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Application of Advanced Technology in Criminal Investigation with Mediating Effects of Technology Training

Abdulla Nasser Salem Nasser Alhadhrami

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

Suzalkimin Mohamed (Corresponding Author)

Faculty of Technology Management and Business

Universiti Tun Hussein Onn Malaysia, Malaysia

E-mail: zakimin@uthm.edu.my

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Abstract

Proactive strategies and tactics are essential in combating crime, making technology-assisted crime prevention methods crucial for effective law enforcement. Technological advancements have provided new perspectives and innovations beyond conventional tactics. This study explores the impact of advanced technological tools on crime investigations, emphasizing the importance of technology training as a mediating factor through the development of a model. Data for this model was collected from 375 respondents from key departments such as the General Department of Criminal Investigations (CID), the General Department of Forensic Science and Criminology (FSCD), and the Operations Division and analyzed using Smart-PLS software. The model revealed that training has a significant positive impact on the relationship between technology use and crime investigation outcomes, with a path coefficient of 0.269 (t-statistic = 6.921, p = 0.000). Specifically, License Plate Recognition (LPR) systems showed a strong positive impact (path coefficient = 0.628, t-statistic = 12.226, p = 0.000), and Crime Mapping Software (CM) also contributed positively (path coefficient = 0.471, t-statistic = 5.871, p = 0.000). However, Facial Recognition (FR) and Crime Cameras (CC) demonstrated negative impacts, with path coefficients of -0.250 and -0.252, respectively. The study concludes that the strategic integration of technology and comprehensive training is crucial for optimizing criminal investigation processes within the Abu Dhabi Police. It emphasizes the need for ongoing adaptation and investment in both technology and training to enhance law enforcement capabilities in the UAE.

Keywords: Technology-Assisted Crime Prevention, Technology Training, Crime Investigation Outcomes

1. Introduction

Proactive strategies and tactics are essential in the fight against crime, making technology-assisted crime prevention methods crucial for effective law enforcement. Technological advancements have provided new perspectives and innovations beyond conventional tactics (Wienroth, 2023). Police departments categorize crimes based on type, magnitude, and frequency, employing criminal analysts with interdisciplinary knowledge and IT skills to identify crime patterns and relationships (Hardyns, Pauwels, & Heylen, 2018).

In an ideal scenario, law enforcement agencies would fully integrate advanced technologies to combat crime effectively, ensuring efficient criminal investigations and public safety. However, the UAE Police, like many departments, show limited utilization of cutting-edge technology in criminal investigations due to challenges such as language barriers in training, cultural complexities, and budget constraints (Hardyns, Pauwels, & Heylen, 2018). Collaboration between police procedures and technological advancements is vital for strategic crime prioritization, particularly in addressing drug-related offenses, gang activities, and property crimes (Griffen, 2022). Such hindrances as linguistic and cultural differences and even less significant budgetary reasons significantly complicate the training conducted in the UAE. Using technology successfully would necessitate translated materials, cost-efficient solutions, and applicable courses to carry this out.

If this trend continues, the sophistication of crimes, particularly those associated with technological advancements such as fraud and cybercrime, will outpace law enforcement's capacity to respond effectively, thus leaving communities exposed to an increase in criminal activity. Ineffective use of technology, brought about by a lack of proper training and resource inadequacies, can also be used to widen the gap between criminal activity and law enforcement responses. While facial recognition technology potentially becomes useful for evidence, challenges concerning biases and accuracy need proper examination before they may widely spread (Alshamsi, Isaac, & Bhaumik, 2019). In addition to these efforts, statistics in criminal investigations by the Abu Dhabi Police are not easily evaluated because the statistics used are not transparent enough in the United Arab Emirates. With pickpocketing and ATM skimming-related risks, crime is still a problem (Alshamsi, Isaac, & Bhaumik, 2019; Albaloushi, 2019).

In contrast to previous studies that focus on widespread technological adoption, this study evaluates the unique influence of technology on improving investigative outcomes in Abu Dhabi, weighing its advantages and disadvantages (Wienroth, 2023). Additionally, it looks at how proper training can mediate the successful integration of technology into law enforcement procedures. An understanding of the distinct technological requirements and potential available solutions for Abu Dhabi's law enforcement agencies will increase crime detection, prevention, and public safety within the United Arab Emirates.

To understand the impact of state-of-the-art technological tools on the criminal investigations performed by the Abu Dhabi Police, specifically on the strategic integration of these tools and intensive training that will usually improve law enforcement. The study, based on the use of crime mapping, data mining, car cameras, body-worn cameras, and license plate readers as independent variables, then creates a conceptual framework to incorporate training as the mediating variable and criminal investigation within the Abu Dhabi Police as the dependent variable (Nikoloska, 2017).

