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A Model of Factors Influencing the Implementation of Artificial Intelligent in Crisis Management: A Case Study of National Crisis and Emergency Management Authority (NCEMA)

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Abstract: This paper outlines the development of a structural equation model focusing on factors influencing the implementation of AI in crisis management within the UAE National Crisis and Emergency Management Authority. Literature has identified 28 factors which are categorized into seven domains that influencing the implementation of AI in crisis management for the model. The model was constructed and evaluated using SmartPLS software. The model was evaluated at its measurement and structural components. The results revealed that at the measurement component, the model met all evaluation criteria. While, at the structural component, the relationship between 'CoV' and 'CrM' was statistically significant (T-statistic = 2.633, P-value = 0.009), indicating a robust connection. However, the links between 'ReF' and 'CrM' and 'LSM' and 'CrM' were not statistically significant (P-values = 0.999 and 0.949, respectively), suggesting limited impact on 'CrM.' Relationships between 'RoB,' 'IoT,' 'DeL,' and 'NLP' with 'CrM' showed moderate evidence but lacked statistical significance, possibly due to data limitations. Furthermore, the model demonstrated a strong fit, with an R-squared (R^2) value of 0.761, explaining approximately 76.1% of the variance in "CrM" with the seven independent variables. Lastly, for predictive relevance, the "CrM" as a dependent construct displayed a Q^2 value of 0.608, indicating that around 60.8% of the variation in "CrM" is explained by the model beyond random chance, confirming its strong predictive value.

Keywords: Influencing AI Factors, crisis management

1. Introduction

Crises can emerge unpredictably, regardless of location or timing. Crisis can happen from two sources which are due to natural occurrences and human actions. Natural disasters exemplify instances where nature exhibits its might, while at other times, crises emerge due to the deterioration of the human-nature relationship. To assert dominance over the natural world, humans engage in various societal, economic, political, and technological pursuits that can exacerbate these crises. Regardless of their origins, crises subject individuals to immense stress, eliciting emotional responses. Organizations are not immune to crises; they share vulnerability with individuals. Crises disrupt the stability, functionality, and objectives of organizations, exerting significant pressure on their financial, physical, and emotional foundations. In some cases, crises can even threaten an organization's survival (Klann, 2018).

Several tragedies that create crisis such as due to terrorist attacks, hurricanes, tsunamis, and others have exerted a significant impact on human society, the economy, and the environment. Then, crisis response which is describe as the swift protection of life and property during crisis is aiming to prevent casualties and injuries. Crisis response entails

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immediate action and the coordination of resources, programs, and facilities. This encompasses actions taken both prior to the crisis event, such as receiving storm warnings, as well as responding to the immediate aftermath and maintaining continuous efforts during the ongoing crisis. The magnitude and complexity of a crisis determine the scale of the response, often involving a collaborative effort spanning multiple organizations, including various levels of government, businesses, volunteer groups, media outlets, and the general public. These organizations collaborate virtually to save lives, safeguard infrastructure and community resources, and restore order to affected areas (Kamil, 2020).

In pursuit of enhancing crisis management processes, artificial intelligence (AI) plays a major role by utilizing robotics for urban search and rescue operations, improving information sharing through ontologies, providing crisis responders with tailored queries, and offering multi-agent systems for real-time support and simulated environments (Al-Karaki et al., 2021). AI endeavours to enhance the effectiveness of crisis response efforts. Hence, this paper presents a study on constructing a Partial Least Squares Structural Equation Modelling (PLS-SEM) model that explains the factors influencing the utilization of Artificial Intelligence (AI) within Crisis and Emergency Management Organizations. It gives an understanding the intricate relationships among various factors that impact the adoption and deployment of AI technologies in organizations, where timely and effective response to crises and emergencies is crucial.

2. Crisis Management

Crisis management aims to control rather than eliminate a crisis, involving quick decision-making based on the best available information (Schulman, 1993; Pearson, 2002). It enhances an organization's ability to respond swiftly to crises and goes beyond technical decisions, encompassing political and governmental aspects (Lockwood, 2005; McConnell & Stark, 2002; Boin et al., 2005). Definitions of crisis management vary: some see it as pre-determined activities for responding to disasters, while others view it as rescue, preparedness, and mitigation (Lockwood, 2005; Waugh & Streib, 2006; Boin et al., 2005; Smith, 2006). Effective crisis management requires coordination, communication, collective decision-making, and control responsibilities (Valackiene, 2011), applying management principles in crisis situations (Samal et al., 2005).

