INVESTIGATING MEDIATING EFFECT OF TRAINING ON THE RELATIONSHIP OF AI APPLICATION FACTORS AND CRISIS MANAGEMENT FOR ABU DHABI POLICE DEPARTMENT

Abdulla Mohammed Saif Ali Alshamsi[1], Abdul Jalil Omar[2]*

[1,2] Faculty of Technology Management and Business, Universiti Tun Hussein Onn Malaysia

*Corresponding E-mail : jalil@uthm.edu.my

ABSTRACT

Objective: This study investigates the mediating effect of AI Training on the relationship between AI application factors and Crisis Management within the Abu Dhabi Police Department. It aims to enhance understanding of how AI integration, particularly through training, can improve crisis response effectiveness.

Research Method: A quantitative approach was employed using Structural Equation Modeling; Partial Least Squares (SEM-PLS) via SmartPLS software. Data were collected from 346 employees working in AI-utilized departments within the Abu Dhabi Police.

Findings: The results demonstrate a robust model with moderate explanatory power and good model fit. AI Training significantly mediates the relationship between Predictive Policing, Data Analysis, Emergency Response, and Surveillance with Crisis Management. However, AI Training does not mediate the relationship between Security and Crisis Management. These findings suggest that AI Training plays a crucial role in optimizing crisis management outcomes.

Originality: This study provides empirical insights into the specific role of AI Training as a mediating factor in AI-based crisis management frameworks, particularly within law enforcement settings. It contributes to a deeper understanding of how training can bridge AI application and practical crisis response.

Keywords: AI Training, Crisis Management, Predictive Policing, SEM-PLS, Abu Dhabi Police, Artificial Intelligence, Emergency Response, Data Analysis, Surveillance.

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1. INTRODUCTION

Recent Artificial Intelligence (AI) advancements have significantly impacted various sectors, including healthcare, finance, transportation, security (Zhang & Aslan (2021) and energy sector (Almarashda et al. 2022). AI's benefits in predictive analytics, real-time decision-making, and process automation are widely acknowledged, especially for sectors requiring immediate, informed decisions such as crisis management (Yeasmin 2019). Despite global progress, the Abu Dhabi Police Department (ADPD) lags in adopting AI for crisis management (Al-Khouri 2017). Current manual processes are manpower-intensive and prone to errors, leading to delays and misjudgments in crises. Effective AI integration can enhance decision-making in high-pressure situations (Smith 2019). Abu Dhabi's unique challenges, such as major events, tourism, and dense populations, further necessitate advanced crisis management strategies (Al-Mansoori 2018). Traditional methods and data overload make manual analysis impractical, highlighting AI's potential for predictive modeling and real-time analysis (Liu et al. 2020).

The use of artificial intelligence (AI) has increased dramatically due to its many advantages. It helps a device to identify its environment and make the right choices (Almarashda et al. 2021) but use of AI as a mediator in training and crisis management within the ADPD is under-explored. AlKaabi and Davies (2022) emphasize the need for evolving knowledge management and human resourcing strategies. AI-driven training mediators are crucial for improving early crisis identification and decision-making during emergencies but are insufficiently discussed (Al Ramahi et al. 2023; Howson 2020). Their role is vital in smart cities, requiring strategic leadership to integrate technology into sustainable planning (Yousfi et al. 2021). Addressing the gap in AI training frameworks can significantly strengthen crisis response capabilities (Al Dhanhani & Al Naqbi, 2022).

A security breach crisis, such as a cyberattack on sensitive databases, can be effectively managed using AI, enhancing threat detection, response times, and mitigation strategies (Albaloushi, 2019). Intentional homicides and fluctuating crime rates in the UAE underscore the need for continued technological integration in police departments (UAE CRS, 2024). AI's role in enhancing crisis management through predictive analytics, real-time decision-making, and other advanced capabilities is crucial for improving public safety and resource allocation (Alshamsi et al. 2023).

Studies highlight a significant gap in AI integration for crisis management, with benefits in enhancing response times, prediction accuracy, and post-crisis analysis (Xiao et al. (2024). Global benchmarks from cities like New York and Tokyo demonstrate AI's potential, despite challenges such as privacy concerns and financial investment (Al Mazrouei, 2022; Rao & Verma 2019). Therefore, a focused study on AI training mediators' impact on crisis management strategies in ADPD will provide valuable insights and practical recommendations for leveraging AI technology to enhance crisis preparedness and response.

2. LITERATURE REVIEW

2.1 APPLICATIONS OF ARTIFICIAL INTELLIGENCE (AI)

Despite the fact that a number of AI technologies have been around for decades, it is only thanks to improvements in hardware and network and data processing speed that commercial applications of AI are now feasible. The growth of AI technologies in the twenty-first century is driven by the advancement of computer capabilities, vast volumes of data, and theoretical understanding. The process of turning AI research and technology into effective products has made significant strides.

2.1.1 SURVEILLANCE

The conventional notion of surveillance, grounded in the physical observation of locations or people, has undergone a transformative shift with the rise of advanced technologies. The emergence of artificial intelligence (AI) has expanded the horizon of what surveillance can achieve, especially in crisis management (Harcourt, 2015). As a tool, AI surveillance has increasingly become indispensable in anticipating, detecting, and resolving crises. One of AI's most potent strengths lies in its capacity for predictive analysis. By analyzing large sets of data, AI can identify patterns and anomalies which may be indicative of an impending crisis. For instance, in areas prone to natural disasters, AI surveillance can predict weather patterns that might result in floods or hurricanes (Chui et al. 2018). Predictive models, fed by countless data sources, enable proactive measures, ensuring minimal harm.

In times of immediate crises, such as terrorist attacks or industrial accidents, real-time surveillance is paramount. AI systems, equipped with facial recognition and anomaly detection algorithms, can quickly identify potential threats in crowded places or detect equipment malfunctions in factories (Jou et al. 2019). This instantaneous identification allows for swift interventions, potentially saving countless lives. A vital aspect of managing crises is ensuring clear, rapid communication among first responders and affected populations. AI-powered surveillance systems, integrated with communication platforms, can automatically notify emergency services when anomalies are detected, reducing response times. Furthermore, they can disseminate critical information, such as safe evacuation routes or emergency contact numbers, to those in danger (Meola, 2020; Hung & Yen, 2021).

