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Artificial Intelligence Adoption in Predictive Policing to Predict Crime Mitigation Performance

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Abstract: The global adoption of AI-powered predictive policing, utilizing big data, is becoming a prevalent strategy for crime control and law enforcement enhancement. Recognizing its potential, Abu Dhabi Police places emphasis on officer training and collaborative efforts for crime prevention. As the integration of predictive policing continues within Abu Dhabi Police, the importance of exploring the value of training and collaborative learning becomes even more crucial (Abu Dhabi Police GHQ, 2020). This study's objective is to uncover the intricate relationship between crime mitigation performance and key factors, encompassing Predictive Policing Adoption, Specialised Technology Training, Innovative Officer Performance, and Collaborative Learning. Questionnaire survey was used to collect data from participants who are employees of the Abu Dhabi Crime Scene Department. A total of 316 valid responses were used in the development of multi-linear regression model to predict crime mitigation performance. By utilizing the developed multi-linear regression model, stakeholders can forecast Crime Mitigation Performance (CMP) by substituting the values of Predictive Policing Adoption (PPA), Specialised Technology Training (STT), Innovative Officer Performance (IOP), and Collaborative Learning (CL) into the formula. This predictive tool offers the Abu Dhabi Crime Scene Department a valuable resource to proactively assess and plan for crime mitigation outcomes, enhancing their strategic decision-making capabilities and fostering a more effective approach to law enforcement operations

Keywords: Predictive policing, crime mitigation performance

1. Introduction

The future of policing is undeniably tied to the integration of computers alongside traditional methods (Adams, 2012). Predictive policing entails utilizing technology, including intelligent algorithms, simulations, and big data analytics, to forecast potential criminal activities (Ferguson, 2019). This approach has been recently applied by law enforcement agencies for guiding patrol officers, targeting expected crimes, and conducting real-time analysis within the critical response division (Saunders et al., 2016). This innovative use of extensive historical and real-time data serves as a powerful tool to proactively address crimes before they happen (Mohler et al., 2015; Ferguson, 2019). Despite the potential benefits of utilizing AI and big data for crime reduction in law enforcement, significant challenges have been emphasized (Ekblom, 2013; Meijer & Wessels, 2019; Richardson et al., 2019). Concerns persist due to compromised public safety, flawed data leading to inaccurate predictions, and increasing rights violations (Richardson et al., 2019, p.16). A systematic literature review by Meijer & Wessels (2019) highlighted drawbacks such as increased crime rates and inadequate implementation. There's a significant conflict between predictive policing and the skills of police officers

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(Ratcliffe et al., 2019), necessitating the resolution of these tensions for the effective realization of predictive policing benefits (Ferguson, 2019).

The successful implementation of predictive technology in law enforcement faces significant challenges due to training requirements, costs, and officers' resistance to changing their roles (Ferguson, 2019). Ferguson (2016) emphasizes the importance of training to ensure the effective application of predictive policing technology, leading to the conclusion that proper officer training is essential for technology adoption. However, evidence shows that officers often struggle with paperwork and technology systems, resulting in low commitment to their use (Kirschner et al., 2018). Effective training is crucial for accurate data input, the appropriate use of predictive policing methods, addressing system vulnerabilities, and correctly interpreting system responses (Mohler et al., 2015; Ferguson, 2016; Ferguson, 2019). The adoption of innovative training and learning approaches is also crucial for realizing the anticipated benefits of predictive policing (Ratcliffe et al., 2019; Meijer & Wessels, 2019; Saunders et al., 2016; Ferguson, 2019; Kirschner et al., 2018). In the effort to combat and prevent crime in the UAE, artificial surveillance, predictive policing, and the use of big data by law enforcement have become increasingly prominent (MENA Herald, 2018; Shouk, 2019a). AI and big data have already demonstrated success in achieving a "zero crime" environment in specific Dubai communities, thanks to an AI-powered program called "Oyoon" (meaning Eyes in English) implemented by the Dubai Police. This system employs AI data analytics to solve crimes and identify security gaps across various types of locations, operating independently across numerous city cameras (Shouk, 2019b). Col Suleiman Al Kaabi, director of innovation and foresight at Abu Dhabi Police, notes the transformative potential of AI in reshaping our perspectives and decision-making as technology bridges the gap between the natural and artificial realms (Malek, 2018, p. 1).