The crisis management process includes different stages: Petak (1985) identifies mitigation, preparedness, recovery, and response; Fink (1986) divides it into prodromal, acute, chronic, and resolution stages; Augustine (1995) outlines prevention, preparation, recognition, containment, resolution, and profiting stages. Burnett (1998) focuses on obstacles and defines crisis management as actions to overcome time constraints, control challenges, danger levels, and reaction constraints. Boin et al. (2005) emphasize leadership tasks of sense-making, decision-making, meaning-making, terminating, and learning. Coombs (2007a) outlines pre-crisis, crisis, and post-crisis stages, encompassing signal detection, prevention, crisis preparation, crisis recognition, containment, information distribution, stakeholder communication, message development, reputation management, and learning.

2.1 Crisis Management in UAE

Multiple studies have investigated into crisis management in the UAE, shedding light on various aspects. Almarshoodi et al. (2021) expanded the Situational Crisis Communication Theory (SCCT) to mitigate reputational threats, finding that employees' positive perceptions may be due to their view of crises as manageable, often attributing crisis responsibility to circumstances rather than the UAE police. Thomas et al. (2021) emphasized the need for psychological intervention after disasters and highlighted the intersection of public health and disaster risk reduction as essential, advocating for new health-disaster risk reduction paradigms in disaster policy. Alketbi (2020) explored the impact of cultural difference courses in the Dubai Police Academy, revealing that students faced challenges in cross-cultural interactions but expressed positive attitudes toward dedicated cultural awareness training. Sahu (2021) investigated public policy measures for COVID-19 crisis management, commending the UAE's effective control of the virus through centralized decision-making, administrative capacity strengthening, collaboration, successful communication, financial resource allocation, and high citizen trust in the government. These studies collectively enrich our understanding of crisis management in the UAE.

3. Implementation of AI in Crisis Management

Understanding the adoption of innovation is critical to assessing the associated dangers for consumers, as highlighted by Mohamed et al. (2013). A particular implementation of technology carries a multitude of risks, and evaluating these risks requires a thorough comprehension of the implementation process. In today's business landscape, one of the foremost risks is the potential loss of market share, a concern raised by Wu et al. (2013). This risk is exacerbated by businesses swiftly embracing new technologies without sufficient understanding. The failure to adapt to technological advancements is a prevalent issue.

While the widespread replacement of humans by computers remains a theoretical concern, it underscores the importance of people having a grasp of AI technology to maintain corporate effectiveness. This underscores the role of a highly advanced technical infrastructure as a potential risk factor for businesses. Kerzner (2013) emphasizes that companies face significant risks, including insufficient staff technological expertise, heightened market competition, rapid technological shifts, the safeguarding of organizational data privacy, and data security risks, among others, which can lead to market failure.

To effectively manage risks in organizational processes, businesses must employ efficient solutions. AI-related risks in these processes encompass concerns such as data loss, data encryption, and the maintenance of well-structured organizational workflows, as pointed out by Debortoli et al. (2014). However, mitigating these risks necessitates a comprehensive understanding of AI applications and their management. Ineffectively managed risks in business processes can result in organizational process failures.

The link between AI and risk management is most noticeable in modern business organisation. To manage risks effectively in this context, it is essential to study risk factors and understand technological advancements. This helps businesses better handle the risks associated with AI in their operations. This study aims to explore the relationships among seven domains of AI influencing factors in crisis management: Large-Scale Machine Learning, Deep Learning, Reinforcement Learning, Robotics, Computer Vision, Natural Language Processing, and Internet of Things.

3.1 Large-scale Machine Learning in Crisis Management

Crisis management is a complex process that involves the coordination of various stakeholders and resources to mitigate the impact of a crisis. With the increasing availability of big data, machine learning has emerged as a promising approach to support crisis management.

Large-scale machine learning is transforming crisis management by making use of extensive data sources for more effective responses. It is capable of early warning systems by processing real-time information from various sources, predicting crisis outcomes, offering real-time decision support, and optimizing resource allocation during emergencies. However, it comes with challenges, including data privacy and ethical concerns. By addressing these challenges and leveraging the power of large-scale machine learning, it can enhance the ability to respond swiftly and efficiently to crises, ultimately leading to safer outcomes (Lwakatare, L.E. et.al. 2020; Sevilla, J. et.al. 2022)

Several studies have explored the use of machine learning in crisis management. Abboodi, B., et.al. (2023) discussed the use of artificial intelligence to detect crises related to events in a firm, which can lead to efficient crisis management. Kraft, A. and Usbeck, R., (2022) reviewed automated machine learning approaches for emergency response and coordination via social media in the aftermath of a disaster. Boumahdi, A., et.al. (2020) leveraged human and machine learning for crisis mapping during disasters using social media.

