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A Study of Factors Influencing the Adoption of Artificial Intelligence in Crisis Management

Ahmed Saeed Ali Rashed Aladawi[1], Ahmad Nur Aizat Ahmad[1*]

[1]Faculty of Technology Management and Business,
Universiti Tun Hussein Onn Malaysia, MALAYSIA

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Abstract: This paper presents a study on the Factors Influencing the Adoption of Artificial Intelligence (AI) in Crisis Management. The research identifies 28 AI usage factors categorized into seven groups: Large-Scale Machine Learning, Deep Learning, Reinforcement Learning, Robotics, Computer Vision, Natural Language Processing, and Internet of Things. The study conducted a questionnaire survey among 281 employees at the UAE National Crisis and Emergency Management Authority, using purposive sampling to assess their opinions regarding the impact of these usage factors on the adoption of AI in crisis management. The collected data underwent descriptive analysis to determine the ranking of AI usage factors within each of the seven groups. In terms of group rankings, Robotic emerged as the top-ranking factor, followed by Reinforcement Learning. Large-Scale Machine Learning occupied the next position, succeeded by Natural Language Processing, Deep Learning, Internet of Things, and Computer Vision, which held the lowest rank. Furthermore, when examining the correlation between these usage factor groups, it was discovered that most of them exhibited strong positive correlations, with correlation coefficients ranging from 0.634 to 0.934. This indicates that changes in one variable are associated with predictable changes in another variable. While this information can be instrumental in understanding relationships and making predictions, it does not establish a causal relationship.

Keywords: Artificial Intelligence, crisis management

1. Introduction

Crises can strike at any time and in any place. Nature and humans are the two fundamental forces that cause crises. Natural disasters are crises caused by nature when it shows its might, and it also generates crises when its relationship with humans deteriorates. And, to preserve its presence and rule nature, humans cause crises through social, economic, political, and technological activities. Whatever the causes of crises, they put people under a lot of stress and cause emotional reactions (Reynolds et al., 2012). Organizations, like individuals, are prone to crises. Organizational stability, function, and goals are all disrupted by crises (Maphanga et al., 2019). Crises can put a lot of strain on an organization's financial, physical, and emotional structures, and they can even put the organization's survival in jeopardy.

Even though crisis is unpleasant and dangerous, it also presents possibilities especially public organisations. Crisis teaches a lot about how to prepare for future crises (Parker et al., 2020). It provides opportunities to examine the performance of government institutions under duress (Parker et al., 2020). Crisis could undermine the status quo and delegitimize the policies and institutions that support it because of their size, uncertainty, and sensitivity (Ansell et al., 2019). More crucially, from a political standpoint, political learning and change processes that occur at a slower rate under normal circumstances may be dramatically accelerated during crisis conditions, since societal and political forces frequently overcome usual inertia and opposition to change (Boin et al., 2005).

In the context of UAE organisations, the causes of crisis is human error which emanate as a result of recklessness of an employee in an organization, human error caused many crisis in UAE organization, this human error also emanate as

*Corresponding author: aizat@uthm.edu.my

a result of poor training or inadequate training among employees especially with the invention of new technology that lead most of the organizations in UAE (Al-Gamrh et al., 2018). Similarly, poor maintenance in UAE organizations result in many crises in the country, maintenance plays a very vital role in making the equipment of an organization safe and perfectly work, but poor maintenance resulted in damages and posed threat to the life of many employees in UAE organizations (Mirzaei, 2019). Material failure is among the main problems and causes of crisis in UAE organizations, it is a failure or breakdown of an object (such as metal, concrete, or plastic) due to various factors that affect the strength, stability and chemical composition of the object's structure, many construction organizations faced these problems and tremendously lead to a huge crisis in UAE organizations. This issue immensely affects the public organizations in UAE (Al-Karaki et al., 2021).