The Abu Dhabi Emirate has diligently prepared its citizens for an AI-driven future, with the Abu Dhabi Police and law enforcement agencies in other Emirates contributing uniquely to this vision (Malek, 2018; Ramahi, 2018; Larsen, 2017; Harrison, 2019). However, there's a notable gap in officer training, particularly for newly introduced intelligent automated tools and maximizing the potential of big data (Babuta, 2017). Babuta (2017) highlights that law enforcement officials manually sift through vast data, often unaware of available automated tools that could save time. Adequate technology training is lacking, yet the effectiveness of analytical tools relies on the proficiency of the operator, warranting investment in officer training for new technology systems. Within the Abu Dhabi Police AI strategy, the Department aims to evolve from reactive policing to full operational predictive policing of Abu Dhabi Police GHQ. The reactive stage involves responding to reported crimes, with no pre-emptive measures. Effectiveness depends on response time. Proactive policing takes some pre-emptive action, often based on general data, including frequent patrols, surveillance, and engagement in crime hotspots. The Department is advancing towards the ultimate stage of its policing strategy: predictive policing. Here, technology is harnessed to proactively generate the intelligence needed to pre-empt crimes, enabling the police to stay ahead and manage crime more effectively. In this pursuit, the significance of Big Data and AI has increasingly needed. Considering this strategic direction, it's crucial to focus on the adoption and optimal implementation of predictive policing through comprehensive training and collaborative learning (Kirschner et al., 2018).

2. Predictive Policing Using AI for Crime Mitigation Performance

The rapid advancement of technology, particularly Artificial Intelligence (AI), is disrupting conventional norms and ushering in an era of uncertainty. AI has proven its effectiveness in handling intricate tasks involving real-time data processing, signal interpretation, and knowledge accumulation (Krasadakis, 2018). In the UAE, the government is leveraging innovation to reshape perspectives, enhance industries, and bolster emerging sectors such as healthcare (Halaweh, 2018; Wehbe & Svetinovic, 2018). A noteworthy approach involves deploying AI across critical domains, leading to significant advancements (Halaweh, 2019). Bessen (2018) highlights AI's ability to streamline work processes, optimize resource allocation, and elevate citizen services. Additionally, AI's potential to create sophisticated roles underscores its impact on workforce augmentation. Bessen (2018) also points out that AI addresses data challenges, enhances cognitive processes, and advances predictive capabilities, enabling informed policy decisions.

The UAE government's use of AI is evident in driving business efficiency, enhancing employee productivity, and revolutionizing customer experiences through technology-driven sales recommendations and fraud detection (Shah & Shaheen, 2016). The UAE's AI strategy (2017) emphasizes the importance of AI in achieving a customer-centric approach, guiding service representatives in delivering effective solutions. Moreover, AI offers cost-saving potentials, with estimated annual savings through automation (UAE AI strategy, 2016). The strategy aims to redirect resources toward enhancing service quality and accommodating evolving needs.

The UAE government's commitment to innovation extends to public services, industrial opportunities, and national well-being (UAE AI strategy, 2016). The strategic use of AI in public services, particularly predictive policing, seeks to expedite service delivery and bolster overall quality (Dave & Sharma, 2019). To align with national visions (UAE vision 2021; UAE vision 2030), AI technology is harnessed to enhance citizen satisfaction.

Despite these advancements, the effective operationalization of predictive policing technology faces challenges related to alignment with police officers' expertise (Ratcliffe et al., 2019). The opacity of predictive models leads to errors that hinder effective application (Meijer & Wessels, 2019; Ferguson, 2019). Meijer & Wessels (2019) emphasize officers' need to comprehend predictive algorithms for optimal decision-making. Addressing the lack of evidence on specialized training for AI and big data usage in crime mitigation, this study aims to illuminate this area (Ferguson, 2019).

Collaborative learning, informed by educational psychology theory, is also crucial for optimizing officer performance (Kirschner et al., 2018).

Given the ongoing implementation of predictive policing across Abu Dhabi Police, investigating the role of training and collaborative learning becomes pivotal (Abu Dhabi Police GHQ, 2020). This study endeavors to uncover the relationship of crime mitigations performance with other contributing factors such as Predictive Policing Adoption; Specialised technology Training; Innovative Officer Performance; and Collaborative Learning.