2. Literature Review

2.1 UAE Police Adopting Technology

The newest technology, brain fingerprinting, is applied by the Dubai Police to increase efficiency in their criminal investigations. In doing so, neuroscience has now found a place at the front of 21st-century law enforcement. By means of memory print technology, the new approach follows suspects' brain activity while the case is still pending, forcing them to wear a skullcap equipped with electrodes. The device is said to detect the P300 signal when suspects are exposed to specific images or objects related to the crime, which in turn indicates the identification of details related to the crime (Alosani, Yusoff, & Al-Dhaafri, 2020).

After one year of evaluation, this technology was implemented, and proved that Dubai Police are very cautious in putting high-tech solutions into their crime investigations (Elnaghi, Alshawi, Kamal, Weerakkody, & Irani, 2019). The UAE has never been more serious than now in using state-of-the-art technology in safeguarding public safety and in the enforcement of law. Furthermore, the proactive use of advanced technologies in improving policing capabilities and maintaining the reputation of being one of the safest countries in the world is demonstrated by the utilization of brain fingerprinting by the UAE (Fakhari, Din, & Romle, 2021). However, the use of such advanced technologies poses big ethical and legal questions. Questions about privacy, consent, and the reliability of the technology are raised by the potential implications for using brain activity as evidence in court. Thus, in this regard, the integration of "brain fingerprinting" into the legal system rests on its implementation being compliant with moral values and securing individual rights. In addition, the use of brain fingerprinting by Dubai Police is part of a bigger strategy to implant high-tech technology in many sectors of law enforcement. This strategy prevents and curbs criminal activities through smart data analytics, predictive policing algorithms, and intelligent surveillance systems. Hence, through careful embedding of technology into the police tactics, the commitment of the UAE to building a technologically sophisticated and secure society is demonstrated (Fakhari, Din, & Romle, 2021).

Although brain fingerprinting has dramatically enhanced criminal investigations, caution must be taken concerning its ethical and legal implications. Hence, in showing that advanced technologies can be brought to improve public safety and justice, UAE's commitment to innovative police work provides a template to other jurisdictions. But to manage the challenges that progress causes, there should be continuous communication among ethicists, law specialists, and policymakers in keeping the balance between the discovery of something new and the rights of a person (Alosani, Yusoff, & Al-Dhaafri, 2020). Besides brain fingerprinting, this research identifies five technological components used by the police forces in the UAE, including: license plate readers, body-worn cameras, automobile cameras, face recognition, and crime mapping.

Crime mapping helps law enforcement officers to come up with policies and deploy resources since, by using GIS, it tries to visualize and analyse the patterns related to space and crime (Johnson, Summers, & Pease, 2009). Face recognition technology uses technology to identify a person as compared to their facial feature shown in digital photos or frames of videos for surveillance purposes and in investigation (Phillips, Flynn, Scruggs, Bowyer, Chang, Hoffman, … Worek, 2005). Another technique of continuous video surveillance of public places is the utilization of car cameras, commonly known as CCTV. It helps in the investigation and prevention of crime and provides live recording (Armitage, 2002). Similarly, body-worn cameras are used by law enforcement officers to record interactions with the public, promoting accountability and transparency while reducing complaints and use-of-force incidents (Ariel, Farrar, & Sutherland, 2015). Finally, license plate readers automatically capture and analyse vehicle license plate numbers, assisting in tracking stolen vehicles and identifying vehicles of interest, though raising privacy concerns (Lum, Hibdon, Cave, Koper, & Merola, 2011). These technological items are used as independent constructs for the model.

2.1.1 Crime Mapping

Police departments use GIS-based crime mapping software to digitally map, visualize, and evaluate reports on crime trends and quality of life over time and space. This technology helps police officers place themselves strategically by highlighting crime pathways and identifying crime clusters. GIS also enables the integration of crime incident data with census demographics or land-use data for a more comprehensive understanding of criminal incidents (Ristea & Leitner, 2020; Anderson, 2010). Despite its widespread use, there is little research on the effectiveness of computerized crime mapping across various law enforcement agencies, and what little that is available focuses primarily on specific GIS-reliant policing strategies. Hemming (Hemming, Hanea, Walshe, & Burgman, 2020), Vivanco (Vivanco, 2019) and Fitzpatrick (Fitzpatrick, Gorr, & Neill, 2019) have all demonstrated that proactive strategies, such as risk terrain mapping and hot-spot policing, are effective in crime reduction and strategic deployment.