Based on the described studies, crisis management is one of the areas that is anticipated to be greatly improved with the introduction of Artificial Intelligence (AI). AI able to discover correlations in data that are not so visible even to the finest human eye. For example, AI can help project managers uncover value and solutions for things like risk estimation which is important element in crisis management. In risk management which covers risk identification, analysis, planning, monitoring, regulating, and communication, it is possible for AI to extract parametric data, for instance, previous start and end dates can be utilised to predict exact timelines for upcoming projects. Numerous AI (AI) technologies, including neural networks, fuzzy logic, and machine learning, have been developed to learn data gathered to detect interdependencies of causes and effects, compute the likelihood of failure occurring, and evaluate the magnitude of risk from both the non-numerical and quantitative perspectives. When faced with uncertainty, AI may be utilised by various teams and work environments to track, identify, analyse, and forecast potential risks in terms of protection, quality, efficiency, and cost. This capability has been primarily employed for risk detection, evaluation, and prioritising. Furthermore, AI-based risk analysis can provide analytical and adaptive insights on risky issues, enabling project managers to manage impending risks and choose proactive measures rather than risk mitigation, such as automating operational processes on the job, adjusting staff organisation, and monitoring projects' on-time and budget completion (Afzal et al., 2019).

Hence, AI presents exceptional opportunities in crisis management. As the world becomes increasingly interconnected and complex, the ability to anticipate, prepare for, and respond to crises swiftly and effectively is paramount. AI, with its powerful data analysis and predictive capabilities, has the potential to revolutionize how organizations approach crisis management. AI can sift through vast amounts of data, identifying early warning signs and patterns that may signify an impending crisis. It can provide real-time monitoring of events, helping organizations respond proactively rather than reactively. Additionally, AI-driven risk assessment and predictive modelling can assist in the development of comprehensive crisis management strategies. The speed and accuracy of AI in processing information are particularly advantageous during high-stress, time-critical situations. AI-driven chatbots and virtual assistants can provide immediate responses, guidance, and support to stakeholders, ensuring clear and consistent communication during a crisis (Wut et al., 2021).

Furthermore, AI enhances the resilience of organizations by enabling efficient resource allocation, enhancing decision-making processes, and optimizing response efforts. It can also facilitate post-crisis analysis and learning, allowing organizations to continually refine their crisis management strategies. While AI offers great promise, it is important to acknowledge that human expertise and judgment will remain essential in crisis management. AI should complement and assist human decision-makers rather than replace them. The effective integration of AI into crisis management will require a strategic approach, continuous learning, and collaboration between human and machine. In this ever-evolving landscape of challenges and uncertainties, organizations that harness the capabilities of AI in crisis management stand to gain a significant advantage in safeguarding their reputation, resilience, and long-term success (Frank, Dalenogare, & Ayala, 2019).

2. Crisis Management

A crisis is an infrequent but severe event that imperils the survival of an organization. It is characterized by uncertainty regarding its origins, consequences, and the necessary actions, often demanding prompt decision-making. Defining a crisis is challenging due to the subjectivity of human perspectives (Paraskevas et al., 2019). Nevertheless, these definitions share commonalities. Firstly, a crisis is a high-impact incident that can significantly affect individuals and an organization's ability to endure. Secondly, crises often manifest suddenly, with minimal forewarning, potentially jeopardizing an organization's relationships with its stakeholders (Saroj et al., 2020). Dai et al. (2020) further elaborate that a crisis is a substantial event with the potential for negative repercussions, impacting not only the organization but also its stakeholders, products, and services.

Conventional view of crisis management has traditionally focused on extinguishing the immediate crisis, with crisis managers closely monitoring the situation as it deteriorates and after the damage has occurred. However, recent shifts in thinking have brought about a change in perspective. To effectively address potential future developments in businesses, it is essential to always have a well-defined set of strategies and action plans in place. Crisis management now emphasizes the importance of anticipation and preparedness for addressing issues that could threaten a company's reputation, profitability, or even its very existence. Additionally, managers should be vigilant about potential future events and remain ready to handle unforeseen circumstances as they arise. It is crucial to differentiate between crisis management and public relations management (Wut et al., 2021).

As Larry Smith, director of the Institute for Crisis Management, points out, a significant disruption within an organization that garners significant media attention and piques public interest can have far-reaching effects on daily operations, potentially disrupting political, legal, financial, and governmental aspects. Furthermore, there are often warning signs that indicate potential problems, allowing for proactive measures to mitigate crises rather than being caught off guard. This concept bears an intriguing resemblance to the biological model of crises, as described by Bundy et al. (2017), where a crisis may follow a sequence like a person's life stages, including birth, growth, maturity, decline, or even termination.