2.1 Predictive Policing and Innovative Officer Performance

The main purpose of predictive policing is the application of analytics to data to reveal promising crime trends and help police officers remain ahead of criminals (Perry et al. 2014). Even though predictive policing as a term has gained popularity ahead of the evolution of artificial intelligence, this era has come to be known as the proactive era of policing, whilst the application of artificial intelligence has increasingly gained consensus as to the application of artificial intelligence to big data (Saunders et al. 2016; Mohler et al. 2015; Ferguson, 2019).

Predictive policing is increasingly gaining recognition in the prediction of crime, predicting offender, predicting perpetrator identities, and predicting crime victims (Ekblom, 2013; Meijer and Wessels, 2019; Richardson et al. 2019; Richardson et al. 2019). In these predictions, predictive policing hold significant potential over conventional crime analysis techniques (Perry et al. 2014). Presented in Figure 1, predictive policing builds on real-time analysis of criminal responses to altering environments. Such systems collect the necessary data and information, analyse this voluminous data to inform police operations.

Such a system environment is equipped with situational awareness as described in the activity and complexity theory to artificial intelligence operationalisation (Ekblom, 2013; Meijer and Wessels, 2019). Building on its situational awareness, the system automatically alters its resources and redirects them towards areas with greater risks based on proven algorithms. With little to no human interventions, predictive policing is able to conduct crime specific interventions and help the police officer operate in a more effective and innovative manner by addressing specific locations and factors driving crime risk.

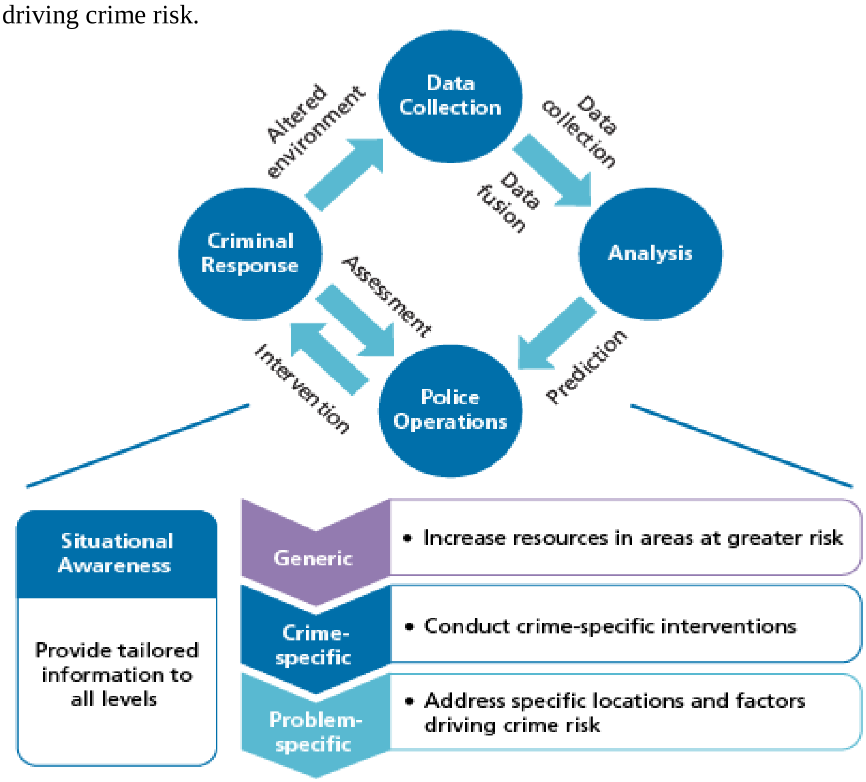

Fig. 1 - Operational predictive Policing Model Source: Perry et al. (2014)

2.2 Innovative Officer and Crime Mitigation Performance

Innovation is characterized as the application of novel methods and ideas to enhance performance effectively (Stanko, 2020). Within the realm of an officer's responsibilities, the significance of innovation performance has been emphasized, particularly in diminishing injuries during physical interventions and problematic arrests (Weisburd and Braga, 2019). Police innovation manifests in various forms and encompasses strategic, tactical, and operational aspects of crime policing endeavours (Vera Jiménez et al., 2020). It has also proven pivotal in enhancing police-community relations, upholding law and order, and contributing to crime prevention and secure arrests (Vera Jiménez et al., 2020; Liaw et al., 2019).