3.2 Deep Learning in Crisis Management

Deep learning, a subset of artificial intelligence, is making waves in the world of crisis management. This technology, inspired by the human brain's neural networks, offers innovative solutions for handling emergencies. Deep learning's applications in crisis management are diverse and impactful. It can predict disasters like hurricanes, analyse images and videos in real-time to identify hazards, understand and process text data from sources like social media, and optimize the allocation of resources during crises.

However, there are challenges to consider, such as the need for abundant high-quality data, ensuring the fairness and ethics of these systems, and making the models understandable. Despite these challenges, deep learning's potential to enhance emergency response is evident. As it continues to advance, it holds promise for saving lives, minimizing damage, and improving the way we handle crises, ultimately contributing to a safer world (Sarker, I.H., 2021; Taye, M.M., 2023; Sabharwal, R., et.al., 2022)

3.3 Reinforce Learning in Crisis Management

Reinforcement learning is a branch of AI that trains algorithms to make sequential decisions. Unlike traditional AI, which relies on preset rules, RL agents learn from their environment. It receives feedback in the form of rewards or penalties and continually improve their decision-making to maximize long-term rewards. In crisis management, RL's adaptability, optimization, and automation capabilities are well-suited for dynamic crisis scenarios. It can adjust to changing circumstances and make decisions that save lives and reduce harm. Applications of RL in crisis management include resource allocation, efficient evacuation planning, disease spread prediction, and infrastructure resilience. It can help optimize resource distribution, plan effective evacuations, predict disease spread, and monitor critical infrastructure during crises. However, there are challenges, including ethical concerns about data privacy and the transparency of AI decision-making. Ensuring that AI operates ethically and without bias is essential in crisis situations.

Hence, reinforcement learning is a game-changer in crisis management. Its adaptability and decision optimization make it invaluable for responding to emergencies. As we continue to develop RL systems, they have the potential to save lives, minimize damage, and improve crisis management overall, ensuring a safer future (Knox, W.B. and Stone, P., 2015; Akalin, N. and Loutfi, A., 2021; Singh, V., et.al., 2022).

3.4 Robotic in Crisis Management

Robotics is an interdisciplinary engineering activity that involves the design, manufacture, operation, and maintenance of robots and other computer actions. Integrating robotics and artificial intelligence (AI) in crisis management is about using sturdy robots with advanced sensors and different levels of autonomy to assist during emergencies. These robots can go into challenging and dangerous situations, like disaster areas, and provide real-time data to help response teams. For example, it can map disaster-stricken areas, detect hazardous materials, or navigate through debris. The choice of autonomy level determines how much robots can operate independently. Some work closely with human teams, while others handle specific tasks without constant supervision. This technology helps improve safety, data collection, and response efficiency, ultimately saving lives and reducing damage during crises. (Abioye, S.O., et.al, 2021; Denecke, K. and Baudoin, C.R., 2022).

3.5 Computer Vision in Crisis Management

Computer vision, a branch of artificial intelligence, plays a crucial role in crisis management, aiding first responders and emergency services in comprehending and addressing various emergencies. It offers diverse applications, as shown in recent studies (Lopez-Fuentes, L et.al. 2018; Kim, D., et.al. 2022; Ulhaq, A. et.al. 2020; Al-Faris, M., et.al. 2020). First, computer vision is employed for disaster assessment, using satellite imagery and machine learning to evaluate the extent of damage caused by natural disasters like floods, earthquakes, and hurricanes. This method is effective in identifying affected areas by analysing pre- and post-disaster images and associated damage labels.

Secondly, computer vision is proving valuable in controlling the spread of COVID-19. It assists in monitoring social distancing, detecting mask-wearing compliance, and identifying individuals with elevated body temperatures in public spaces. This aids authorities in promptly isolating infected individuals and curbing the virus's transmission. Thirdly, computer vision is used for human action recognition, particularly in emergency situations. This technology can identify various actions and behaviours in different environmental conditions, enhancing the understanding of crisis scenarios and guiding appropriate responses.

Lastly, computer vision expedites disaster response by automatically detecting damaged areas in satellite images through deep learning models. This quick identification enables emergency services to allocate resources efficiently and respond promptly to critical areas. Computer vision is an indispensable tool in crisis management, facilitating the rapid assessment of disaster damage, monitoring pandemic control measures, recognizing human actions in emergencies, and expediting disaster response efforts. As computer vision technology advances, it can anticipate even more innovative applications in crisis management.