3. Application of AI in Crisis Management

AI is now an integral part of our daily lives and gains more prominence in society, the focus has shifted from merely creating intelligent systems to creating intelligent systems that are reliable and mindful of human interaction. Numerous factors have driven the AI revolution, with the most significant being the advancement of machine learning. This progress has been greatly aided by the availability of cloud computing resources and the widespread collection of data via the internet. Machine learning has made significant strides, particularly due to deep learning, a form of adaptive artificial neural networks trained through a process called back propagation. Together with these improvements in information processing algorithms, there have been major advancements in hardware technology, especially in areas like sensing, vision, and object recognition (Wenger, 2014).

The growth of AI has been made possible by the rise of new platforms and markets that heavily rely on data-driven products. Moreover, there are financial incentives to encourage the development of innovative products and the exploration of fresh markets. Currently, significant areas of AI research that garner attention include Large-Scale Machine Learning Factors, Deep Learning Factors, Reinforce Learning Factors, Robotic Factors, Computer Vision Factors, Natural Language Processing Factors, and Internet of Things Factors. It is important to emphasize that the current popularity of these areas does not necessarily equate to their greater worth or significance compared to other domains. Some of the fields currently in the spotlight may have been less prominent in the past, while others may see a resurgence in the future (Gasser et al., 2014; Afzal et al., 2019; Wut et al., 2021).

3.1 Large-Scale Machine Learning

Large-scale machine learning is a vital part of artificial intelligence (AI) that deals with processing and learning from massive datasets. In a world where enormous amounts of data are generated, this field specializes in managing and making sense of this information efficiently. It uses powerful algorithms that can work in parallel across many machines, making it possible to handle vast amounts of data quickly. Large-scale machine learning finds applications in various areas, such as natural language processing, computer vision, fraud detection, and self-driving cars. However, it comes with challenges related to data storage, computational resources, and ensuring privacy and security. The potential of large-scale machine learning is immense, as it helps AI systems uncover valuable insights from extensive datasets, leading to more accurate predictions and recommendations in various industries. (Gasser et al., 2014).

3.2 Deep Learning

Deep learning is a vital part of AI that has transformed the field by allowing machines to learn complex patterns from large datasets automatically. It relies on neural networks inspired by the human brain and excels at handling unstructured data like images, audio, and text. One of its key strengths is its ability to represent data effectively, eliminating the need for manual feature engineering. Deep learning has various architectures like Convolutional Neural Networks (CNNs) for images and Recurrent Neural Networks (RNNs) for sequential data. It thrives on extensive datasets and has powered applications like image recognition, speech understanding, and self-driving cars. Despite its progress, challenges like model interpretability and computing power persist. Ongoing research in deep learning continues to push the boundaries of AI capabilities, making it a fundamental driver of AI advancement.

3.3 Reinforcement Learning

Reinforcement learning is a pivotal approach that holds the potential to drive AI further into the realm of understanding and executing actions in the real world. In stark contrast to classical machine learning, which has predominantly focused on uncovering patterns, reinforcement learning places its emphasis on the art of decision-making. This technique has served as a model for experience-driven sequential decision-making for many years. However, the practical application of reinforcement learning has often been hindered by challenges related to representation and scalability. Nonetheless, reinforcement learning has witnessed significant advancements, largely owing to the integration of deep learning techniques. A noteworthy example of the transformative power of reinforcement learning is AlphaGo, a computer program developed by Google DeepMind. AlphaGo gained international acclaim by defeating a human Go champion in a five-game match. Initially, AlphaGo was trained using a database of insights from human experts.

However, its performance was greatly enhanced by competing against itself in a substantial number of games, all while utilizing reinforcement learning techniques to refine its decision-making processes (Michalski et al., 2013).

3.4 Robotics

In robotics, significant progress has already been made in the navigation of robots, particularly in static environments. The primary focus of current research in this field centres around how to effectively train a robot to interact with the external world in a consistent and universally applicable manner. Another noteworthy area of ongoing research pertains to manipulation, a fundamental aspect that finds its roots in social contexts. The integration of deep learning, which has already revolutionized various AI fields, is now gradually beginning to impact robotics. This delay in adoption can be attributed to the relative scarcity of massive labelled datasets for robotic applications compared to other AI domains. To address this gap, reinforcement learning emerges as a promising avenue, as it does not rely on labelled data. However, it necessitates the development of systems capable of exploring a policy space safely, without committing errors that could pose risks to the system or others. The trajectory of robotics is poised for significant advancement, largely due to the continual improvement in reliable machine perception technologies. These technologies encompass various facets, including computer vision, force sensing, and tactile sensing, and are increasingly driven by machine learning techniques, heralding a promising future for the field of robotics (Varakantham et al., 2017).

