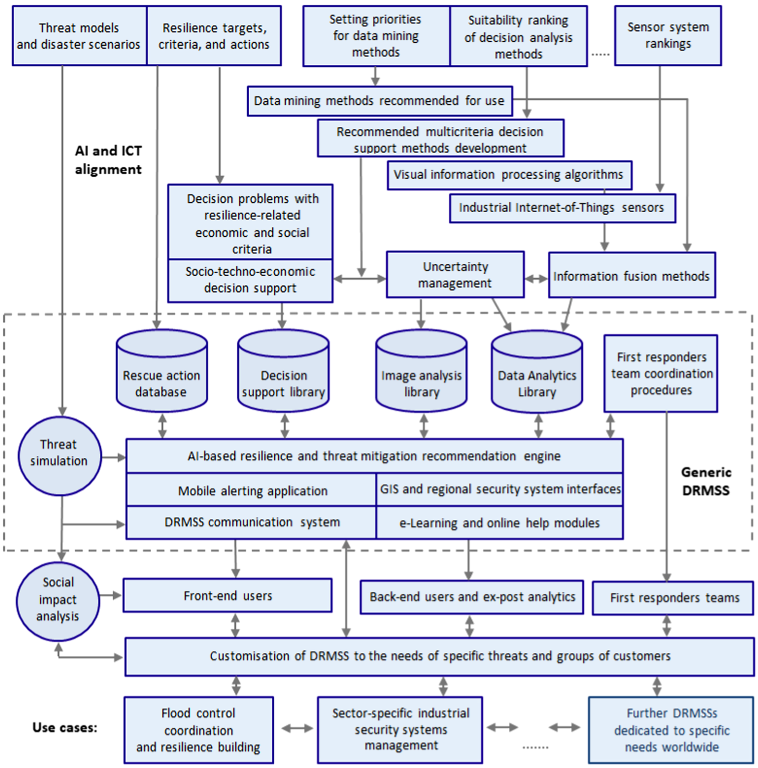


**Fig. 1.** A generic software architecture and uses scheme of the DRMSS coupled with an AIEM.

A scheme of the above-presented architecture in case of a single DRMSS coupled with an AIEM ensuring the AI alignment is shown in Fig. 1 above.

The AIEM building consists of four interdependent phases, interlaced with the implementation of selected methods in the core DRMSS. These phases will be repeated iteratively, based on learning from implementation outcomes.

Phase I. Multi-level AIEM design, featuring expert information gathering and update exercises such as Delphi surveys interlaced with quantitative trend and qualitative scenario generation.

Phase II. AI-related technological needs and impact model building. The natural disaster and anthropogenic threat characteristics will be optimally matched with the AI methods and tools to be deployed in the DRMSS. The impact modelling will be simulation-based and will stick to anticipatory network principles [19]. The impact assessment will cover at least three technology review periods.

Phase III. Implementation. The AIEM will gather sufficient information to implement the AI methods selected in Phase II into the core DRMSS.

Phase IV. Testing and learning. The DRMSS's capabilities in solving real-life threat resilience problems, specifically those related to unauthorized intrusions and thefts, equipment damages related to fuel or gas leaks, landslides, and weather-dependent disasters such as floods, strong winds etc. will be tested and validated. The learning process will update the AIEM's technology selection procedures as well as the their implemention in the DRMSS.

The implementation order of specific DRMSS modules in Phase III should follow the ranking of the enterprise's security needs. For example, the system to be implemented may be focused on preventing and mitigating floods, the accompanying disastrous events, such as flood-related landslides and soil contamination, and on ensuring the resilience of endangered critical infrastructure. The most suitable AI methods and tools should be selected in compliance with the above scope. Specifically, these can include intelligent decision support technologies, team coordination and group decision making dedicated to managing threat prevention and mitigation operations, as well as the autonomous SRR. The forward-looking knowledge of evolution and development scenarios of AI methods can be a base of long-term flood resilience building.

### 4.1 The AIEM Implementation

The AI technology scanning and modelling tool can combine several modules, acting at different time scales, and yielding multi-purpose output information. These include:

- User needs analysis module, a part of the AIEM Graphical User Interface (GUI).
- Intelligent bots for web, bibliographic and patent databases scanning.
- Real-time data streams retrieval and analysis module, suitable for processing both, quantitative and qualitative information about AI techniques available in different social media. It performs sensitivity analysis and cascade effects for the detection of hidden technological 'black swans' in AI research data [5].
- A multi-level intelligent technological evolution model comprising quantitative expert Delphi and a group model building module [18].
- Technological evolution simulation based on various game models: cooperative, Stackelberg, and conflicting games [12].
- A set of technology ranking and recommendation algorithms, embedded in GUI.

At least one prospective technological analysis tool must be contained in the basic configuration of AIEM. The scope of database and web searches as well as the overall information processing in AIEM depends on the needs analysis outcomes. This is a supervised activity performed periodically according to the scheme: (Threat) Detection → Mitigation → Resilience Building, which is to be repeated for each class of threats. Table 1 shows a sample process referring to a real-life case of a quarry.