2.3 Specialized Technology Training in Predictive Policing

The pressing requirement for training in predictive policing arises due to the realization that expected advantages often diminish in both experimental and real-world scenarios (Meijer and Wessels, 2019). To unlock the heightened potential of predictive policing, it becomes imperative to equip human actors with training to address inherent shortcomings. Amid various challenges linked to predictive policing, the central predicament revolves around the lack of alignment between technology and police human resources (Ekblom, 2013; Meijer and Wessels, 2019; Richardson et al., 2019).

A vital focus is the necessity to adopt and prepare for effective system utilization, as outlined by Richardson et al. (2019). This challenge underscores the core research gap in this study and aligns with what Ensign et al. (2017) refer to as the "runaway feedback" loop within predictive policing. With rapid technological advancements expanding the potential applications of predictive technology (Shapiro, 2017), law enforcement officers must adeptly engage with these systems to comprehend their capabilities and how they can complement their operational tasks (Meijer and Wessels, 2019).

2.4 Collaboration in Learning and Training

Collaboration continues to hold a pivotal role in achieving shared learning objectives among members within collaborative settings, particularly in the context of Predictive Policing (Teasley and Roschelle, 1993). It serves as a platform for idea sharing and fosters innovation towards common objectives (Scheuer et al., 2010). In the current technological landscape, collaboration can take place either in person or through technological systems (Le et al., 2013).

In collaborative endeavours, tasks or problems can be initiated through shared learning activities. These tasks may vary in clarity, either well-defined or open-ended. Based on the problem's nature, participants in the collaboration may assume specific roles to address the task or problem (Le et al., 2013; Scheuer et al., 2010).

Although collaboration is instrumental in finding short-term solutions, its long-term impact results in enhanced group versatility due to accumulated experience over time (Kirschner et al., 2018). In the law enforcement domain, collaborative learning has demonstrated effectiveness in fostering a productive work environment, given its synergistic role with other social structures (Tomsic and Suthers, 1993). Furthermore, Zaman et al. (2006) highlight that law enforcement officers should recognize the potential to reduce crime and enhance overall work efficiency through robust collaborative education efforts.

3. Data Collection

A questionnaire survey was utilized to collect data from participants who are employees of the Abu Dhabi Crime Scene Department. The distribution of questionnaires aligns with the department's demographic profile. The study employs the probability sampling technique, ensuring equal participation opportunities for all members, as recommended by Saunders et al. (2016). The replication of the department's gender structure supports the use of random sampling for representativeness. The survey received 434 completed questionnaires, yet only 316 responses are undergoing further analysis. In the preliminary analysis, 118 cases were removed at different stages to enhance data quality, reliability, and validity. The removal of unengaged responses and outliers aims to ensure precise findings and data conciseness.

According to the demography of the respondents, 93 were males and 213 were females, accounting for 29.4% and 67.4% respectively. The age group with the lowest representation was 41-45 years, comprising 12 respondents (3.8%). This was followed by respondent’s aged 18 to 25, constituting 6.3% or 20 participants. The highest age group consisted of individuals aged 31 to 35 years, with 119 crime officers falling within this range. The crime scene department comprises employees at three primary tiers, akin to operational, middle, and top levels in traditional organizations. The survey gathered data on this distribution. Lower-level employees constitute 21.8% or 69 respondents. The middle level is the largest, encompassing 196 employees or 62% of total respondents. The top-level crime scene experts make up the remaining 16.1%, the lowest proportion within the dataset. This data closely mirrors the internal human resources distribution within the Abu Dhabi Police GHQ crime scene department. The most prevalent segment in working experiences was individuals with 11 to 15 years of tenure, comprising 22.8% or 54 participants. Following closely were those with less than five years (22.4%) and 6-10 years (21.1%) in the Abu Dhabi Crime Scene Department. Subsequent groups encompassed those with 16 to 20 years (14.3%) within the organization, preceding those with 20 years and above.

4. Results and Analysis

4.1 Reliability Assessment

Reliability assessment is essential for ensuring the consistency and stability of the collected survey data. It guarantees that the measurement tools used in the survey consistently produce accurate results, enhancing the credibility of the findings. By evaluating the internal consistency and reproducibility of responses, reliability assessment provides a robust foundation for drawing meaningful conclusions from the data (Hair et al., 2014). Reliability was assessed with the help of the Cronbach Alpha test for internal consistency as presented in Table 1.