3.6 Natural Language Processing in Crisis Management

Natural Language Processing (NLP) is becoming an essential tool in crisis management, where swift communication and decision-making are crucial. NLP, a part of artificial intelligence, empowers computers to understand and work with human language. It helps during crises in several ways. It swiftly extracts and organizes information from various sources, like social media and news, keeping responders up to date. NLP also gauges public sentiment, aiding authorities in understanding the emotional context of the situation. Additionally, it offers automated translation for multi-lingual environments and chatbots for crisis communication. NLP helps verify the accuracy of information, crucial in preventing misinformation from spreading. Challenges include privacy, biases in algorithms, and maintaining transparency. NLP enhances crisis management, facilitating better decision-making and communication, ultimately contributing to safer crisis responses (Dale, R., Moisl, H. and Somers, H. eds., 2000; Lutkevich, B. and Burns, E., 2021; Patel, A.A. and Arasanipalai, A.U., 2021; Gruetzemacher, R., 2023)

3.7 Internet of Things in Crisis Management

The Internet of Things (IoT) is changing how crises are handled. IoT involves connecting devices and sensors to the internet, allowing them to share information. In the context of crisis management, this technology offers several benefits. It helps with early warnings by sensing changes in the environment and can give real-time updates during emergencies, enabling better decision-making. IoT also monitors infrastructure, ensuring it remains in good condition, and provides tools for emergency responders to stay safe and work efficiently. Additionally, it helps distribute resources effectively. However, it needs to consider data security and privacy to make the most of IoT in crisis management. IoT is making our responses to emergencies more efficient and safer. (Elgazzar, K., et.al. 2022)

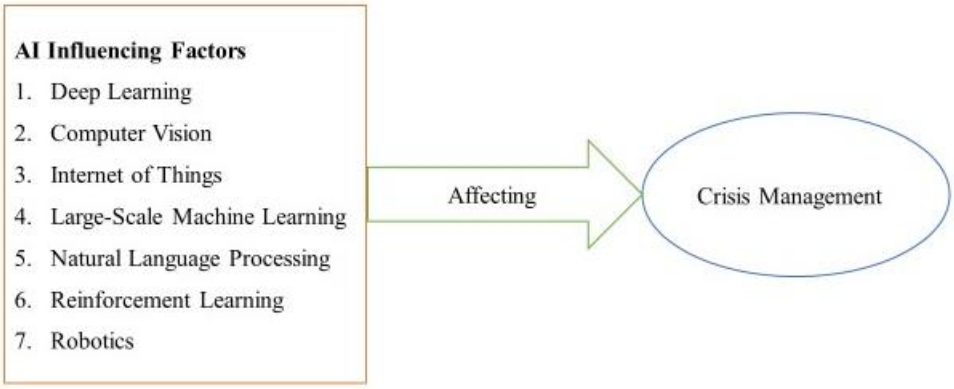
4. Data for Modelling

Data used to develop the model of AI influencing factors in crisis management in United Arab Emirates (UAE) organisation was gathered through questionnaire survey. The respondents of the survey were employees in the UAE National Crisis and Emergency Management Authority. The main contents of the questionnaire are list of 28 AI influencing factors in seven domains and six attributes of crisis management. Respondents were requested to gauge each of the factors and attributes using 5-point Likert scale of the level of agreeability. A total of 300 questionnaires sets were distributed using a purposive sampling technique. However. 281 valid responses were used for formulating the model. To determine the internal consistency of the collected data, a reliability test was conducted and the result is as in table 1.

Table 1 - Results of reliability test on the collected data

Constructs	Code	No. of factors or attributes	Cronbach's Alpha values
Computer Vision	CoV	4	0.908
Deep Learning	DeL	4	0.897
Internet of Things	IoT	5	0.937
Large-Scale Machine Learning	LSM	4	0.909
Natural Language Processing	NLP	4	0.926
Reinforcement Learning	ReF	4	0.908
Robotics,	RoB	3	0.880
Crisis Management	CrM	6	0.747

Table 1 displays eight constructs, with seven, namely CoV, DeL, IoT, LSM, NLP, ReF, and RoB, serving as independent variables, while CrM functions as the dependent variable. All the constructs exhibit Cronbach's Alpha values ranging from 0.747 to 0.937, indicating strong internal consistency among their respective factors or attributes. The data was imported into SmartPLS software in CSV format and utilized for modelling purposes. The developed model is based on the framework as in figure 1



Fig, 1 - Model framework

Figure 1 illustrates the connection between AI influencing factors that impact crisis management within an organization. There are 28 AI influencing factors grouped into seven domains or constructs, serving as independent variables, while crisis management constitutes the dependent construct, comprising six attributes.