Assessing the prevalence of GIS use in law enforcement is difficult because of the diverse methodologies and levels of integration. Some agencies utilize GIS to visualize local crimes, while others conduct comprehensive spatial analyses to comprehend the correlation between crime and physical or social factors (Phalane, 2020). The use of GIS varies by geographic location and agency size; larger, more urban agencies are more likely to employ this technology (Russo, 2021; Zehr, 2019). Technical challenges, inadequate documentation, and insufficient user training impede the integration of crime mapping. Despite the challenges, GIS offers significant advantages to law enforcement (Mohamed, Al-Jaroodi, & Jawhar, 2020; Moshood, Nawanir, Sorooshian, Mahmud, & Adeleke, 2020).

2.1.2 Face Recognition

Facial recognition software relies on the principle of face matching, where two faces are compared to determine similarity without relying on memory. This software quantifies differences in facial features, such as nose shape and lip thickness, to identify and match faces. In law enforcement, humans have traditionally matched faces, with some individuals known as “super recognizers” being exceptionally skilled at this task. Facial recognition algorithms typically follow five steps: detection, alignment, normalization, representation, and matching. The algorithm first identifies basic facial traits, aligns the face for accurate analysis, normalizes the image, converts measurements into a code, and finally matches the face data with stored information. Law enforcement agencies, including the UAE Department of Public Safety and the Abu Dhabi police, have adopted facial recognition software to enhance criminal investigations, primarily using it for identification in active cases rather than surveillance. Despite its benefits, the use of this technology raises privacy concerns and legal restrictions (Stacchi, Huguenin-Elie, Caldara, & Ramon, 2020; Robertson, Noyes, Dowsett, Jenkins, & Burton, 2016; Bonsor & Johnson, 2001; Schuba, 2020).

2.1.3 Car Cameras

Dashboard cameras, or dash cams, became widely used in police patrol cars in the early 2000s, driven by increased awareness of drunk driving, the war on drugs, claims of institutional bias, and calls for greater officer safety (Bhikarry, 2020). The Department of Justice’s COPS division launched the In-Car Camera Incentive Program in the late 1990s, significantly boosting the adoption of in-car cameras by providing funding to state police agencies. By 2004, more than 75% of state and highway patrol agencies had in-car video systems, up from just 11% in 2000. Municipal governments have also increasingly adopted these systems, with 68% of local police agencies using them by 2013, according to a survey (Diab & Putnam, 2021).

Research by the International Association of Chiefs of Police (IACP) in 2002 highlighted several benefits of in-car cameras, including increased agency accountability, positive community attitudes, reduced officer misconduct, and valuable footage for training and court prosecutions. However, issues such as the high demands of storing video evidence, different technological formats, maintenance costs, poor audio quality, and limited audio transmitter range were identified. Concerns also arose about officers feeling monitored and lacking training on using the equipment. While the IACP study provided insights into the use of in-car cameras, it mainly focused on state police agencies and did not address the majority of law enforcement agencies, such as city and county sheriff's offices. Additionally, it did not differentiate between agencies that use or do not use in-car cameras, despite all sampled agencies receiving funding to install them.

2.1.4 Body-Worn Cameras (BWC)

Following high-profile police encounters in various cities, Body-Worn Cameras (BWCs) have garnered significant public attention. Approximately one-third of local police departments currently use BWCs, with expectations for this number to increase (Reaves, 2015). President Obama proposed reimbursing cities for half the cost of BWCs in 2014 (Koper & Lum, 2019). While officers report benefits like resolving complaints and enhancing accountability, concerns about privacy and community trust persist (Miller & Toliver, 2014).

Studies reveal BWCs can reduce citizen complaints and use-of-force incidents. For example, the Rialto Police Department saw complaints drop significantly with BWC use, and similar positive results were observed in Mesa and Phoenix (Taylor & Lee, 2019; Snyder, Crow, & Smykla, 2019). However, problems like implementation costs, privacy, and data management still exist. Establishing precise guidelines and requesting community input is crucial for the ethical and successful implementation of BWC use. Stakeholders must work together and carry out regular assessments in order to maximize the benefits of BWCs and responsibly handle concerns.

BWCs aim to increase accountability, transparency, and trust between the community and law enforcement. Despite their potential, the complexity of privacy concerns, legal issues, and the need for cautious policymaking highlights how important it is to have ongoing conversations and research to maximize their use (Ariel et al., 2016).

2.1.5 License Plate Reader (LPR)

Automated license plate readers (LPRs), which are high-speed cameras capable of reading and recording hundreds of license plates per minute, record the date, time, and location of each scan. These devices, which can be mobile or stationary, alert patrolling officers when matches are found between collected data and hotlists kept by the agency. Privacy concerns have led to calls for more stringent regulations, even though LPRs aid law enforcement in better-identifying suspects and stolen vehicles. The American Civil Liberties Union (ACLU) and other advocates have expressed concerns about the potential for widespread surveillance and the erosion of privacy rights, which has led some states to restrict their use. Research indicates that larger law enforcement agencies are more likely to adopt LPR technology, with varying degrees of implementation and effectiveness.