3.5 Computer Vision

In contemporary AI, computer vision stands as the most prevalent form of machine perception. The advent of deep learning has brought about a transformative impact on this facet of AI. Until just a few years ago, support vector machines were the preferred method for most visual classification tasks. However, several converging factors, including the availability of substantial computational power, especially in the form of GPUs, the accessibility of vast datasets via the internet, and the continuous evolution of neural network algorithms, have collectively driven substantial improvements in performance on standard tasks, such as ImageNet classification. A noteworthy milestone is that, for the first time, computers have outperformed humans in various broadly defined visual classification tasks, a testament to the significant strides made in this field. Currently, substantial research efforts are dedicated to the domain of automatic image and video captioning, reflecting the ongoing exploration and advancement in this area (Varakantham et al., 2017).

3.6 Natural Language Processing

Natural Language Processing (NLP), often integrated with automatic speech recognition, stands as a highly dynamic and progressive domain within the field of machine perception. Notably, for major languages endowed with extensive data sets, NLP is swiftly transitioning from a specialized field to a mainstream technology. This transformative technology not only comprehends human language but also enables meaningful interactions with individuals through spoken communication, rather than merely responding to predefined commands. The fusion of NLP with automatic speech recognition is catalysing an era where machines can engage in natural, context-aware conversations, marking a significant milestone in human-computer interaction and further underscoring the pivotal role of NLP in reshaping the way we communicate and interact with technology (Kodratoff et al., 2014).

3.7 Internet of Things (IoT)

IoT represents a expanding field of study cantered on the idea that a diverse array of devices can be interconnected to collect and exchange sensory data. These devices encompass a wide range, including appliances, vehicles, buildings, cameras, and various objects. While wireless networking and technology are essential for connecting these devices, it's artificial intelligence (AI) that can make sense of the extensive data generated and utilize it for intelligent and practical purposes. Currently, these devices communicate using a complex mix of incompatible protocols. Artificial intelligence has the potential to streamline and harmonize this intricate network of communication protocols, essentially acting as a unifying force (Kodratoff et al., 2014).

4. Factors Influencing Adoption of AI Crisis Management

Adoption of AI in crisis management is influenced by several key factors. Firstly, the recognition of AI's potential to enhance decision-making, improve response times, and provide critical insights during crises is a significant driver. Secondly, the availability of advanced AI technologies, including machine learning and natural language processing, plays a pivotal role in adoption. Additionally, organizational readiness, including the willingness to invest in AI infrastructure and data analytics capabilities, is a key factor. Moreover, the regulatory environment, data privacy concerns, and ethical considerations impact the adoption process. Finally, successful pilot projects and the ability to demonstrate tangible benefits and return on investment serve as catalysts for broader adoption in crisis management. Based on this information, the adoption factors are as in table 1.