Table 1 - Cronbach's Alpha test for reliability

Groups of factors	Code of constructs	No. of Factors	Cronbach's Alpha
Predictive Policing Adoption	PPA	7	0.786
Specialized Technology Training	STT	7	0.794
Innovative Officer Performance	IOP	7	0.785
Collaborative Learning	CL	7	0.821
Crime Mitigation Performance	CMP	7	0.824

First, the Cronbach Alpha test for reliability was significant for all the constructs within the model; on a visual inspection, all the constructs were above the 0.7 significance threshold for reliability test (Hair et al., 2014).

4.2 Descriptive Statistics on Key Variables of The Study

Conducting descriptive analysis on the survey data pertaining to factors related to crime mitigation performance, including Predictive Policing Adoption, Specialised Technology Training, Innovative Officer Performance, and Collaborative Learning, is a fundamental step in understanding the distribution, central tendencies, and variability of these variables. Descriptive analysis provides insights into the basic characteristics of the data, helping researchers and practitioners gain a comprehensive overview of the dataset's structure. By calculating measures such as means, standard deviations, skewness, and kurtosis, researchers can assess the central tendencies and dispersion of the variables. The mean offers a sense of the average values, while the standard deviation indicates the degree of variability around the mean. Skewness and kurtosis measurements provide insights into the shape and tail behaviour of the distributions. Furthermore, conducting descriptive analysis is pivotal for summarizing the data in a manner that is accessible and interpretable. This process assists researchers in uncovering initial trends and potential relationships among the variables, which can guide further inferential analysis and hypothesis testing. It also aids in identifying potential issues such as data entry errors, missing values, or unusual patterns that might require further investigation or data cleaning. Ultimately, the requirement for conducting descriptive analysis on the survey data of factors related to crime mitigation performance, including Predictive Policing Adoption, Specialised Technology Training, Innovative Officer Performance, and Collaborative Learning, underscores the foundational role of this analysis in providing an initial understanding of the dataset's characteristics and facilitating informed decision-making throughout the research process. The descriptive statistics for this study are outlined in Table 2.

Table 2 - Descriptive statistics

	Mean	Std.	Skewness		Kurtosis	
Factors	Statistic	Dev	Stat	Std. Error	Stat	Std. Error
PPA1	2.9082	1.34086	.057	.137	-1.151	.273
PPA2	3.5798	1.10027	-.508	.137	-.289	.273
PPA3	3.7976	1.09386	-.790	.137	.031	.273
PPA4	3.5712	1.21764	-.750	.137	-.352	.273
PPA5	3.5554	1.26617	-.604	.137	-.629	.273
PPA6	3.6090	1.22757	-.685	.137	-.457	.273
PPA7	3.5288	1.23479	-.614	.137	-.550	.273
PPA Avg.	3.5072	.80398	-.045	.137	-.515	.273
STT1	2.8449	1.38404	.020	.137	-1.330	.273
STT2	3.5759	1.10004	-.526	.137	-.339	.273
STT3	3.6239	1.18546	-.668	.137	-.367	.273
STT4	3.6466	1.13845	-.742	.137	-.070	.273
STT5	3.6635	1.22913	-.778	.137	-.301	.273
STT6	3.5612	1.23040	-.643	.137	-.531	.273
STT7	3.6688	1.12679	-.698	.137	-.299	.273
STT Avg.	3.5121	.80449	.026	.137	-.712	.273