Despite their advantages, LPRs face challenges such as high costs, technical difficulties, and false positive results. Successful LPR implementation necessitates striking a balance between legal compliance and privacy protection, including the establishment of clear guidelines for responsible use. To address these concerns while maintaining public trust, technological advancements such as anonymization and encryption are being developed (Armitage, 2002; Koper & Lum, 2019; Cullison, 2018; Berry, 2019).

2.2 Application Crime Pattern Theory

The Crime Pattern Theory was first presented by Patricia and Paul Brantingham and other environmental criminologists in their seminal work published in 1981. This theory aims to comprehend how criminals plan and carry out their crimes, emphasizing how they take advantage of fraud opportunities in their day-to-day operations. According to the theory, criminals, like insurgents, actively seek out these opportunities, meaning that crime is not random. The decision-making process that criminals go through when determining their likelihood of committing a crime is explained by crime pattern theory. In particular, it connects crime mapping to insurgency trends, which helps law enforcement pinpoint crime hotspots and create suppression plans. Paths, nodes, and edges are the three fundamental components of the theory and are very important. Workplaces, residences, and leisure destinations are examples of nodes that are regularly visited. The region surrounding these nodes constitutes an individual's activity space, which includes everyday pursuits like employment, militant activities, social interactions, or criminal activity (Eck & Weisburd, 2015). Movement from one node to another occurs along established paths, where criminals and insurgents search for crime targets and opportunities. Conversely, edges mark the boundaries of these activity areas.

When choosing victims, criminals use predictable routes through their daily activity nodes (De la Calle & Sánchez-Cuenca, 2015). Therefore, the intersection of a criminal's awareness space with a suitable target increases the likelihood of crime. According to this study, the Abu Dhabi Police can effectively use Crime Pattern Theory to understand the temporal and spatial dynamics of criminal activity in their criminal investigations. According to this theory, using state-of-the-art technologies can help identify crime hotspots and trends. This study aims to develop a framework that includes training as the mediating variable and criminal investigation in the Abu Dhabi Police as the dependent variable. It will do this by using state-of-the-art technological tools, such as data mining, body-worn cameras, car cameras, license plate readers, and crime mapping, as independent variables. The Abu Dhabi Police's investigative processes will eventually be improved by using these tools and training sessions to apply Crime Pattern Theory in practical settings.

2.3 Technology Training as a Mediator

Modern technologies like data mining, license plate readers, body-worn cameras, automobile cameras, and crime mapping are necessary for criminal investigations. These tools assist law enforcement in identifying patterns in criminal activity, forecasting criminal activity, and responding to incidents more rapidly and accurately by simplifying the collection, analysis, and interpretation of vast amounts of data (Smith, Li, & Rafferty, 2020). To ensure that police officers can use these state-of-the-art tools, training programs are also required. Officers will be better equipped to use and analyse data from these technologies if they receive the appropriate training. Furthermore, training fosters a deeper comprehension of how to integrate these tools into routine investigative procedures in order to maximize their usefulness (Brown & Green, 2019).

The relationship between the effectiveness of criminal investigations and the adoption of technological tools is reinforced by the inclusion of training as a mediator. In particular, training guarantees that officers are not only adept at utilizing the technologies but also able to apply their theoretical knowledge in real-world situations. This leads to better decision-making during investigations, more precise crime detection, and efficient data management. Empirical research indicates that law enforcement's adoption of technology is positively impacted by training. For example, Antrobus (Antrobus, Thompson, & Ariel, 2019) found that investing in comprehensive training programs greatly improved the investigative outcomes of police departments. According to the study, officers who received specialized training in data mining and crime mapping methods were better equipped to identify crime hotspots and predict trends in criminal activity

The importance of continuing professional development and training for law enforcement personnel was also emphasized in Garcia (Garcia, 2024). The study found that officers were better prepared to use the latest technological advancements in criminal investigations if they were regularly trained in them. In this case, mediator training requires specialized programs that consider the particular needs and challenges of the Abu Dhabi Police's investigative processes. The technical and real-world applications of emerging technologies ought to be emphasized heavily in these courses. Ensuring that officers have regular access to training sessions, seminars, and workshops is another way to foster a culture of continuous learning within the police force. This approach not only enhances the immediate effectiveness of technological tools but also fosters a long-term commitment to innovation and excellence in law enforcement.