Table 1 - List of factors influencing adoption of AI crisis management

Code	Large-Scale Machine Learning Factors
LSM1	To what extent do you agree that large-scale machine learning can improve the utilization of data for better crisis assessment and decision-making?
LSM2	How strongly do you agree that real-time data analysis using large-scale machine learning algorithms is crucial for timely crisis response?
LSM3	To what extent do you agree that large-scale machine learning can provide accurate predictions of crisis developments and outcomes?
LSM4	How strongly do you agree that large-scale machine learning can optimize the allocation of resources during crisis management?
Code	**Deep Learning Factors**
DeL1	To what extent do you agree that deep learning can improve the utilization of data for better crisis assessment and decision-making?
DeL2	How strongly do you agree that real-time data analysis using deep learning algorithms is crucial for timely crisis response?
DeL3	To what extent do you agree that deep learning can provide accurate predictions of crisis developments and outcomes?
DeL4	How strongly do you agree that deep learning can optimize the allocation of resources during crisis management?
Code	**Reinforce Learning Factors**
ReF1	To what extent do you agree that reinforcement learning can improve real-time decision-making and policy implementation during crises?
ReF2	How strongly do you agree that reinforcement learning algorithms can adapt and learn from dynamic crisis situations for better response strategies?
ReF3	To what extent do you agree that reinforcement learning can optimize the allocation of resources during crisis management?
ReF4	How strongly do you agree that reinforcement learning can provide accurate predictions of crisis developments and outcomes?
Code	**Robotic Factors**
RoB1	To what extent do you agree that robotics can automate certain tasks and processes, thereby improving the efficiency of crisis response?
RoB2	How strongly do you agree that robotic systems can operate in hazardous environments, reducing the risk to human responders?
RoB3	To what extent do you agree that robotics can optimize the allocation of resources during crisis management?
Code	**Computer Vision Factors**
CoV1	To what extent do you agree that computer vision can improve the utilization of visual data for better crisis assessment and decision-making?
CoV2	How strongly do you agree that real-time analysis of visual data using computer vision algorithms is crucial for timely crisis response?
CoV3	To what extent do you agree that computer vision can optimize the allocation of resources during crisis management?
CoV4	How strongly do you agree that computer vision can provide accurate predictions of crisis developments and outcomes based on visual data analysis?
Code	**Natural Language Processing Factors**
NLP1	To what extent do you agree that NLP can improve the utilization of text data for better crisis assessment and decision-making?
NLP2	How strongly do you agree that real-time analysis of text data using NLP algorithms is crucial for timely crisis response?
NLP3	To what extent do you agree that NLP can extract critical information and generate summaries from large volumes of text data during crises?
NLP4	How strongly do you agree that NLP's ability to process multiple languages is advantageous for global crisis management efforts?
CODE	**Internet of Things Factors**
IoT1	To what extent do you agree that IoT can enable real-time data collection and monitoring during crises, improving situational awareness?
IoT2	How strongly do you agree that IoT sensors and devices can provide valuable insights into environmental conditions and hazards?
IoT3	To what extent do you agree that IoT data analytics can provide early warning systems and predictive capabilities for crisis events?

IoT4	To what extent do you agree that IoT can facilitate the coordination of crisis response efforts through automated processes and communication?
IoT5	How strongly do you agree that IoT-connected devices can be used to remotely control critical infrastructure during crises?

The factors in table 1 were used as the main content in designing a questionnaire that was used to gauge the respondents' opinions in influencing the adoption of AI in crisis management.

5. Results and Analysis

This study investigates the AI factors affecting crisis management in United Arab Emirates (UAE) organisation. The study adopted a quantitative approach of data collection using structured questionnaire and the collected data was analysed statistically. The questionnaire was designed based on factors influencing the adoption of AI in crisis management. Respondents were required to gauge each of the factors using 5-points Likert scale on the agreeability of the factor in influencing the adoption of AI in crisis management. The population of this research is the total number of employees in the UAE National Crisis and Emergency Management Authority. A total of 300 questionnaires sets were distributed using a purposive sampling technique. However, the study managed to secure 281 valid responses for the analysis.

5.1 Normality Test

Skewness and kurtosis analysis serves the purpose of understanding data distribution characteristics. Skewness measures asymmetry in the data, while kurtosis indicates the tailedness and peakedness of the distribution. Thus, skewness and kurtosis provide essential insights into the shape and nature of data, facilitating informed decision-making and analysis. In assessing a dataset normality, skewness value of 0 and kurtosis value of 3 are typical for a normal distribution. Deviations from these values can suggest non-normality (George, D. and Mallery, P., 2018).

Table 2 - Result of skewness and Kurtosis

Factors'	N	Skewness		Kurtosis	
Code	Statistic	Statistic	Std. Error	Statistic	Std. Error
LSM1	281	-3.306	.145	10.574	.290
LSM2	281	-2.614	.145	5.865	.290
LSM3	281	-2.277	.145	4.327	.290
LSM4	281	-2.701	.145	6.964	.290
DeL1	281	-2.701	.145	6.964	.290
DeL2	281	-2.472	.145	5.566	.290
DeL3	281	-3.089	.145	9.499	.290
DeL4	281	-2.751	.145	7.245	.290
ReF1	281	-2.647	.145	6.646	.290
ReF2	281	-2.497	.145	5.781	.290
ReF3	281	-2.717	.145	6.881	.290
ReF4	281	-2.770	.145	7.221	.290
RoB1	281	-2.878	.145	8.067	.290
RoB2	281	-2.472	.145	5.566	.290
RoB3	281	-2.324	.145	4.580	.290
CoV1	281	-2.530	.145	5.744	.290
CoV2	281	-2.906	.145	8.116	.290
CoV3	281	-2.587	.145	6.080	.290
CoV4	281	-2.324	.145	4.580	.290
NLP1	281	-2.424	.145	5.129	.290
NLP2	281	-2.837	.145	7.654	.290
NLP3	281	-2.691	.145	6.869	.290
NLP4	281	-3.219	.145	10.339	.290
IoT1	281	-3.219	.145	10.339	.290
IoT2	281	-2.530	.145	5.744	.290
IoT3	281	-2.770	.145	7.221	.290
IoT4	281	-2.707	.145	6.816	.290
IoT5	281	-3.423	.145	11.973	.290