5. Modelling of Factors Influencing in the Implementation of AI in Crisis Management

In this modelling process, the collected data was imported in the SmartPLS software and the model was then constructed in the software according to the framework. Once the model was developed, then PLS Algorithm was run to evaluate the measurement component of the model. Then, bootstrapping function was run on the model to evaluate the structural path of the model. Finally, the blindfolding was run on the model to validate the model predictive relevance (Hair Jr, et.al.2016).

5.1 Measurement Evaluation

After running the PLS Algorithm function on the model, the model outlook is as figure 2.

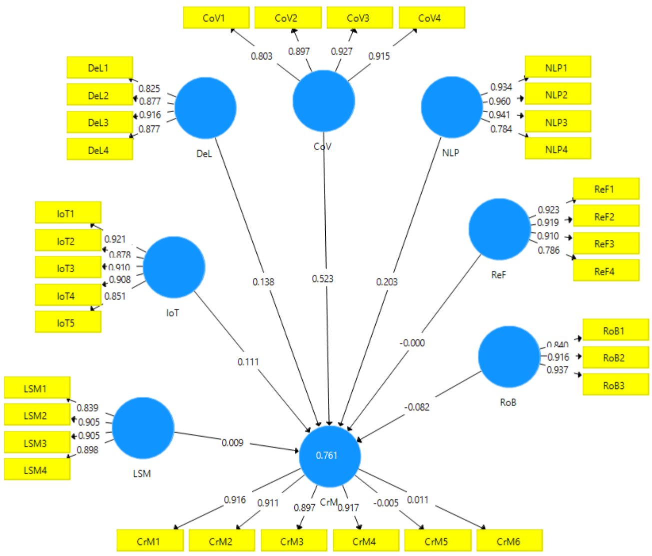


Fig. 2 - Initial modelling

5.1.1 Indicator Reliability

The first evaluation on the measurement model is to asses the outer loadings of the indicators where all indicators should be greater than 0.6 (Hair Jr, et.al.2016). The extracted outer loadings after the first modelling are presented in Table 2

Table 2 - Outer Loading after first PLS Algorithm process

	Constructs							
Factors	CoV	CrM	DeL	IoT	LSM	NLP	ReF	RoB
CoV1	0.803							
CoV2	0.897							
CoV3	0.927							
CoV4	0.915							
CrM1		0.916						
CrM2		0.911						
CrM3		0.897						
CrM4		0.917						
CrM5		-0.005						
CrM6		0.011						
DeL1			0.825					
DeL2			0.877					
DeL3			0.916					
DeL4			0.877					
IoT1				0.921				
IoT2				0.878				
IoT3				0.910				
IoT4				0.908				
IoT5				0.851				
LSM1					0.839			
LSM2					0.905			
LSM3					0.905			
LSM4					0.898			
NLP1						0.934		
NLP2						0.960		
NLP3						0.941		
NLP4						0.784		
ReF1							0.923	
ReF2							0.919	
ReF3							0.910	

ReF4	0.786	
RoB1		0.840
RoB2		0.916
RoB3		0.937

Table 2 shows that there are two indicators having outer loading less than 0.6. Hence, these indicators which are CrM5 with -0.005 and CrM6 with 0.011 need to be deleted from the model. Then the model was then rerun using PLS Algorithm and the final model outlook is as in figure 3.