IOP1	2.9114	1.40466	-.084	.137	-1.349	.273
IOP2	3.7210	1.05674	-.724	.137	.106	.273
IOP3	3.6799	1.21713	-.694	.137	-.441	.273
IOP4	3.5665	1.19204	-.662	.137	-.346	.273
IOP5	3.6746	1.21267	-.698	.137	-.420	.273
IOP6	3.5380	1.23513	-.622	.137	-.565	.273
IOP7	3.7616	1.19277	-.804	.137	-.297	.273
IOP Avg.	3.5504	.80626	-.039	.137	-.599	.273
CL1	3.1361	1.49830	-.177	.137	-1.432	.273
CL2	3.6466	1.15925	-.677	.137	-.314	.273
CL3	3.6872	1.20552	-.757	.137	-.257	.273
CL4	3.7499	1.17023	-.771	.137	-.258	.273
CL5	3.6883	1.23363	-.696	.137	-.507	.273
CL6	3.6050	1.32063	-.642	.137	-.739	.273
CL7	3.5242	1.18348	-.537	.137	-.591	.273
CL Avg.	3.5767	.87309	-.154	.137	-.549	.273
CMP1	2.8956	1.38879	-.019	.137	-1.275	.273
CMP2	3.6971	1.10751	-.605	.137	-.353	.273
CMP3	3.7495	1.23339	-.775	.137	-.347	.273
CMP4	3.6883	1.22739	-.756	.137	-.371	.273
CMP5	3.6160	1.23510	-.559	.137	-.764	.273
CMP6	3.7596	1.21961	-.801	.137	-.351	.273
CMP7	3.5528	1.21661	-.645	.137	-.472	.273
CMP Avg.	3.5656	.85991	-.245	.137	-.432	.273
Valid N (listwise)						

Table 2 shows mean statistics are provided for both individual items and composite scores across dimensions. On a five-point Likert scale, all responses and average composite scores surpass the midpoint. These composite scores represent the average total of individual items. Among the five estimated composite scores, Predictive Policing Adoption (PPA) (Mean = 3.5072, SD = .804), Specialised Technology Training (STT) (Mean = 3.5121, SD = .804), Innovative Officer Performance (Mean = 3.5504, SD = .806), Collaborative Learning (CL) (Mean = 3.5767, SD = .873), and Crime Mitigation Performance (CMP) (Mean = 3.5656, SD = .860).

The table demonstrates relatively controlled deviation and variance levels as evidenced by the standard deviation values. Skewness statistics generally remain below 1 on a five-point scale, considering the standard error estimate of approximately 0.137. Additionally, the kurtosis statistics indicate values generally below 1, with a standard error of 0.273. These skewness and kurtosis figures suggest that the data align reasonably well with normality. Nearly all items and composite distributions exhibit a negatively skewed and negatively kurtotic distribution. Following Hair et al.'s (2010) guideline, where an absolute value of |3| is a benchmark for non-normality detection using skewness and kurtosis, the statistics fall within an acceptable range, indicating a generally normal distribution.

4.3 Correlations

Correlations play a vital role in understanding relationships between variables in a dataset. Nonetheless, an excessive number of correlations can lead to undesired associations and introduce bias in predictive modelling, potentially over-explaining the variance in the dependent variable (Hair et al., 2010). Using the bivariate Pearson correlation function in IBM SPSS Statistics, the correlations between dimensions were examined. The outcomes are displayed in Table 3, illustrating the correlations among all five dimensions in the model.

Table 3 - Correlation between constructs

		PPA Avg.	**STT Avg.**	**IOP Avg.**	**CL Avg.**	**CMP Avg.**
PPA Avg.	Pearson Correlation (R)	1	.768**	.739**	.761**	.770**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	319	319	319	319	319

STT Avg.	Pearson Correlation (R)	.768**	1	.803**	.810**	.788**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	319	319	319	319	319
IOP Avg.	Pearson Correlation (R)	.739**	.803**	1	.855**	.816**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	319	319	319	319	319
CL Avg.	Pearson Correlation (R)	.761**	.810**	.855**	1	.873**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	319	319	319	319	319
CMP Avg.	Pearson Correlation (R)	.770**	.788**	.816**	.873**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	319	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

In Table 3, a correlation of 0.7 or higher indicates the presence of excessive correlations and the potential for multicollinearity. Notably, robust correlations were observed among all factors in the model. Particularly strong correlation was observed between innovative officer performance (IOP) and collaborative learning (CL) (R = .855). The elevated correlation levels highlight the importance of monitoring for multicollinearity, which will be discussed in the subsequent sections. Additional tests for excessive collinearity or multicollinearity involve the utilization of variance inflation factor (VIF) and tolerance levels.