3. Modelling the Relationships

Based on the gap analysis, the study established a mediation model that includes Crime Investigation as the dependent construct, Technology Training as the mediator construct, and independent constructs such as Crime Mapping, Face Recognition, Car Camera, Body-Worn Cameras, and License Plate Reader. Data for this model was collected from 375 respondents from key departments, including the General Department of Criminal Investigations (CID), the General Department of Forensic Science and Criminology (FSCD), and the Operations Division. The model was developed and analysed using Smart-PLS software, which employs the partial least squares (PLS) approach for theory development, as shown in Figure1.

3.1 Outer Model Assessment

Once the model has been constructed in the SmartPLS software, it is assessed at the outer model level. This includes some key tests to establish the robustness and validity of the model. First is Indicator Reliability, which focuses on checking the factor loading of each indicator. Generally, anything above 0.70 is acceptable (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Memon, Rahman, & Azis, 2013). This step establishes that each measure is reliable for its construct. Then, Internal Consistency Reliability takes place by using composite reliability as well as Cronbach's alpha for each construct. Generally, composite reliability values above 0.70 and Cronbach's alpha values above 0.60 are acceptable to ensure that constructs are measured consistently (Henseler, Ringle, & Sinkovics, 2009). From here, Convergent Validity is evaluated through the Average Variance Extracted (AVE) of each construct. AVE must be higher than 0.50 to mean that the constructs explain more than half the variance of their indicators (Fornell & Larcker, 1981; Almansoori, Rahman, Memon, & Nasaruddin, 2021; Memon, Memon, Soomro, Memon, & Khan, 2023). Finally, Discriminant Validity is also assessed via both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. This is to ensure that measures of two constructs expected to be distinct are indeed different (Henseler, Ringle, & Sarstedt, 2015). The foregoing evaluations have been undertaken in this study and the measurement model has proven reliable and valid to assess the structural model freely.

However, the processes of these evaluations are not elaborated on in this paper since the emphasis is placed on the structural model, which reflects the relationships among the independent, mediator, and dependent constructs. This allowed a deeper understanding of how interactions amongst these constructs were taking place and impacting each other within the milieu of the Abu Dhabi Police's investigation processes.