As with any surveillance tool, AI systems pose potential threats to personal privacy. An AI's ability to process and store vast amounts of personal data presents challenges in ensuring that individuals' rights are not infringed upon (Zuboff, 2019). It's crucial that the adoption of AI in crisis management is accompanied by robust privacy regulations to safeguard individuals' rights. Another point of contention is the inherent bias that might exist within AI surveillance systems. If not properly trained, AI can perpetuate harmful biases that exist in its training data, potentially leading to misidentification or discrimination (Buolamwini & Gebru, 2018). It's essential to be vigilant in the deployment of AI surveillance, ensuring that it aids rather than complicates crisis management.

AI surveillance is most effective when integrated with conventional crisis management tools. Drones equipped with AI can provide aerial surveillance during natural disasters, guiding search and rescue teams. Similarly, AI-powered surveillance cameras can interface with alarm systems in buildings, ensuring quick evacuation during emergencies (Peters, 2019). This synergy ensures comprehensive and effective crisis management. A unique attribute of AI surveillance systems is their ability to learn and adapt. Post-crisis analysis is crucial for improving future responses. With each crisis encountered, AI systems can refine their algorithms, ensuring improved detection and mitigation of future crises (Knight, 2017). This iterative learning is vital in an ever-evolving world with new, unprecedented challenges.

Implementing AI in surveillance for crisis management can also bring about significant economic benefits. Human surveillance requires vast manpower and is subject to human errors. In contrast, AI systems can work tirelessly, ensuring constant monitoring at a fraction of the cost (Vinuesa et al. 2020). Additionally, their scalability ensures coverage of larger areas, which might be logistically challenging with traditional means. The potential of AI in reshaping crisis management is vast. As the technology continues to mature, it promises not only enhanced predictive capabilities but also a seamless integration with other technological advancements. While challenges remain, especially concerning ethical considerations, AI surveillance stands as a beacon of hope in fostering a safer, more resilient world (Russell & Norvig, 2010).

2.1.2 SECURITY

The role of AI in the law enforcement domain has grown immensely in the past few years. With advanced technologies and the proliferation of data, police departments worldwide are embracing AI to bolster their crisis management capabilities. Abu Dhabi Police, as part of its visionary approach to law enforcement, has been at the forefront of leveraging AI to enhance its crisis response strategies. Crisis management is the systematic process by which organizations deal with unexpected emergencies or significant challenges. For Abu Dhabi Police, crisis management means the rapid and efficient response to various situations, from traffic accidents to potential terrorist threats. Historically, their approach has been a combination of manpower, conventional technologies, and strategic planning. However, the unpredictable nature of crises necessitates a more adaptable and intelligent response system.

One of the primary benefits of AI in crisis management is its ability to aid decision-making processes. Machine learning algorithms can analyze vast amounts of data at unparalleled speeds, offering insights that might be impossible or very time-consuming for humans to discern. In the context of the Abu Dhabi Police, AI systems can evaluate real-time data from various sources such as CCTV feeds, social media, traffic systems, and more. This data amalgamation offers a holistic view of a developing crisis, enabling quicker and more informed decisions. For instance, in managing traffic accidents, AI can predict congestion points and optimize the deployment of emergency services (Ali et al. 2023). The potential for AI to predict potential crisis points is another significant advantage. Predictive analysis uses past data to anticipate future events. Abu Dhabi Police could employ these predictive models to foresee potential areas of unrest, probable accident hotspots, or even potential criminal activities. Such foresight allows for a proactive approach, possibly preventing the crisis from occurring in the first place (Rashid, 2018).

However, the incorporation of AI in crisis management is not without its challenges. Data privacy and surveillance concerns are paramount. The utilization of AI in surveillance and predictive policing can inadvertently lead to the infringement of civil liberties. Additionally, while AI can enhance decision-making, it's not infallible. Biases in data or in the programming of the AI can lead to skewed or incorrect analyses, potentially exacerbating a crisis rather than mitigating it (Harari, 2018). Given the immense potential and challenges, the future of AI in Abu Dhabi Police's crisis management looks to be a blend of human expertise and technological assistance. The key is to strike a balance, ensuring that AI aids the decision-making process without completely sidelining human judgment. Training programs could be established to ensure officers understand the capabilities and limitations of AI, making them more effective partners in the crisis management process (Al-Raisi & Al-Khouri, 2017).

The integration of AI in the crisis management framework of Abu Dhabi Police signifies a transformative step towards a modern and efficient response system. While challenges exist, the potential benefits of predictive analysis, enhanced decision-making, and proactive policing are undeniable. As technology evolves, it is imperative for institutions like Abu Dhabi Police to adapt, ensuring that the safety and security of its citizens remain a top priority.

2.1.3 PREDICTIVE POLICING

Artificial Intelligence (AI) has made significant inroads into a variety of sectors and public services in the 21st century, transforming operations and efficiencies. One of the emergent AI applications, especially in law enforcement, is predictive policing. The Abu Dhabi Police, as part of their strategic vision to incorporate modern technologies for improved security, have started exploring predictive policing tools. Predictive policing involves utilizing algorithms, statistical analyses, and AI models to forecast potential criminal activities (Ali et al. 2023). It amalgamates massive datasets from crime reports, social media, and other sources to pinpoint potential hotspots or individuals prone to criminality. While predictive policing started as rudimentary statistical models, advancements in AI have now enabled real-time predictions with enhanced accuracy.

Abu Dhabi, as a burgeoning global hub, has witnessed an influx of diverse populations and rapidly evolving urban landscapes. While it boasts of one of the lowest crime rates globally, the challenges lie in managing potential crises before they escalate. Incidents like traffic congestions, protests, or even potential terrorist threats necessitate advanced tools for proactive measures. Predictive policing can aid in identifying patterns and trends before they culminate in significant crises (Mohler et al. 2015). Crisis management necessitates prompt and informed decisions to mitigate threats. By offering insights into potential crisis hotspots, predictive policing enables law enforcement to pre-position resources, engage in proactive community outreach, and deter potential culprits. For instance, if a particular sector in Abu Dhabi is predicted to witness a surge in traffic violations during a festival, pre-emptive measures can ensure smoother flow and fewer incidents.