**Table 1.** Sample technological (AI and IT) needs analysis

| Threat name | Detection | Mitigation | Resilience |
|---|---|---|---|
| Unauthorized intrusions | Visual monitoring, scene understanding | Supervised recommendations issued to security teams | Sound & light warning systems, optimal arrangement of fences |
| Rockfalls | Ground- and drone-based sensors, radars, pattern recognition | Warnings generated automatically and communicated to the staff, connecting the devices via the IIoT | Photogrammetry, rock dynamics analysis updated regularly, protection nets and fences |
| Rockslides and landslides | Photogrammetry with drones, remote sensing, risk maps, ground-based inspection robots | Adaptively calculating refuge areas and evacuation paths | Risk maps and rock mass dynamics analysis, earthquake warning systems |
| Incidental technical gas or liquid leaks | Inspection robots, gas and vapor sensors | Human-robot team actions defined based on threat assessment | Optimal coverage of the protected area by inspection robots |

Out of the threats presented in Table 1, only intrusions may be related to the use of adversarial AI, such as detection of monitoring and other sensors or disturbing them. The corresponding mitigating AI tools serve as detectors and neutralizing devices which will be selected as solutions of Problem 1 and installed as DRMSS actuators. Problem 2 - related technology scanning will yield new photogrammetric techniques, image analysis, robust drones, and inspection robots. The DRMSS decision engine will be updated to include control of new devices and pattern recognition algorithms.

## 4.2 The Implementation of the DRMSS Operational Modules

The above-outlined DRMSS will process and fuse heterogeneous data coming from sensors, information provided in real-time by first responder teams human and robot, and from the enterprise management. The corresponding methods and algorithms will be recommended by the above AI technology scanning and modelling tool taking into account relevant uncertainty modelling techniques. The main processes performed by the DRMSS analytic engine are given below.

- Information fusion algorithms will process the sensor and response team data. This functionality will be used persistently to monitor threat mitigation activities. The data gathered will be verified when an information misrepresentation is likely.

- Intelligent DSS architecture will implement multicriteria decision making methods capable of processing validated preference information in a transparent way. These include, for example, the reference sets method [17] and direct decision consequences modelling. The DSS functionalities of the DRMSS will assist in selecting a compromise between an optimal system performance and the promptness of the response to a threat.
- The software architecture of DRMSS will include as one of its principal components a mobile, Android-, or IOS-based application to be installed on user smartphones or built in robots as an Internet of Vehicles (IoV) component. An analytic application will be installed in the crisis management headquarters.
- Depending on particular needs, the above architecture will be supplemented with robotic system supporting software as the fourth component including a SLAM module, mobile disaster knowledge base, monitoring and rescue robot coordination software, sensor and communication equipment.
- The DRMSS may include cognitive emotion recognition, such as stress measurement of the human rescue team, and its analysis, based on (i) basic physiological stress indicators measured by sensors, (ii) subjective stress assessment input to the system by the users. Stress may strongly influence the efficiency of rescue teams.

The design of the AI-based DRMSS architecture will benefit from the outcomes of the AIEM linking the threat management needs, DSS functionalities, and best-performing AI methods. The DSS is typically built with a modular architecture, while the individual modules will be interoperable and allow for easy replacements of an implemented method with an improved option recommended by the AIEM. A built-in library of algorithms assures that a replaced analytic method will be stored for an eventual later re-use. The human-DRMSS communication will be supported by GUI for back-end managers and a mobile application with front-user interface.

## 5 Summary and Conclusions

Full achievement of the research aims formulated in Sect. 1 of this paper, will be facilitated with an improved understanding of the interdependence of resilience needs of a complex socio-technological system, the DRMSS design and implementation constraints, and an insight into the advantages and risks related to using of AI tools.

As shown in Sect. 2, the literature on resilience support methods is fragmented and, as for now, there is no implementation of a DRMSS that would encompass a sufficiently broad spectrum of AI methods required to serving as a target reference solution for systems ensuring complex industrial plant resilience. Thus, the system architecture described in Sect. 4 and fed by the data streams from sensors should be regarded as an advent of a "*living information system*". By definition, such systems evolve being continually aligned to recent AI and IT trends and the best business practices derived therefrom. This is why an important role will be played by system operators who will report relevant findings arising from system uses. These findings will be stored and presented as 'periodic reports' and taken into account in system updates.

AI development scanning brings a broad spectrum of methods and implementation of intelligent systems that can prevent or mitigate different threats. In case of disasters, robotic systems can rescue human lives, while multi-agent models can help to understand collective human-robot cooperation. Machine learning methods with quick fusion of big data streamed from endangered areas, processed in rule- and case-based reasoning together with decision analytics, will yield optimal decisions. Progress in AI will be scanned, verified, ranked, and finally, the best subset of AI methods will be selected and recommended for implementation in DRMSSs. Communication technologies and data science will create the background for a system's robust performance. In contradistinction to emergency management systems that use inflexible data structures and have little capacity to anticipate events that have never occurred, this disadvantage can be removed in our system design by employing intelligent anticipatory network planning [19] with artificial creativity features. Another advantage of DRMSS, compared to existing technology for emergency management, is the continual modelling of disaster characteristics and use of current updates immediately after a threat is detected. The software architecture presented in Sect. 3 builds an ecosystem of valid AI solutions to support business processes within the overall emergency management cycle: preparation, prevention, detection, response, and recovery.

The threat-related needs analysis merged with AI technology recommendations delivered by the AI evolution model, disaster data analysis and decision support engine yield a robust DRMSS with a radically novel and flexible "living system" architecture. We expect that the proposed business process management approaches oriented towards AI alignment for industrial threat resilience building and continual improvement of DRMSS architecture and design methodology can be applied to a large class of EIS that will benefit from the deployment of AI tools and techniques. This methodology is first validated and tested on two real-life cases in Poland and Spain to extend the capacity for further applications.

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