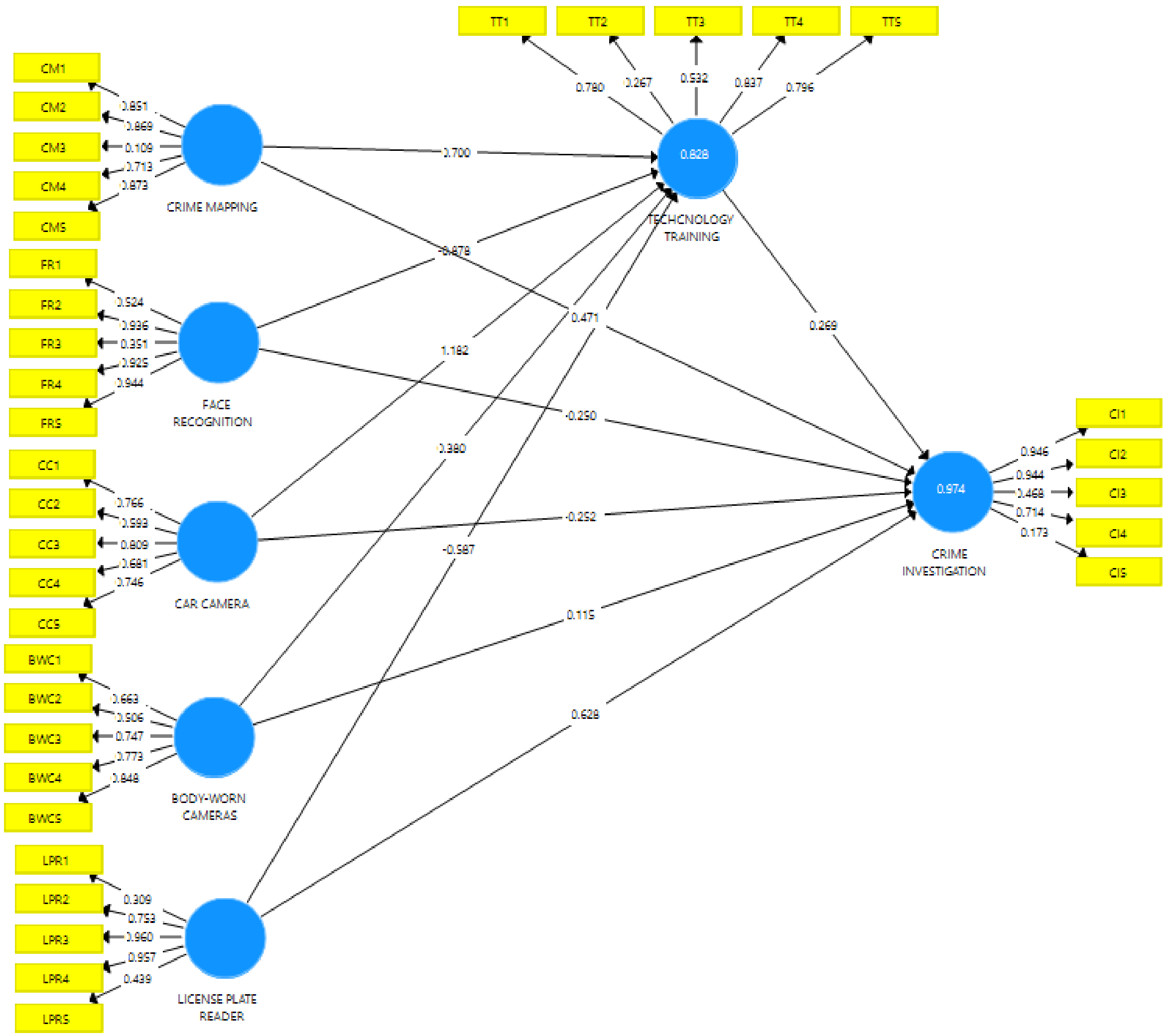

Figure 1. PLS model of the study

3.2 Coefficient of Determination

The coefficient of determination is sometimes termed the R2 value and serves as an important criterion to gauge the quality of a structural model in Partial Least Squares Structural Equation Modelling (PLS-SEM). R^2 expresses the predictive ability of a model by showing the variance accounted for in the constructs within the model due to the variance present in the exogenous constructs respectively (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Memon & Rahman, 2013). Although there is no general threshold that can be used in evaluating R^2 values, the field often uses a guideline proposed by Hair (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). The guideline suggests that an R^2 value of 0.25 is weak, a value of 0.50 is moderate, and a value of 0.75 is substantial (Hair, Sarstedt, Hopkins, &

Kuppelwieser, 2014; Wong, 2016). The R^2 value for this study model is shown in Table 1.

Table 1. Generated R^2 value

Endogenous constructs	R Square
CRIME INVESTIGATION - DV	0.974
TECHNOLOGY TRAINING - Mediator	0.828

Table 1 shows that for Crime Investigation (CI) as the dependent construct, the R square value is 0.974, indicating that approximately 97.4% of the variance in CI can be explained by the exogenous constructs included in the model. This again establishes that when TT is a mediator construct, the R square is 0.828. Thus, about 82.8% of the variance in TT could be attributed to exogenous constructs. In turn, these high R square values imply that the chosen exogenous constructs exert a significant influence on the variance shown in both Crime Investigation (CI) and Technology Training (TT), further enhancing the model to explain and predict the variance in these constructs (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Rahman, Memon, Aziz, & Abdullah, 2013).

3.3 Model Fit

Model fit indices play a critical role in determining the adequacy of a structural equation model for use in SmartPLS. Some of the most commonly used indices that have been proposed to compare observed data and predicted data to gauge the extent to which the model fits are SRMR, d_ULS, and NFI. These indices enable researchers to enhance their models, thereby increasing validity and reliability through a deeper understanding of the model's overall fit and predictive accuracy (Ringle, Wende, & Becker, 2024). Table 2 reports the fit indices established for a model fitness assessment.

Table 2. Model fitness

Indices	**Saturated Model**	**Estimated Model**
SRMR	0.172	0.172
d_ULS	18.549	18.549
d_G	n/a	n/a
Chi-Square	infinite	infinite
NFI	n/a	n/a

For most of the critical fit indices employed in structural equation modelling, Table 2 compares the Saturated Model with the Estimated Model. In both models, d_ULS is 18.549, and SRMR is 0.172. As these values indicate moderate fit, there is still scope for improvement. Some indices, like the geodesic distance (d_G) and the Normed Fit Index

(NFI), are not applicable. Also, the Chi-Square of both models is infinite, which implies that the model might be flawed in its ability to replicate the covariance matrix. Overall, results show a mediocre fit, and much more work and refinement have to be done to improve the fit of the model.

3.4 Hypothesis Testing

In SmartPLS software, the bootstrapping process is performed on the model to carry out hypothesis testing Hair Jr, Matthews, Matthews, & Sarstedt, 2017; Rahman, Memon, Abdullah, & Azis, 2013). This being a mediation model, the testing results are presented in the form of direct and indirect relationships, which gives an overall picture of how independent variables impact the dependent variable through the mediating constructs (Henseler, Ringle, & Sarstedt, 2015). This bootstrapping process generates standard errors and confidence intervals for the estimated coefficients, thereby helping to assess the statistical significance of these relationships (Preacher & Hayes, 2008). It makes strong hypothesis testing possible and sheds light on the indirect effects of other model constructs besides the direct effects of independent variables on the dependent variable (Zhao, Lynch Jr, & Chen, 2010). Table 3 shows the results of the hypothesis testing.