While the prospects of predictive policing in crisis management are promising, ethical concerns loom large. Reliance on historical data can perpetuate systemic biases and lead to targeted surveillance of marginalized communities (Lum & Isaac, 2016). For the Abu Dhabi Police, it's imperative that any deployment of predictive policing tools remains transparent, unbiased, and constantly evaluated for potential discrimination. Acknowledging the global best practices and potential pitfalls, the Abu Dhabi Police have undertaken measures to implement AI in a balanced manner. They have collaborated with international AI experts, sought community feedback, and have instituted regular checks and balances in their predictive models. By ensuring that their models are transparent and adaptable, they strive to employ AI as a tool for public good, rather than unchecked surveillance.

The potential of AI in revolutionizing policing for Abu Dhabi is immense. Predictive policing, if executed with precision, transparency, and ethics, can transform crisis management from a reactive to a proactive endeavour. Future endeavours may also witness collaboration with tech companies, research institutions, and community organizations to refine and democratize predictive policing models. The dawn of AI in the realm of policing presents both unmatched opportunities and challenges. For the Abu Dhabi Police, predictive policing can serve as a lighthouse, guiding their crisis management strategies to ensure the safety and security of its citizens. While challenges exist, with a vigilant and progressive approach, the city can pave the way for an AI-driven policing model that is both effective and equitable.

2.1.4 DATA ANALYSIS

The 21st century has witnessed an acceleration of global crises, ranging from natural disasters to security threats. One of the most pressing challenges in the modern world is the need for effective crisis management. The Abu Dhabi Police, tasked with maintaining the safety and security of the emirate's citizens, has turned to artificial intelligence (AI) and data analysis as critical tools for responding to crises.

Crisis management involves a coordinated response to emergency situations, often characterized by uncertainty, risk, and time constraints (Smith, 2020). For police forces worldwide, especially in bustling urban areas like Abu Dhabi, responding rapidly and effectively to crises is paramount. However, traditional methods of crisis management may be inadequate given the complexity and dynamism of modern threats (Al-Khouri, 2017).

AI systems depend on vast amounts of data to learn and make decisions (Russell & Norvig, 2010). By analysing these datasets, AI algorithms can identify patterns, make predictions, and suggest optimal courses of action. In recent years, advances in data analytics have enabled the construction of AI models with unprecedented accuracy and utility. As Watson and Finn (2017) argue, "the marriage of AI and data analysis has created a transformative toolset for a variety of applications."

The Abu Dhabi Police has embraced technology as a cornerstone of its operations. Al-Raisi and Al-Khouri (2018) detail the police force's utilization of AI-driven data analytics in various capacities. For instance, predictive analytics aids in forecasting potential security threats or disturbances, allowing pre-emptive action. Additionally, AI-enhanced surveillance systems in Abu Dhabi use real-time data analysis to identify suspicious activities or individuals, facilitating rapid response (Ahmad & Hamdan, 2020). Abu Dhabi, being a global hub for tourism and events, often hosts large-scale gatherings, such as the Formula 1 Grand Prix. These events pose significant security and logistical challenges. By employing AI-driven data analysis, the Abu Dhabi Police can monitor crowd movements, predict potential flashpoints, and deploy resources effectively (Al-Mazrouei, 2021). Such measures not only ensure public safety but also enhance the overall experience for attendees.

While AI and data analysis present vast potential, there are limitations and ethical concerns. Reliance on AI can lead to over-automation, where human judgment is sidelined (Bostrom, 2014). Moreover, extensive surveillance and data collection might infringe upon individual privacy rights (Zuboff, 2019). The Abu Dhabi Police, like other institutions, must balance technological advancements with ethical imperatives. For AI and data analysis tools to be effective, proper training is essential. The Abu Dhabi Police has invested in capacity building, ensuring officers are well-versed in these technologies (Al-Neyadi & Al-Mazrouei, 2019). Moreover, collaborations with global tech firms and universities have facilitated knowledge exchange, fortifying the police force's capabilities.

The integration of AI-driven data analysis in crisis management reflects the Abu Dhabi Police's commitment to leveraging cutting-edge technologies for the well-being of its citizens. As the world grapples with ever-evolving challenges, such proactive and future-forward approaches will be instrumental in ensuring safety and resilience.

2.1.5 EMERGENCY RESPONSE

In the age of rapid technological advancements, Artificial Intelligence (AI) is shaping the dynamics of various sectors globally. One of the areas experiencing a profound transformation due to AI integration is emergency response and crisis management. The Abu Dhabi Police, known for their proactive approach to technological advancements, have championed the implementation of AI to bolster their crisis management capabilities (Al Ali, 2020). The inclusion of AI in the force's modus operandi promises faster response times, predictive analysis, and smarter coordination, thereby enhancing public safety and trust in the system. Emergency response systems are the linchpin of any successful police force. Their efficiency determines the timeliness and effectiveness of intervention in crises. Historically, Abu Dhabi Police, like many other police forces globally, depended on human-centric operations for crisis response. These methods, though effective, had their limitations in terms of speed, accuracy, and foresight (Al Muhairi, 2018). With Abu Dhabi's rapid urbanization and the UAE's vision of emerging as a global tech hub, it was only apt for the police to lean on AI to meet the evolving demands of urban security.

One of the most significant advantages AI brings to the table is its ability to process vast amounts of data in real-time (West, 2019). For a police force, this implies immediate access to relevant information during a crisis. With the integration of AI, Abu Dhabi Police can instantly collate data from various sources such as CCTV feeds, traffic sensors, social media, and emergency calls. This data amalgamation ensures the department gets a holistic view of the situation, enabling them to deploy resources more efficiently and make informed decisions promptly (Al Raisi, 2020).