Table 2 shows that the skewness values for all the factors are negative, indicating a left-skewed distribution for each of them. This suggests that the data for these factors are skewed towards the lower end of the scale, with a longer tail on the left side. While the kurtosis values for most factors are well above 3, which is the kurtosis value for a normal distribution. This indicates that the distributions of these factors are leptokurtic, meaning they have heavier tails and are more peaked compared to a normal distribution (Marshall, G. and Jonker, L., 2010). This indicates that many of the factors exhibit similar skewness and kurtosis values, suggesting a degree of consistency in their data distributions.

5.2 Ranking of Factors in Implementation of AI in Crisis Management

Ranking the AI factors offers valuable insights into how these factors are perceived within their respective domains by the survey respondents. The data collected through the questionnaire survey reflects the opinions of participants regarding the level of agreement with each AI factor's impact on their organization's crisis management. Respondents used a 5-point Likert scale to rate these factors. Descriptive analysis of this data was conducted using SPSS software to calculate the mean and standard deviation scores for each factor. Consequently, the ranking is determined by comparing the mean scores of each factor with others in its domain. In cases where mean scores are tied, factors with lower standard deviation values receive a higher rank (Marshall, G. and Jonker, L., 2010). The resulting rankings for AI factors across seven domains are presented in Table 3.

Table 3 - Rank of the AI factors affecting crisis management

Group	Factors	N	Mean	Std. Deviation	Rank
Large-Scale Machine Learning	LSM1	281	4.91	.297	1
	LSM2	281	4.67	.337	2
	LSM3	281	4.31	.383	4
	LSM4	281	4.42	.407	3
Deep Learning	DeL1	281	4.18	.407	4
	DeL2	281	4.22	.389	3
	DeL3	281	4.88	.371	1
	DeL4	281	4.68	.373	2
Reinforce Learning	ReF1	281	4.44	.410	4
	ReF2	281	4.63	.419	2
	ReF3	281	4.53	.444	3
	ReF4	281	4.88	.352	1
Robotic	RoB1	281	4.87	.365	1
	RoB2	281	4.55	.389	3
	RoB3	281	4.75	.380	2
Computer Vision	CoV1	281	4.16	.366	3
	CoV2	281	4.88	.344	1
	CoV3	281	4.56	.363	2
	CoV4	281	4.05	.380	4
Natural Language Processing	NLP1	281	4.25	.373	4
	NLP2	281	4.48	.348	2
	NLP3	281	4.36	.376	3
	NLP4	281	4.90	.327	1
Internet of Things	IoT1	281	4.90	.327	1
	IoT2	281	4.06	.366	5
	IoT3	281	4.28	.352	3
	IoT4	281	4.17	.356	4
	IoT5	281	4.78	.338	2

Table 3 provides a summary of mean scores, standard deviations and rank for various AI factors within different groups or domains. For Large-Scale Machine Learning, the factors within this group have mean scores ranging from 4.31 to 4.91. LSM1 has the highest rank. Deep Learning, the factors in the Deep Learning category have mean scores ranging from 4.18 to 4.88. DeL3 has the highest rank. Reinforcement Learning, the factors in the Reinforcement Learning group have mean scores ranging from 4.44 to 4.88. ReF4 has the highest rank. The Robotic group consists of three factors with mean scores ranging from 4.55 to 4.87. RoB1 has the highest rank within this group. The Computer Vision group includes four factors with mean scores ranging from 4.05 to 4.88. CoV2 has the highest rank within this group. Natural Language Processing factors have mean scores ranging from 4.25 to 4.90. NLP4 has the highest rank within this group. Finally, for

Internet of Things (IoT): IoT factors have mean scores ranging from 4.06 to 4.90. IoT1 has the highest rank within this group.

5.3 Ranking of Factors' Groups

In order to establish the ranking of AI factors within each group, the mean values of all the factors in a given group are averaged to obtain the group's mean score. Subsequently, these mean scores for each group are compared with one another to determine the rankings, as depicted in Figure 1.