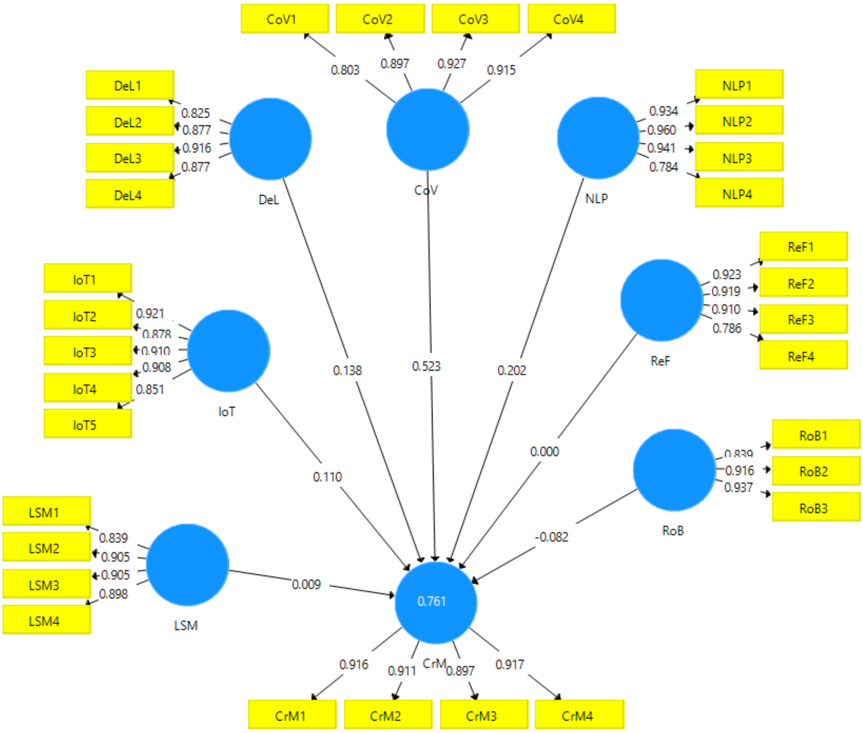


Fig. 3 - Final model

Then, the extracted outer loadings after the second modelling process are presented in Table 3

Table 3 - Outer Loading after second PLS Algorithm process

	Constructs							
Factors	CoV	CrM	DeL	IoT	LSM	NLP	ReF	RoB
CoV1	0.803							
CoV2	0.897							
CoV3	0.927							
CoV4	0.915							
CrM1		0.916						
CrM2		0.911						
CrM3		0.897						
CrM4		0.917						
DeL1			0.825					
DeL2			0.877					
DeL3			0.916					
DeL4			0.877					
IoT1				0.921				
IoT2				0.878				
IoT3				0.910				
IoT4				0.908				
IoT5				0.851				
LSM1					0.839			

LSM2	0.905			
LSM3	0.905			
LSM4	0.898			
NLP1		0.934		
NLP2		0.960		
NLP3		0.941		
NLP4		0.784		
ReF1			0.923	
ReF2			0.919	
ReF3			0.910	
ReF4			0.786	
RoB1				0.839
RoB2				0.916
RoB3				0.937

Table 3 shows that all the indicators are having values of more than 0.6. Hence, it can be considered that all the indicators have achieved item reliability.

5.1.2 Construct Reliability and Validity

In PLS modelling, construct reliability assesses how well latent constructs represent observed variables, while construct validity ensures constructs measure their intended concepts accurately. Both are vital for model credibility and utility. Careful model design and rigorous assessments are crucial for reliability and validity. Researchers typically assess construct reliability using metrics like composite reliability (CR), which should ideally exceed 0.7, and construct validity using metrics like Average Variance Extracted (AVE), which should ideally exceed 0.5 (Hair Jr, et.al.2016).

Table 4 - Construct reliability and validity

Constructs	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CoV	0.908	0.912	0.936	0.786
CrM	0.931	0.932	0.951	0.828
DeL	0.897	0.903	0.928	0.764
IoT	0.937	0.947	0.952	0.799
LSM	0.909	0.912	0.937	0.787
NLP	0.926	0.933	0.949	0.824
ReF	0.908	0.919	0.936	0.786
RoB	0.880	0.886	0.926	0.807

Table 4 provides insights into the reliability and validity of various constructs of the model. The constructs exhibit high internal consistency, with Cronbach's Alpha values exceeding 0.7 for all constructs. Composite Reliability (rho_A) values also confirm strong reliability. While the Average Variance Extracted (AVE) values, which assess construct validity, generally demonstrate moderate to good convergent validity, a few constructs fall slightly below the ideal threshold of 0.7. Overall, the PLS model is reliable and valid for research purposes.

5.1.3 Discriminant Validity

Fronell-Larcker criterion is one of the most popular techniques used to check the discriminant validity of measurements models. According to this criterion, the square root of the average variance extracted by a construct must be greater than the correlation between the construct and any other construct (Hair Jr, et.al.2016).

Table 5 - Discriminant validity

Constructs	CoV	CrM	DeL	IoT	LSM	NLP	ReF	RoB
CoV	0.887							
CrM	0.862	0.91						
DeL	0.838	0.767	0.874					
IoT	0.854	0.781	0.748	0.894				
LSM	0.79	0.731	0.858	0.786	0.887			
NLP	0.934	0.839	0.799	0.883	0.827	0.907		
ReF	0.856	0.762	0.856	0.766	0.861	0.855	0.887	
RoB	0.814	0.706	0.749	0.789	0.772	0.816	0.839	0.899

Table 5 presents the Fornell-Larcker values of the model. These values show the discriminant validity of the model's constructs. In the context of Fornell-Larcker values, the diagonal elements represent the square root of the Average Variance Extracted (AVE) for each construct, while the off-diagonal elements indicate the correlations between constructs. Strong diagonal values compared to off-diagonal values suggest good discriminant validity, signifying that the constructs are well-differentiated from one another in the model.