While immediate response is crucial, the real power of AI in crisis management lies in predictive analytics. Leveraging vast datasets from past incidents, AI algorithms can recognize patterns and predict potential threats or disruptions (Brynjolfsson & McAfee, 2016). For Abu Dhabi Police, this means they can be more proactive rather than reactive. By identifying potential high-risk areas or situations before they escalate, resources can be pre-positioned, saving valuable time and potentially lives. Coordination during emergencies is vital. AI tools assist in ensuring seamless communication among various departments of the police and other emergency services. For example, chatbots and virtual assistants, powered by AI, can provide real-time updates to ground teams, ensuring everyone is on the same page (Smith, 2020). Moreover, with natural language processing capabilities, these tools can interpret and transmit multilingual communications, crucial feature given Abu Dhabi's cosmopolitan demographics.

Integrating AI does not just streamline operations internally for the Abu Dhabi Police; it also plays a pivotal role in fortifying public trust. Citizens can benefit from AI-powered platforms, providing them real-time updates and safety precautions during a crisis. Such transparency not only keeps the public informed but also empowers them to take proactive measures, resulting in a collaborative approach to crisis management (Kaplan & Haenlein, 2019).

The infusion of AI in emergency response and crisis management signifies a monumental shift in the paradigms of policing, especially in the dynamic and evolving landscape of Abu Dhabi. While the benefits are manifold, it is also essential to ensure the ethical use of AI and regular oversight to avoid potential pitfalls. The Abu Dhabi Police, by adopting AI-driven strategies, are setting a precedent not just for the region but for global police forces, heralding a new era of tech-driven policing that promises efficiency, foresight, and enhanced public trust.

2.2 AI TRAINING

AI training significantly enhances staff competency across various domains by developing advanced technical skills, improving problem-solving and decision-making capabilities, and fostering a culture of innovation. According to the World Economic Forum's "The Future of Jobs Report 2020," upskilling and reskilling programs, including those focused on AI, are crucial for preparing the global workforce for technological transformations. Training in AI equips staff with the expertise to effectively navigate and leverage AI tools, fostering proficiency in emerging technologies. Moreover, as highlighted by Barron & Harrow (2018) in the Journal of Artificial Intelligence Research, AI training enhances critical thinking and the ability to analyse complex datasets, enabling employees to make informed, data-driven decisions. This is particularly valuable across diverse sectors where decision-making is essential for success. Furthermore, AI training promotes innovation within organizations. As noted by Chen (2020) in the Harvard Data Science Review, well-versed staff in AI concepts are better positioned to identify opportunities for automation and AI-driven solutions, actively contributing to organizational goals.

AI training significantly enhances staff productivity across various industries by automating routine tasks, enabling employees to focus on more complex activities. According to McKinsey & Company, automation technologies, including AI, can potentially automate about 45% of paid activities, thus freeing up time for higher-value tasks (McKinsey, 2017). Through AI training, staff members acquire the skills necessary to implement and manage automation solutions, thereby increasing overall productivity. Furthermore, AI training empowers employees to leverage data-driven insights for informed decision-making. This enhanced data literacy, as highlighted by Thota (2019) in the Journal of Organizational Effectiveness: People and Performance, enables employees to efficiently analyse and interpret information, leading to more strategic actions. Additionally, AI training fosters a culture of continuous learning and adaptability. Ongoing training ensures that staff remains current with the latest advancements, crucial for organizations aiming to stay competitive. A white paper by PwC emphasizes the importance of upskilling and reskilling employees to meet digital age demands, highlighting AI training as essential for building a skilled and agile workforce (PwC, 2021).

2.3 CRISIS MANAGEMENT IN ABU DHABI POLICE UAE

The Abu Dhabi Police, a key component of the UAE's law enforcement, plays a crucial role in maintaining safety, order, and public trust in Abu Dhabi. Beyond traditional policing, they manage complex crises such as natural disasters, terrorism, and major accidents. According to Neyroud et al. (2023), the police are committed to a proactive and integrated crisis management approach, coordinating with local and federal entities, conducting rigorous training, and running public awareness campaigns (Hussain et al. 2023). AI applications have significantly enhanced their crisis management capabilities. The integration of AI in various aspects of their operations allows for real-time data analysis, predictive policing, and efficient resource allocation. For instance, AI-powered surveillance systems and drones provide advanced monitoring and rapid response during crises, ensuring public safety. AI also facilitates better decision-making through predictive analytics, helping to anticipate potential threats and optimize response strategies.

The integrated framework ensures collaboration with various governmental and non-governmental entities, exemplified by the Abu Dhabi Emergency, Crisis, and Disasters Committee. This committee comprises representatives from multiple sectors, facilitating a multi-faceted emergency response. The Abu Dhabi Police have conducted joint exercises and simulations with the armed forces and civil defense to ensure a coordinated crisis response (Gulf News, 2019). Training is a cornerstone of their strategy, with advanced courses for officers focusing on capacity building, strategic decision-making, and using the latest technologies, including AI (The National, 2016). The adoption of AI technologies such as smart towers, facial recognition systems, and advanced surveillance capabilities enables rapid and informed responses during crises (Khaleej Times, 2018).

Effective crisis management also involves proactive public engagement. The Abu Dhabi Police run public awareness campaigns and use social media to provide timely updates, leveraging AI-driven tools for better communication and outreach. This approach strengthens public trust and ensures safety during emergencies (Abu Dhabi Police Official Portal, 2020). In summary, the Abu Dhabi Police's commitment to an integrated, technologically advanced, and community-centric crisis management approach, enhanced by AI applications, positions them as a model for other entities. This approach emphasizes anticipation, collaboration, rapid response, and public trust, demonstrating how AI can be leveraged to improve crisis management outcomes.

3. FORMULATING CONCEPTUAL FRAMEWORK

A conceptual framework is a research tool that illustrates the ideas and beliefs guiding a study, providing a structure to support its theory. It identifies key concepts or variables and elucidates their relationships, offering clarity for interpreting study findings (Varpio et al. 2020). The framework can be developed from existing theories, previous research, or new ideas, forming the basis for specifying research objectives and hypotheses (Scudder & Colson, 2019). Hypotheses, derived from the framework, are testable predictions about relationships between variables that set the stage for further investigation. The framework proposes relationships that can be empirically tested, supporting or refuting the theory (Kaimowitz et al. 2019).