4.4 Multicollinearity

Analysing multicollinearity in collected data is crucial to ensure the validity and reliability of regression results. Multicollinearity occurs when independent variables in a regression model are highly correlated, which can lead to unstable coefficient estimates and difficulties in interpreting the effects of individual variables. To assess multicollinearity, two common statistics, tolerance and variance inflation factor (VIF), are used. Tolerance measures the proportion of variance in one independent variable that is not predictable from the other independent variables. A low tolerance value suggests high multicollinearity, indicating that a variable can be predicted well by other variables in the model. On the other hand, a high tolerance value indicates that a variable is not highly correlated with other variables, thus reducing the risk of multicollinearity. VIF, on the other hand, quantifies how much the variance of an estimated regression coefficient is increased due to multicollinearity. A high VIF value indicates that a variable is highly correlated with other variables, leading to inflated standard errors and reduced precision in coefficient estimates.

Analysing both tolerance and VIF helps researchers identify variables that might be causing multicollinearity issues. By addressing multicollinearity, researchers can ensure that the regression model provides accurate and interpretable results, allowing for a better understanding of the relationships between the independent variables and the dependent variable. Ultimately, proper assessment and handling of multicollinearity contribute to the overall quality and reliability of regression analysis.

As part of this study's regression model development, tolerance and VIF statistics were computed to assess multicollinearity. Hair et al. (2014) propose that tolerance should be under .1 and VIF values above 10 to indicate multicollinearity concerns. The outcomes of the multicollinearity analysis are shown in Table 4.

Table 4 - Multicollinearity result

		Collinearity Statistics	
Model		**Tolerance**	**VIF**
1	(Constant)		
	PPA Avg.	.320	3.121
	STT Avg.	.233	4.292
	IOP Avg.	.210	4.759
	CL Avg.	.202	4.940

a. Dependent Variable: CMP_Avg

The findings displayed in Table 4 reveal that despite the notably high correlations observed earlier, the collinearity statistics remain relatively low and fall within an acceptable range. However, these indices are still higher compared to benchmarks proposed by certain studies, such as Johnston et al. (2018), who suggest a VIF limit of 2.5. Therefore, while the VIF scores pass the multi-collinearity test, the results are not significantly different from those in other literature.

4.5 Multi Linear Regression

Developing a multi-linear regression model for crime mitigation performance, considering the variables of Predictive Policing Adoption, Specialised Technology Training, Innovative Officer Performance, and Collaborative Learning, holds paramount significance in advancing our understanding of effective crime prevention strategies within the realm of law enforcement. Crime mitigation is a complex endeavour influenced by numerous interconnected factors. By harnessing the power of a multi-linear regression model, we can systematically unravel the intricate relationships between these variables and crime reduction outcomes. Predictive Policing Adoption, a pioneering approach powered by advanced technology, Specialised Technology Training for law enforcement personnel, Innovative Officer Performance, and Collaborative Learning among officers, are all critical dimensions that collectively shape crime mitigation efforts.

A multi-linear regression model enables us to quantify the individual and combined effects of these variables on crime reduction. By analysing their interactions, we gain insights into how each component contributes to the overall efficacy of crime prevention initiatives. This understanding empowers law enforcement agencies to allocate resources strategically, prioritizing interventions that yield the most substantial impact. Moreover, this modelling approach enables the identification of potential synergies among the variables. For instance, how does the integration of Predictive Policing Adoption interact with the presence of Specialised Technology Training in enhancing Innovative Officer Performance and Collaborative Learning? Such insights help agencies fine-tune their strategies and capitalize on the interplay between these dimensions for optimal crime mitigation outcomes. A multi-linear regression model also facilitates predictive capabilities, allowing us to forecast crime mitigation performance under various scenarios. This aids agencies in proactively adapting their approaches to changing circumstances, ultimately leading to more efficient crime prevention and safer communities.

In essence, the development of a multi-linear regression model for crime mitigation performance encapsulates the complex dynamics of contemporary law enforcement efforts. By embracing these multifaceted variables, agencies can make data-driven decisions that enhance the precision, effectiveness, and adaptability of their crime prevention strategies, leading to more secure and harmonious societies (Memon,et.al. 2013).