5.2 Structural Evaluation

5.2.1 Path Coefficients

Path coefficients represent the strength and direction of the relationships between latent constructs or factors within the model. These coefficients indicate how much change in one construct is associated with a unit change in another construct, considering the entire model (Hair Jr, et.al.2016).

Table 6 - Path coefficients

	Dependent Construct
Independent Constructs	CrM
CoV	0.523
DeL	0.138
IoT	0.111
LSM	0.009
NLP	0.203
ReF	0.000
RoB	-0.082

Table 6 provides the relationships between the dependent construct "CrM" and seven independent constructs. Among these relationships, "CoV" stands out as having the strongest positive influence on "CrM" with a substantial path coefficient of 0.523. This indicates that as "CoV" increases, there is a notable increase in "CrM." Additionally, "NLP" and "DeL" also contribute positively to "CrM" but to a somewhat lesser extent, with path coefficients of 0.203 and 0.138, respectively, signifying moderate positive influences. "IoT," while exhibiting a positive influence, has a weaker effect with a path coefficient of 0.111. On the other hand, "LSM" and "ReF" appear to have minimal to no direct impact on "CrM," as their path coefficients are close to zero. Furthermore, "RoB" has a negative influence on "CrM," as indicated by a path coefficient of -0.082, suggesting that an increase in "RoB" is associated with a decrease in "CrM." These findings help illuminate the complex web of relationships within the structural model, offering valuable insights for analysis and decision-making.

5.2.2 Model Fitness

In Partial Least Squares (PLS) modelling, the R-squared (R^2) value gauges how much of the dependent variable's variance is explained by the model's factors. A high R^2 suggests a strong relationship, but it should be assessed alongside other metrics due to PLS's suitability for complex data. Careful factor selection is vital as it affects R^2 and model accuracy (Hair Jr, et.al.2016). The R-squared (R^2) value for this model is as in table 7.

Table 7 - R squared value of the model

Dependent Construct	R Square	R Square Adjusted
CrM	0.761	0.755

Table 7 shows that the PLS-SEM regression model has a strong fit, with an R-squared (R^2) value of 0.761, indicating that approximately 76.1% of the variance in "CrM" is explained by the seven independent variables. The adjusted R-squared value, at 0.755, reaffirms this strong model fit, considering the model's complexity. In summary, the model effectively captures a significant portion of the variability in "CrM," making it a robust representation of the relationship between the dependent and independent variables.

5.2.3 Hypothesis Testing

Bootstrapping is a critical component of hypothesis testing in Partial Least Squares (PLS) modelling. It involves resampling the data multiple times to re-estimate model parameters. This process assesses the stability and significance of these parameters, allowing researchers to test their hypotheses. By calculating p-values or confidence intervals for parameters, researchers can determine whether relationships in the PLS model are statistically significant. Bootstrapping ensures robust inference, aiding in the assessment of the validity and significance of model hypotheses within PLS modelling (Hair Jr, et.al.2016). After the bootstrapping process, the established model is as figure 4