In the context of this study, the framework includes independent variables (IV) representing AI application factors, categorized into Surveillance, Security, Predictive Policing, Data Analysis, and Emergency Response. The dependent variable (DV) is Crisis Management within the Abu Dhabi Police, UAE, with the mediator being AI training. Utilizing the principle of causal relationship theory (Sfetcu 2020), this study aims to elucidate the intricate dynamics among these variables, illustrating how AI training can impact crisis management outcomes, as depicted in the conceptual framework shown in Figure 1.

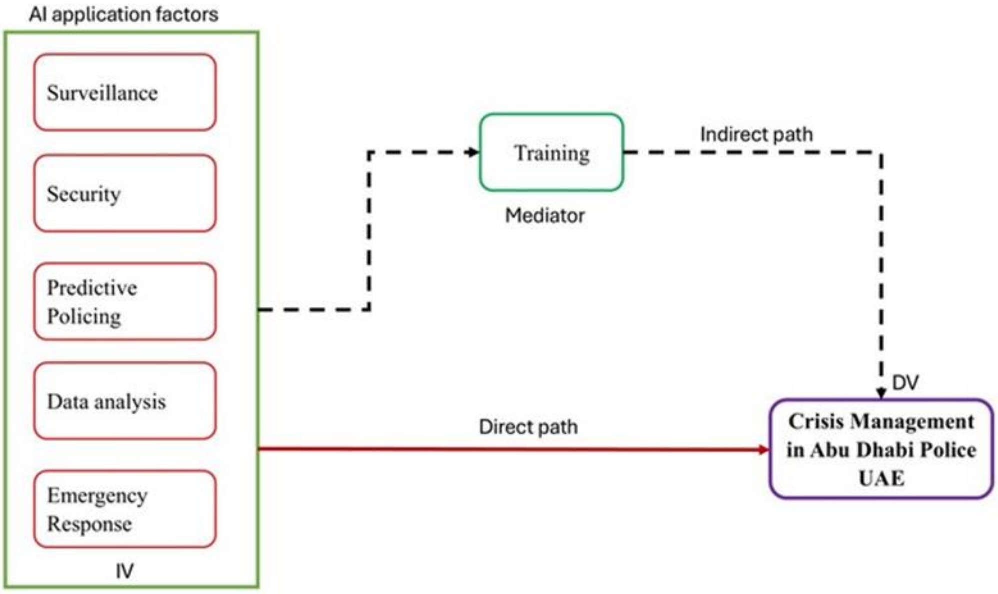

Figure 1: Conceptual framework

4. VALIDATING CONCEPTUAL FRAMEWORK

Structural Equation Modelling (SEM) is widely divided into two approaches: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) (Memon et al. 2015). CB-SEM replicates the covariance matrix of observed data and is commonly used for hypothesis testing and confirmation. It necessitates high sample sizes and emphasises the model's overall goodness-of-fit with the data. CB-SEM is well-suited for complicated theoretical models and is implemented using software such as AMOS, LISREL, and Mplus (Kline 2015).

In contrast, PLS-SEM is a variance-based technique that seeks to maximise the explained variance of the dependent variables (Memon 2013). It is more adaptable in terms of sample size and is frequently used for exploratory research and theory development. PLS-SEM is especially useful for predictive modelling and can handle complicated models with many components and indicators. SmartPLS and WarpPLS (Hair et al. 2017) are popular software platforms for implementing PLS-SEM. These two methodologies serve unique research purposes, offering researchers versatile tools based on their analytical goals and the type of their data.

Given that the goal of this study is to test a conceptual framework and investigate complicated interactions between components, the use of Partial Least Squares Structural Equation Modelling (PLS-SEM) is particularly relevant. Its adaptability for exploratory research and its capacity to handle sophisticated models make it perfect for studying the dynamic interactions within the proposed framework (Hair et al. 2017).

This study specifically uses PLS-SEM to investigate the impact of AI application elements, namely Surveillance, Security, Predictive Policing, Data Analysis, and Emergency Response, on Crisis Management, with AI training acting as a mediating variable. This method allows for a full examination of the interrelationships between these constructs and the building of a predictive model that may assist strategic decision-making and policy formation in the context of law enforcement and crisis management in the Abu Dhabi Police.

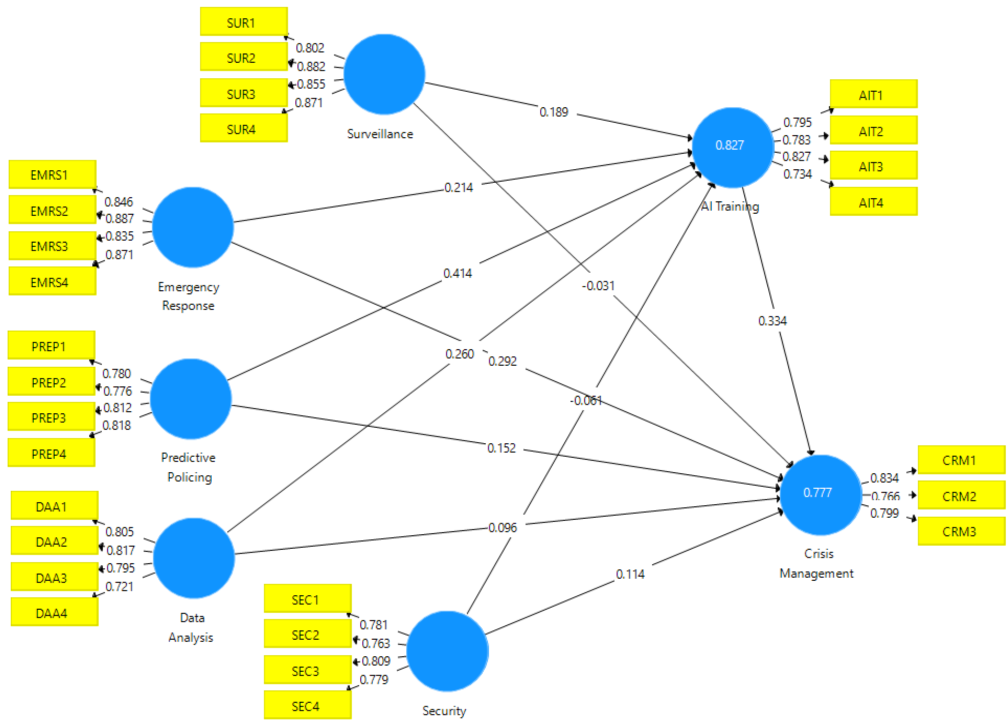

Figure 2: Model after PLS algorithm process

4.1 EVALUATION OF MEASUREMENT MODEL

After constructing the model in SmartPLS software, it is assessed using the PLS Algorithm function. The measurement component of the model is evaluated based on two main parameters: construct reliability and validity, and discriminant validity. Construct reliability and validity ensure that the constructs used in the model are consistent and accurately represent the intended variables. Discriminant validity confirms that the constructs are distinct and measure different concepts, which is crucial for the model's overall accuracy and robustness.