Table 3. Results of hypothesis testing of direct relationship

Nos.	**Direct relationship [IV to DV]**	**Path strength [Beta value]**	**T Statistics >1.96**	**Remark**
1	CRIME MAPPING-> CRIME INVESTIGATION	0.471	5.871	Significant
2	FACE RECOGNITION-> CRIME INVESTIGATION	-0.250	5.344	Significant
3	CAR CAMERA -> CRIME INVESTIGATION	-0.252	5.439	Significant
4	BODY-WORN CAMERAS-> CRIME INVESTIGATION	0.115	3.616	Significant
5	LICENSE PLATE READER -> CRIME INVESTIGATION	0.628	12.226	Significant

Table 3 displays the direct correlations between various independent variables (IVs) and the dependent variable (DV) of the crime investigation. There is a significant positive correlation between crime mapping and crime investigation, as indicated by a positive beta value of 0.471 and a T statistic of 5.871. In contrast, the Face Recognition to Crime Investigation pathway exhibits a negative beta value of -0.250 with T Statistics of 5.344, signifying a significant negative impact. Similarly, the relationship between Car Cameras to Crime Investigation has a negative beta value of -0.252 and a T Statistic of 5.439, highlighting a significant negative impact. On the other hand, the connection between Body-Worn Cameras and Crime Investigation holds a positive beta value of 0.115 and a T Statistic of 3.616, marking it as significant as well. Finally, the pathway from License Plate Reader to Crime Investigation presents the highest positive beta value of 0.628 and a T Statistic of 12.226, demonstrating a significant positive impact. Overall, the independent variables significantly impact crime investigation, with both positive and negative influences, as indicated by their respective beta values. The results of the hypothesis for indirect relationships are presented in Table 4.

Table 4. Results of hypothesis testing of indirect relationship

Nos.	Indirect relationship [IV to Mediator to DV]	Path strength [Beta value]	T Statistics >1.96	Remark
1	CRIME MAPPING -> TECHCNOLOGY TRAINING -> CRIME INVESTIGATION	0.188	4.443	Significant
2	FACE RECOGNITION ->TECHCNOLOGY TRAINING-> CRIME INVESTIGATION	-0.236	6.766	Significant
3	CAR CAMERA -> TECHCNOLOGY TRAINING -> CRIME INVESTIGATION	0.317	6.432	Significant
4	BODY-WORN CAMERAS -> TECHCNOLOGY TRAINING -> CRIME INVESTIGATION	0.102	3.887	Significant
5	LICENSE PLATE READER -> TECHCNOLOGY TRAINING -> CRIME INVESTIGATION	-0.158	4.592	Significant

Table 4 outlines the indirect relationships between various independent variables (IVs) and the dependent variable (DV) of crime investigation, mediated through technology training. Firstly, the relationship between Crime Mapping and Crime Investigation, mediated by Technology Training, shows a positive beta value of 0.188 and T Statistics of 4.443, indicating a significant positive relationship. Secondly, the Face Recognition to Crime Investigation pathway, also mediated by Technology Training, exhibits a negative beta value of -0.236 with T Statistics of 6.766, signifying a significant negative relationship.

Thirdly, the relationship from Car Camera to Crime Investigation, through Technology Training, demonstrates a positive beta value of 0.317 and T Statistics of 6.432, highlighting another significant positive relationship. Fourthly, the connection between Body-Worn Cameras and Crime Investigation, mediated by Technology Training, holds a positive beta value of 0.102 and T Statistics of 3.887, marking it as significant as well. Lastly, the pathway from License Plate Reader to Crime Investigation, through Technology Training, presents a negative beta value of -0.158 and T Statistics of 4.592, indicating a significant negative relationship. Therefore, all the independent variables significantly impact crime investigation through the mediator, technology training, with varying degrees of positive or negative influence, as indicated by their respective beta values.

4. A Framework and Previous Studies

A framework has been developed based on the modelling results, as shown in Figure 2. This framework depicts the significant correlations between various technological instruments and crime investigation outcomes as mediated by technology training. By visually depicting these relationships, the framework provides a clear picture of how sophisticated technologies and comprehensive training jointly boost the performance of crime investigations within the Abu Dhabi Police.