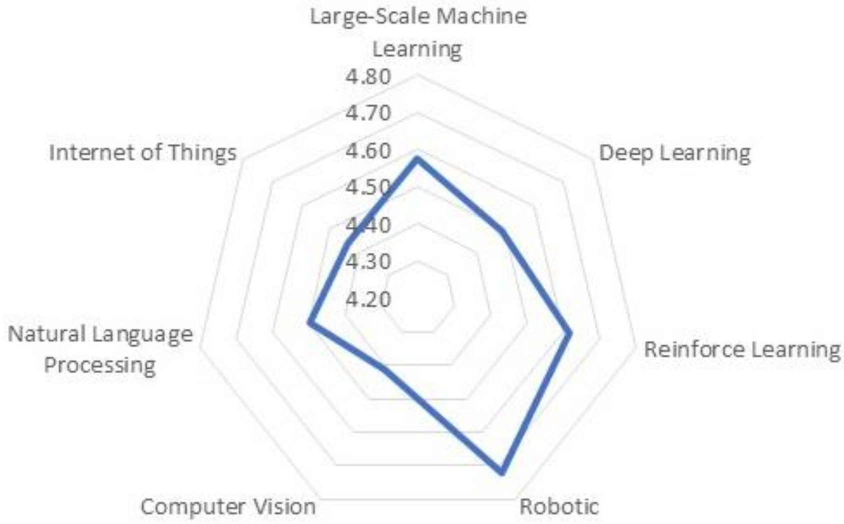

Fig. 1 - Ranks of AI factors groups

In Figure 1, the average scores for the seven groups range from 4.41 to 4.72. The findings indicate that Robotic achieved the highest ranking, followed by Reinforcement Learning. Large-Scale Machine Learning came next, followed by Natural Language Processing, Deep Learning, Internet of Things, and Computer Vision, which was ranked the lowest.

5.4 Correlation of Factors' Groups

Pearson correlation analysis is used to understand and quantify linear relationships between seven groups of AI factors. It reveals how one variable's changes relate to another's. This analysis also uncovers patterns, confirms hypotheses, and aids predictive modelling. Strong correlations can simplify data and spot data quality problems (Marshall, G. and Jonker, L., 2010). These insights support data-driven decision-making across different fields, as seen in Table 4.

Table 4 - Results of Pearson correlation among the 7 AI groups

		LSM	DeL	ReF	RoB	CoV	NLP	IoT
LSM	Pearson Correlation	1	.863**	.864**	.773**	.793**	.829**	.784**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
DeL	Pearson Correlation	.863**	1	.853**	.750**	.838**	.799**	.742**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
ReF	Pearson Correlation	.864**	.853**	1	.839**	.856**	.854**	.764**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000
RoB	Pearson Correlation	.773**	.750**	.839**	1	.824**	.818**	.793**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000
CoV	Pearson Correlation	.793**	.838**	.856**	.824**	1	.934**	.845**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000

NLP	Pearson Correlation	.829**	.799**	.854**	.818**	.934**	1	.878**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000
IoT	Pearson Correlation	.784**	.742**	.764**	.793**	.845**	.878**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	

Table 4 provides Pearson correlation coefficients between seven groups of AI Usage factors. These coefficients measure the strength and direction of linear relationships between these variables. All correlations are statistically significant at the 0.01 level (2-tailed). Strong positive correlations are observed among most variables, with coefficients ranging from .634 to .934. It can be summarised that there are strong and statistically significant relationships among many of them. When variables have a strong correlation, it means that changes in one variable are associated with predictable changes in the other variable. This information can be valuable in understanding relationships and making predictions, but it does not prove relationship.

6. Conclusion

This paper presents a study on the Factors Influencing the Adoption of Artificial Intelligence (AI) in Crisis Management. The research identifies 28 AI usage factors categorized into seven groups: Large-Scale Machine Learning, Deep Learning, Reinforcement Learning, Robotics, Computer Vision, Natural Language Processing, and Internet of Things. The study conducted a questionnaire survey among employees at the UAE National Crisis and Emergency Management Authority, using purposive sampling to assess their opinions regarding the impact of these usage factors on the adoption of AI in crisis management. The collected data underwent descriptive analysis to determine the ranking of AI usage factors within each of the seven groups. In terms of group rankings, Robotic emerged as the top-ranking factor, followed by Reinforcement Learning. Large-Scale Machine Learning occupied the next position, succeeded by Natural Language Processing, Deep Learning, Internet of Things, and Computer Vision, which held the lowest rank. Furthermore, when examining the correlation between these usage factor groups, it was discovered that most of them exhibited strong positive correlations, with correlation coefficients ranging from 0.634 to 0.934. This indicates that changes in one variable are associated with predictable changes in another variable. While this information can be instrumental in understanding relationships and making predictions, it does not establish a causal relationship.