4.1.1 CONSTRUCT RELIABILITY AND VALIDITY

The matrix of construct reliability and validity typically includes measures such as Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) to assess the reliability and validity of the constructs. For Cronbach's Alpha, it indicates the internal consistency of the constructs, with values above 0.7 generally considered acceptable (Nunnally & Bernstein, 1994; Zainun et al. 2014). Composite Reliability measures the reliability of the constructs, with values above 0.7 indicating good reliability (Hair et al. 2010). Average Variance Extracted (AVE) assesses the amount of variance captured by the construct compared to the variance due to measurement error. Values above 0.5 are desirable, indicating that the construct explains more than half of the variance of its indicators (Fornel & Larcker, 1981). This matrix helps ensure that the constructs used in the study are reliable and valid, supporting the robustness of the measurement model (Hair et al. 2010; Almanssori et al. 2021).

Table 1: Matrix of Construct reliability and validity

Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)

0.793	0.794	0.866	0.617
0.718	0.719	0.842	0.64
0.792	0.791	0.866	0.617
0.882	0.883	0.919	0.74
0.808	0.808	0.874	0.635
0.79	0.79	0.864	0.613
0.875	0.88	0.914	0.727

Table 1 presents key metrics for evaluating the reliability and validity of constructs used in a study. Cronbach's Alpha indicates internal consistency, with values above 0.7 generally considered acceptable for reliable constructs. Rho_A is another reliability measure, similar to Cronbach's Alpha, assessing the consistency of indicators within a construct. Composite Reliability measures the overall reliability of a construct, with values above 0.7 indicating good reliability. Average Variance Extracted (AVE) assesses the amount of variance captured by the construct compared to the variance due to measurement error. Values above 0.5 are desirable, indicating that the construct explains more than half of the variance of its indicators. Each row represents a different construct in the study, with values provided for Cronbach's Alpha, rho_A, Composite Reliability, and AVE, ensuring that all constructs meet the necessary reliability and validity criteria.

4.1.2 DISCRIMINANT VALIDITY

The Fornell-Larcker criterion evaluates discriminant validity by comparing the square root of the Average Variance Extracted (AVE) of each construct to the correlations with other constructs. The diagonal values in the table, representing the square root of the AVE for each construct, should be higher than the off-diagonal values in the same row and column. This indicates that the construct shares more variance with its own indicators than with other constructs, thus confirming discriminant validity (Fornel & Larcker, 1981 as cited by Rahman et al. 2013).

Table 2: Matrix of Construct reliability and validity

Constructs	**AI Training**	**Crisis Management**	**Data Analysis**	**Emergency Response**	**Predictive Policing**	**Security**	**Surveillance**
AI Training	0.786						
Crisis Management	0.841	0.845					
Data Analysis	0.820	0.787	0.860				
Emergency Response	0.796	0.804	0.784	0.812			
Predictive Policing	0.851	0.793	0.764	0.729	0.863		
Security	0.782	0.756	0.820	0.697	0.806	0.832	
Surveillance	0.735	0.655	0.664	0.626	0.693	0.777	0.853

Table 2 shows that the square root of the AVE for AI Training is 0.786, which is higher than its correlations with other constructs such as Crisis Management (0.841) and Data Analysis (0.820). Similarly, each construct in the table has its square root of the AVE value bolded along the diagonal, showing that they are distinct from one another as unique measures. This demonstrates that the constructs in the study have good discriminant validity, meaning they are sufficiently distinct from each other. The discriminant validity, illustrated by the Fornell-Larcker criterion, supports the robustness of the measurement model used in the study.

4.3 EVALUATION OF STRUCTURAL MODEL

Evaluation of the structural component of the model is conducted after the bootstrapping process. This process involves generating multiple subsamples from the original data to assess the stability and accuracy of the parameter estimates. Once bootstrapping is complete, various criteria are used to evaluate the structural model, including path coefficients, t-values, and p-values (Hair et al. 2017). These criteria help determine the significance and strength of the relationships between constructs in the model. Additionally, the coefficient of determination (R^2) is assessed to evaluate the model's explanatory power (Chin 1998). This comprehensive evaluation ensures that the structural model is robust and reliable, providing meaningful insights into the relationships among the variables (Hair et al. 2010).