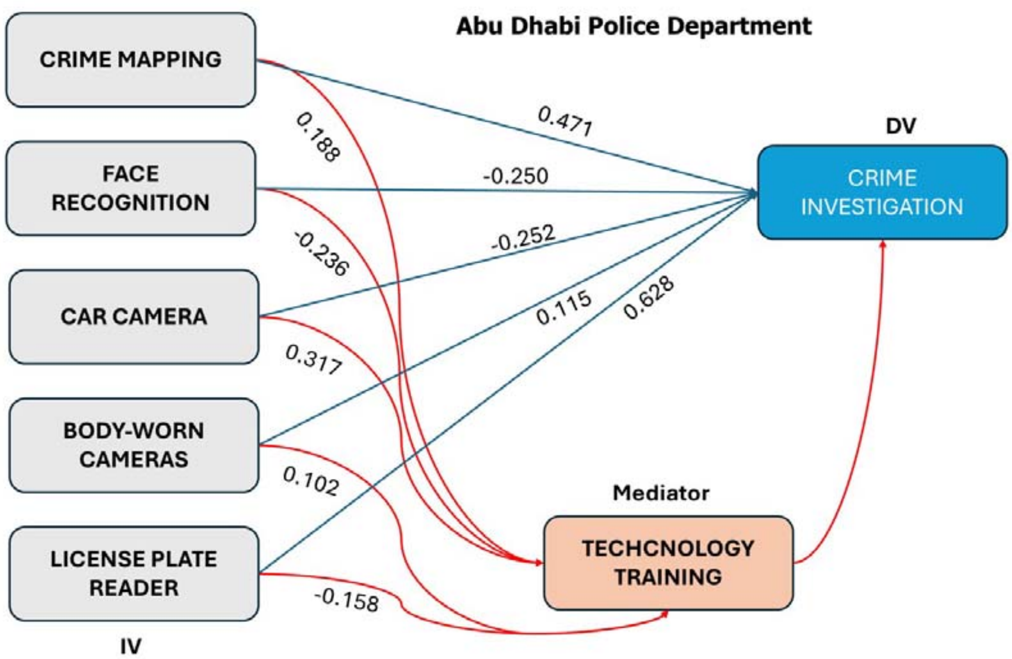

Figure 2. Framework of the findings

Figure 2 depicts a substantial positive link between Crime Mapping and Crime Investigation, which is mediated by Technology Training, with a positive beta value of 0.188 and T Statistics of 4.443. This is consistent with earlier research that has demonstrated how crime mapping, particularly when integrated with Geographic Information Systems (GIS), can considerably benefit in criminal investigation by detecting trends and hotspots (Johnson, Summers, & Pease, 2009; Chainey & Ratcliffe, 2013).The second finding on the relationship between Face Recognition and Crime Investigation, mediated by Technology Training, exhibits a negative beta value of -0.236 with T Statistics of 6.766, signifying a significant negative relationship. Studies have highlighted both the potential and challenges of face recognition technology in crime investigation, noting accuracy issues in real-world scenarios (Phillips et al., 2018; Klare et al., 2015).

The third finding, the relationship from Car Camera to Crime Investigation, through Technology Training, demonstrates a positive beta value of 0.317 and T Statistics of 6.432, highlighting another significant positive relationship. Research on the use of car cameras

(CCTV) has shown their effectiveness in crime prevention and investigation (Armitage, 2002; Welsh & Farrington, 2009). The fourth finding, the connection between Body-Worn Cameras and Crime Investigation, mediated by Technology Training, holds a positive beta value of .102 and T Statistics of 3.887, marking it as significant as well. Studies have found that body-worn cameras can reduce use-of-force complaints and improve transparency (Ariel, Farrar, & Sutherland, 2015).

Lastly, the pathway from License Plate Reader to Crime Investigation through Technology Training presents a negative beta value of -0.158 and T Statistics of 4.592, indicating a significant negative relationship. Previous research has shown mixed results for license plate readers, with some studies indicating effectiveness in tracking stolen vehicles but also raising privacy concerns (Lum, Hibdon, Cave, Koper, & Merola, 2011; Brayne, 2017).

5. Conclusion

In conclusion, this study underscores the crucial role of proactive strategies and technology-assisted crime prevention methods in ineffective law enforcement. Technological advancements have introduced new perspectives and innovations, surpassing conventional tactics. This research specifically examined the impact of advanced technological tools on crime investigations, emphasizing the importance of technology training as a mediating factor within the developed model. The findings indicate that License Plate Recognition (LPR) systems had the most substantial positive impact, while Crime Mapping Software (CM) also contributed positively. Conversely, Facial Recognition (FR) and Crime Cameras (CC) demonstrated negative impacts. These results highlight the essential need for strategically integrating technology with comprehensive training to optimize the criminal investigation processes within the Abu Dhabi Police. To further enhance law enforcement capabilities in the UAE, it is imperative to continue investing in both advanced technologies and robust training programs. This dual approach will ensure that the police force remains adept at utilizing cutting-edge tools, ultimately improving the effectiveness of criminal investigations and overall public safety.

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