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References

Afzal, F., Yunfei, S., Nazir, M., & Bhatti, S. M. (2019). A review of AI based risk assessment methods for capturing complexity-risk interdependencies: cost overrun in construction projects. International Journal of Managing Projects in Business, 14(2), 300-328.

Al-Gamrh, B., Ku Ismail, K. N. I., & Al-Dhamari, R. (2018). Corporate Governance during the Financial Crisis: Evidence from the United Arab Emirates (UAE). Corporate Governance during the Financial Crisis: Evidence from the United Arab Emirates (UAE)(June 22, 2018). Applied Economics, Forthcoming.

Al-Karaki, J. N., Ababneh, N., Hamid, Y., & Gawanmeh, A. (2021). Evaluating the Effectiveness of Distance Learning in Higher Education during COVID-19 Global Crisis: UAE Educators' Perspectives. Contemporary Educational Technology, 13(3), ep311.

Ansell, C., & Boin, A. (2019). Taming deep uncertainty: The potential of pragmatist principles for understanding and improving strategic crisis management. Administration & Society, 51(7), 1079-1112.

Boin, A.,'t Hart, P., Stern, E., Sundelius, B. (2005). The Politics of Crisis Management: Public Leadership under Pressure, Cambridge University Press, New York.

Bundy, J., Pfarrer, M. D., Short, C. E., & Coombs, W. T. (2017). Crises and crisis management: Integration, interpretation, and research development. Journal of management, 43(6), 1661-1692.

Dai, S., & Zhang, W. (2020). Knowledge map of environmental crisis management based on keywords network and co-word analysis, 2005–2018. Journal of Cleaner Production, 262, 121168.

Frank, A.G., Dalenogare, L.S. and Ayala, N.F., 2019. Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics, 210, pp.15-26

Gasser, L. (Eds.)., & Bond, A. H. (2014). Readings in distributed artificial intelligence. Morgan Kaufmann.

George, D. and Mallery, P., 2018. Descriptive statistics. In IBM SPSS Statistics 25 Step by Step (pp. 126-134). Routledge.

Kodratoff, Y. (2014). Introduction to machine learning. Elsevier.

Maphanga, P. M., & Henama, U. S. (2019). The tourism impact of Ebola in Africa: Lessons on crisis management. African Journal of Hospitality, Tourism and Leisure, 8(3), 1-13.

Marshall, G. and Jonker, L., 2010. An introduction to descriptive statistics: A review and practical guide. Radiography, 16(4), pp.e1-e7.

Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (Eds.). (2013). Machine learning: An artificial intelligence approach. Springer Science & Business Media.

Mirzaei, A. (2019). Market power among UAE banks: The 2008 financial crisis and its impact. The quarterly review of economics and finance, 71, 56-66.

Paraskevas, A., & Quek, M. (2019). When Castro seized the Hilton: Risk and crisis management lessons from the past. Tourism Management, 70, 419-429.

Parker, C. F., Nohrstedt, D., Baird, J., Hermansson, H., Rubin, O., & Baekkeskov, E. (2020). Collaborative crisis management: a plausibility probe of core assumptions. Policy and Society, 39(4), 510-529.

Reynolds, D., & Reason, M. (Eds.). (2012). Kinesthetic empathy in creative and cultural practices. Intellect Books.

Saroj, A., & Pal, S. (2020). Use of social media in crisis management: A survey. International Journal of Disaster Risk Reduction, 48, 101584.

Varakantham, P., An, B., Low, B., & Zhang, J. (2017). Artificial intelligence research in Singapore: assisting the development of a smart nation. Ai Magazine, 38(3), 102-105.

Wenger, E. (2014). Artificial intelligence and tutoring systems: Computational and cognitive approaches to the communication of knowledge. Morgan Kaufmann.

Wut, T. M., Xu, J. B., & Wong, S. M. (2021). Crisis management research (1985–2020) in the hospitality and tourism industry: A review and research agenda. Tourism Management, 85, 104307.