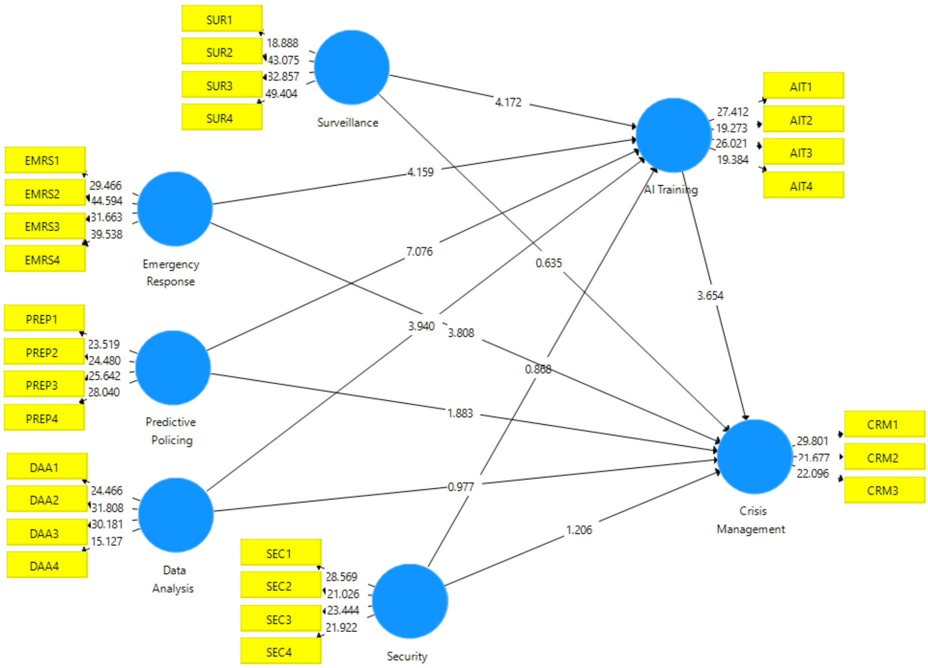

Figure 3: Model after bootstrapping process

4.3.1 QUALITY OF THE MODEL (R^2 VALUE)

The quality of the model is reflected through the R^2 values of the endogenous constructs. In this case, the constructs are AI training as the mediator and crisis management as the dependent construct. The generated R^2 values are shown in Table 3.

Table 3: R^2 values of endogenous constructs

Endogenous construct	R Square
AI Training - Mediator	0.827
Crisis Management – Dependent construct	0.777

Table 3 shows the R Square values for the endogenous constructs in the model, which indicate the proportion of variance in the dependent variables explained by the independent variables. AI Training as a mediator has an R Square value of 0.827, suggesting that 82.7% of the variance in AI Training can be explained by the independent variables in the model. This high value indicates a strong explanatory power, reflecting the significant influence of the factors considered in the model (Hair et al. 2017).

Crisis Management serves as a dependent construct with an R Square value of 0.777, meaning that 77.7% of the variance in Crisis Management is explained by the model's independent variables. This also demonstrates a substantial explanatory capacity, highlighting the model's effectiveness in capturing the key factors affecting crisis management Chin (1998). These R Square values suggest that the model is robust and provides a meaningful understanding of the factors influencing both AI Training and Crisis Management (Hair et al., 2010).

4.3.2 MODEL FIT

Model fit assesses how well a statistical model describes the observed data. Important indices include SRMR (acceptable if < 0.08), d_ULS, d_G (lower values indicate better fit), Chi-Square (non-significant is better but sensitive to sample size), and NFI (values closer to 1 are better) [68].

Table 4: Results of model fit

Model Fit Index	Saturated Model	Estimated Model
SRMR	0.076	0.076
d_ULS	2.196	2.196
d_G	1.119	1.119
Chi-Square	2419.243	2419.243
NFI	0.711	0.711

Table 4 show the the summary of how well the model fits the data. SRMR (Standardized Root Mean Square Residual): An index that measures the difference between the observed and predicted correlations. A value of 0.076 indicates an acceptable fit, as values below 0.08 are generally considered acceptable. d_ULS (Squared Euclidean Distance): This index measures the discrepancies between the observed and modeled matrices. A value of 2.196 suggests a reasonable level of fit. d_G (Geodesic Distance): Similar to d_ULS, this index also assesses the fit by measuring the distance between the observed and model-implied matrices. A value of 1.119 indicates a good fit. Chi-Square: This statistic tests the overall fit of the model. A chi-square value of 2419.243 indicates the model fits the data reasonably well, although lower values are preferable. NFI (Normed Fit Index): An index that compares the fit of the model to a null model. An NFI value of 0.711 indicates moderate fit, as values closer to 1 represent better fit.

Both the saturated model and the estimated model have the same values for each index, suggesting that the hypothesized model fits the data as well as the fully specified saturated model, which includes all possible paths.

4.3.3 PATH ANALYSIS

This study employs a mediation model, incorporating both direct and indirect relationships. The direct relationships are between the independent variables (IV) and the mediator, as well as between the mediator and the dependent variable (DV). In contrast, the indirect relationships involve the IVs influencing the DVs through the mediator. The results from the bootstrapping process, which provide insights into these relationships, are detailed in Table 5 and 6.

Table 5: Direct relationships

Direct relationship [IV to Mediator] and [IV to DV] and [mediator to DV]	**Path strength** [Beta value]	**T Statistics** >1.96	**Status**
AI Training -> Crisis Management	0.334	3.654	Significant
Data Analysis -> AI Training	0.260	3.94	Significant
Data Analysis -> Crisis Management	0.096	0.977	Not Significant
Emergency Response -> AI Training	0.214	4.159	Significant
Emergency Response -> Crisis Management	0.292	3.808	Significant
Predictive Policing -> AI Training	0.414	7.076	Significant
Predictive Policing -> Crisis Management	0.152	1.883	Significant
Security -> AI Training	-0.061	0.868	Not Significant
Security -> Crisis Management	0.114	1.206	Not Significant
Surveillance -> AI Training	0.189	4.172	Significant
Surveillance -> Crisis Management	-0.031	0.635	Not Significant

Table 5 presents the direct relationship results generated from the bootstrapping process. For the direct relationship between the independent variables (IV) and the mediator (AI Training), four out of five relationships are significant, with only the Security to AI Training relationship being non-significant. In terms of strength, the strongest relationship is between Predictive Policing and AI Training, with a beta value of 0.414. Regarding the direct relationship between the independent variables (IV) and the dependent variable (DV, Crisis Management), three out of five relationships are not significant, which are Data Analysis to Crisis Management, Security to Crisis Management, and Surveillance to Crisis Management. The strongest relationship in this context is between Emergency Response and Crisis Management, with a beta value of 0.292. Finally, the relationship between the mediator (AI Training) and the DV (Crisis Management) is significant, with a beta value of 0.334.