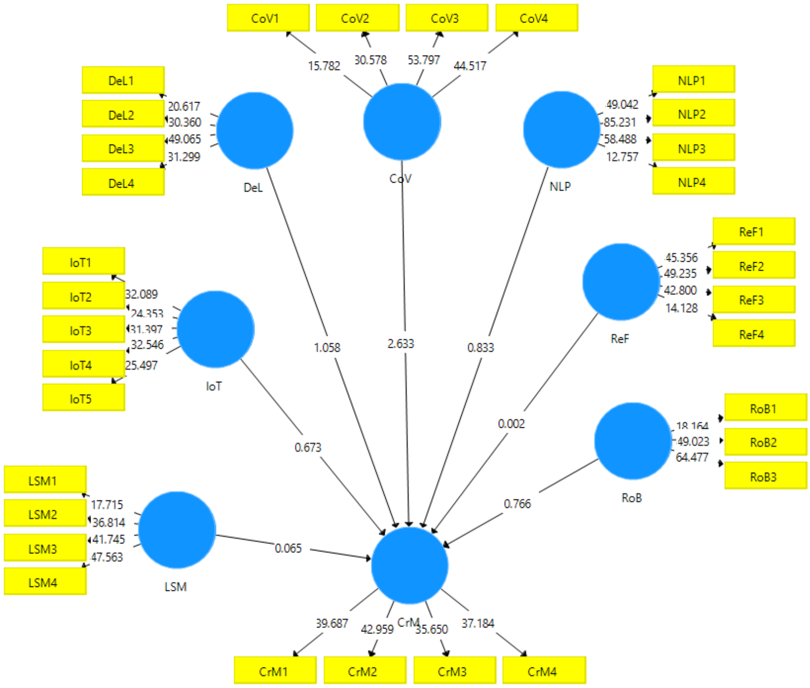


Fig. 4 - Model outlook after bootstrapping process

Based on figure 4, the generated results of the bootstrapping process on the model is as in table 7

Table 7 - Hypothesis testing results

Relationship	T Statistics (|O/STDEV|)	P Values
RoB -> CrM	0.766	0.444
ReF -> CrM	0.002	0.999
LSM -> CrM	0.065	0.949
IoT -> CrM	0.673	0.501
DeL -> CrM	1.058	0.290
NLP -> CrM	0.833	0.405
CoV -> CrM	2.633	0.009

Table 7 presents the results of hypothesis testing for the relationships between the independent constructs (RoB, ReF, LSM, IoT, DeL, NLP, CoV) and the dependent construct (CrM). It can be concluded that the relationship between ‘CoV’ and ‘CrM’ stands out as statistically significant, as indicated by a T statistic of 2.633 and a corresponding P value of 0.009. This suggests strong evidence supporting a meaningful relationship between ‘CoV’ and ‘CrM.’ However, the relationships between ‘ReF’ and ‘CrM,’ as well as ‘LSM’ and 'CrM,' are not statistically significant. Their associated P values of 0.999 and 0.949, respectively, suggest that these relationships may not have a meaningful impact on 'CrM.' The relationships between 'RoB,' 'IoT,' 'DeL,' and 'NLP' with 'CrM' show moderate T statistics, indicating some evidence of a relationship. However, their associated P values are relatively high, suggesting that these relationships are not statistically significant at conventional significance levels. This phenomenon may be attributed to the data collected, which may not provide sufficient strength to establish significant relationships for all the hypothesized paths.

5.3 Predictive Relevance

Blindfolding in PLS modelling assesses predictive relevance, guards against overfitting, validates the model, and guides refinement. It ensures the model's ability to make accurate predictions on unseen data, enhancing its real-world applicability (Hair Jr, et.al.2016). The main result of blind folding is Construct Cross Validated redundancy as in table 8.

Table 8 - Results of Construct Cross Validated redundancy

Constructs	SSO	SSE	Q² (=1-SSE/SSO)
CoV	1124	1124	
CrM	1124	440.377	0.608
DeL	1124	1124	
IoT	1405	1405	
LSM	1124	1124	
NLP	1124	1124	
ReF	1124	1124	
RoB	843	843	

Table 8 presents the results Construct Cross Validated redundancy. It focuses on the Q^2 metric, which assesses predictive relevance. The dependent construct “CrM” exhibits a Q^2 value of 0.608, indicating that the model explains approximately 60.8% of the variation in “CrM” beyond random chance, demonstrating reasonably good predictive relevance.

6. Conclusion

This paper has presented the development of structural equation modelling of AI influencing factors in crisis management for UAE National Crisis and Emergency Management Authority. This study has identified 28 AI influencing factors that are classified in seven domains that influence the crisis management in the UAE National Crisis and Emergency Management Authority. The model was developed and evaluated in SmartPLS software. The evaluation was conducted at measurement and structural components of the model. It was found the at the measurement component, the model has achieved all the evaluation criteria. While at structural component, it was found that the relationship between 'CoV' and 'CrM' is statistically significant (T-statistic = 2.633, P-value = 0.009), indicating a strong connection. However, the relationships between 'ReF' and 'CrM' and 'LSM' and 'CrM' are not statistically significant (P-values = 0.999 and 0.949, respectively), suggesting they may not significantly impact 'CrM.' The relationships between 'RoB,' 'IoT,' 'DeL,' and 'NLP' with 'CrM' show moderate evidence but aren't statistically significant due to potentially weak data strength. Also, found that the model has a strong fit, with an R-squared (R^2) value of 0.761, indicating that approximately 76.1% of the variance in "CrM" is explained by the seven independent variables. Finally, it was found that for predictive relevance, the "CrM" as dependent construct has a Q^2 value of 0.608, suggesting that the model explains about 60.8% of the variation in "CrM" beyond chance, showing strong predictive relevance.

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