Table 6: Indirect relationships

Indirect relationship [IV to Mediator to DV]	**Path strength** [Beta value]	**T Statistics** >1.96	**Status**
Surveillance -> AI Training -> Crisis Management	0.063	2.651	Significant
Emergency Response -> AI Training -> Crisis Management	0.071	2.766	Significant
Predictive Policing -> AI Training -> Crisis Management	0.138	3.225	Significant
Security -> AI Training -> Crisis Management	-0.020	0.793	Not Significant
Data Analysis -> AI Training ->	0.087	2.462	Significant

Table 6 shows the indirect relationship results between the independent variables (IV), the mediator (AI Training), and the dependent variable (DV, Crisis Management). The strongest and significant indirect relationship is the Predictive Policing -> AI Training -> Crisis Management pathway, with a beta value of 0.138. This is followed by the Data Analysis -> AI Training -> Crisis Management pathway, which has a beta value of 0.087. The Emergency Response -> AI Training -> Crisis Management pathway comes next, with a beta value of 0.071. Finally, the Surveillance -> AI Training -> Crisis Management pathway has a beta value of 0.063. Unfortunately, the relationship of Security -> AI Training -> Crisis Management, which has a beta value of -0.020, is not significant. These findings highlight that AI Training mediates the relationships between Predictive Policing and Crisis Management, Data Analysis and Crisis Management, Emergency Response and Crisis Management, and Surveillance and Crisis Management, but does not mediate the relationship between Security and Crisis Management.

Previous studies have also explored the role of AI in crisis management. For instance, Bjola (2022) discusses how AI can assist diplomats and decision-makers in managing international crises by providing descriptive, predictive, and prescriptive analytics. Similarly, Comes (2024) highlights the potential of AI to support rapid decision-making during urban crises. Darban et al. (2023) emphasize the importance of AI in enhancing crisis management capabilities, aligning with the findings presented in Table 6. These studies underscore the significance of AI training in mediating the effects of various factors on crisis management, reinforcing the importance of integrating AI technologies into strategic planning and decision-making processes.

4.3.3 PREDICTIVE RELEVANCE (Q^2 value)

Predictive Relevance is measured through Q^2 values, generated using the blindfolding procedure. This technique assesses the model's predictive accuracy by systematically omitting and predicting data points. A Q^2 value greater than zero indicates that the model possesses predictive relevance. Construct Cross-Validated Redundancy (CVR) and Construct Cross-Validated Communality (CVC) are key metrics derived from the blindfolding process. CVR indicates how well the model can predict the omitted data points, while CVC assesses the proportion of the variance in the indicators explained by the latent constructs. High values of CVR and CVC suggest strong predictive relevance and a robust model.

Table 7: Results of Cross-Validated Redundancy (CVR)

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
Mediator - AI Training	1592	805.137	0.494
DV - Crisis Management	1194	624.213	0.477
Data Analysis	1592	1592	
Emergency Response	1592	1592	
Predictive Policing	1592	1592	
Security	1592	1592	
Surveillance	1592	1592	

Table 7 presents the results of Cross-Validated Redundancy (CVR) for various constructs. The Q^2 values indicate the predictive relevance of the model for each construct. AI Training (Mediator) has a Q^2 value of 0.494, suggesting moderate predictive relevance. Crisis Management (Dependent Variable) has a Q^2 value of 0.477, also indicating moderate predictive relevance. The other constructs like Data Analysis, Emergency Response, Predictive Policing, Security, and Surveillance do not have Q^2 values calculated, as their SSO and SSE values are equal, implying no redundancy. These results highlight the model's ability to predict outcomes for AI Training and Crisis Management constructs effectively.

Table 8: Results of Construct Cross-Validated Communality (CVC)

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
AI Training	1592	1020.702	0.359
Crisis Management	1194	855.566	0.283
Data Analysis	1592	1020.798	0.359
Emergency Response	1592	711.468	0.553
Predictive Policing	1592	979.578	0.385
Security	1592	1031.376	0.352
Surveillance	1592	738.566	0.536

Table 8 presents the results of Construct Cross-Validated Communality (CVC) for various constructs, with Q^2 values indicating the degree to which each construct's variance is explained by its indicators. AI Training has a Q^2 value of 0.359, indicating moderate communality. Crisis Management has a Q^2 value of 0.283, suggesting lower communality. Data Analysis shows a Q^2 value of 0.359, indicating moderate communality. Emergency Response has the highest Q^2 value of 0.553, indicating strong communality. Predictive Policing shows a Q^2 value of 0.385, indicating moderate communality. Security has a Q^2 value of 0.352, suggesting moderate communality. Surveillance has a Q^2 value of 0.536, also indicating strong communality. These results highlight that Emergency Response and Surveillance have the highest communality values, suggesting that a substantial portion of the variance in these constructs is explained by their respective indicators. In contrast, Crisis Management has the lowest communality, indicating that less of its variance is explained by its indicators.

The results of Cross-Validated Redundancy (CVR) demonstrate the model's effective predictive ability for the AI Training and Crisis Management constructs. Meanwhile, Construct Cross-Validated Communality (CVC) shows that Emergency Response and Surveillance have the highest communality values, meaning a substantial portion of their variance is explained by their indicators. Conversely, Crisis Management has the lowest communality, indicating less variance explained by its indicators. Hence, while the model demonstrates strong predictive relevance for AI Training and Crisis Management, the communality results suggest that Emergency Response and Surveillance are better explained by their respective indicators. This implies that these constructs are more robust and reliable within the model, while Crisis Management may require further refinement to improve its explanatory power. These insights can guide future improvements and optimizations of the model.

5. CONCLUSION

In conclusion, this study demonstrates that integrating AI into crisis management can significantly enhance decision-making, operational readiness, and efficiency in high-pressure scenarios. AI's predictive analytics and real-time data processing capabilities are particularly advantageous for addressing complex crises. The study on the mediating effect of AI Training on the relationship between AI application factors and Crisis Management for the Abu Dhabi Police Department reveals that the model is robust, with meaningful insights into the factors influencing both AI Training and Crisis Management. The SEM-PLS analysis of data from 346 employees indicates that the constructs have moderate explanatory power, suggesting robustness and reliability. The model fit analysis confirms that the hypothesized model aligns well with the data. Path analysis highlights that AI Training effectively mediates relationships between Predictive Policing, Data Analysis, Emergency Response, Surveillance, and Crisis Management, but not between Security and Crisis Management. These findings underscore the importance of integrating AI training within police departments to optimize crisis management strategies. By enhancing decision-making processes, operational readiness, and efficiency, police departments can be better equipped to handle complex crises, ensuring improved public safety and resource allocation.

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