Hence, the collected survey data of Abu Dahbi police department was used to develop the model using SPSS software and the generated coefficients for the model are as table 5

Table 5 - Regression coefficients

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	.073	.106		.690	.491
	PPA Avg.	.194	.046	.180	4.193	.000
	STT Avg.	.116	.053	.108	2.206	.028
	IOP Avg.	.165	.056	.156	2.950	.003
	CL Avg.	.510	.054	.515	9.424	.000

a. Dependent Variable: **CMP Avg**

Displayed in Table 5 are the derived regression coefficients of the multi-linear regression model. The table reveals that all four independent variables/constructs are statistically significant, with p-values below 0.05. Nevertheless, the constant is not significant and can be omitted in the mathematical representation of the multi-linear regression model as follows:

$$\mathbf{CMP\_Avg = 0.194PPA\_Avg + 0.116STT\_Avg + 0.165IOP\_Avg + 0.510CL\_Avg}$$

Utilizing this multi-linear regression model, one can forecast Crime Mitigation Performance (CMP) by substituting the values of Predictive Policing Adoption (PPA), Specialised Police Training (SPT), Innovative Officer Performance (IOP), and Collaborative Learning (CL) into the formula. Employing this regression model empowers the Abu Dhabi Crime Scene Department to anticipate crime mitigation performance, facilitating strategic planning efforts.

By leveraging the insights provided by this multi-linear regression model, stakeholders can anticipate and estimate Crime Mitigation Performance (CMP) by inputting the corresponding values of Predictive Policing Adoption (PPA), Specialised Police Training (SPT), Innovative Officer Performance (IOP), and Collaborative Learning (CL) into the established formula. This predictive tool offers the Abu Dhabi Crime Scene Department a valuable resource to proactively assess and plan for crime mitigation outcomes, enhancing their strategic decision-making capabilities and fostering a more effective approach to law enforcement operations.

4.5.1 Model Fitness

The coefficient of determination, often denoted as R^2, is a key measure used to assess the fitness of a multi-linear regression model. It quantifies the proportion of the variance in the dependent variable that is explained by the independent variables included in the model. R^2 ranges between 0 and 1, with higher values indicating a better fit of the model to the data. An R^2 value of 0 implies that the model does not explain any of the variability in the dependent variable, while an R^2 of 1 indicates that the model perfectly predicts the dependent variable (Rahman. et.al. 2013). The multi-linear regression model's fitness is indicated by various goodness-of-fit measures presented in Table 6.

Table 6 - Model fitness

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.894[a]	.800	.797	.39089
a. Predictors: (Constant), CL Avg., PPA Avg., STT Avg., IOP Avg.				
b. Dependent Variable: CMP Avg.				

The coefficient of determination (R^2) is 0.800, implying that approximately 80% of the variability in the dependent variable (CMP Avg.) can be explained by the combination of the independent variables (Constant, CL Avg., PPA Avg., STT Avg., IOP Avg.). The adjusted R^2, accounting for the number of predictors, is 0.797, suggesting a robust model fit. The standard error of the estimate is 0.39089, reflecting the average distance between the observed and predicted values. These results indicate a strong overall fitness of the multi-linear regression model in explaining the variance in Crime Mitigation Performance (CMP Avg.) based on the specified predictors.

5. Conclusion

This study was aimed to develop a multi-linear regression model to predict crime mitigation performance of predictive policing in adopting artificial intelligence. The study used questionnaire survey to collect data from participants who are employees of the Abu Dhabi Crime Scene Department. A total of 316 valid responses were used in the development of multi-linear regression model to predict crime mitigation performance. By utilizing the developed multi-linear regression model, stakeholders can forecast Crime Mitigation Performance (CMP) by substituting the values of Predictive Policing Adoption (PPA), Specialised Police Training (SPT), Innovative Officer Performance (IOP), and Collaborative Learning (CL) into the formula. It was found that there is a strong overall fitness of the multi-linear regression model in explaining the variance in Crime Mitigation Performance based on the specified predictors.

This predictive tool offers the Abu Dhabi Crime Scene Department a valuable resource to proactively assess and plan for crime mitigation outcomes, enhancing their strategic decision-making capabilities and fostering a more effective approach to law enforcement operations.

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References

Abu Dhabi Police GHQ, 2020. Abu Dhabi Police AI Roadmap, Strategy and Experience. Abu Dhabi Police GHQ: Abu Dhabi, UAE

Adams, 2012. The Sci-Fi Solution to Real Crime, Independent (London) - Cops: Can Police Really Predict Crime before It Happens? http://www.slate.com/articles/news_and_politics/crime/2011/01/time_cops.single.htm

Babuta, A., 2017. Big data and policing: an assessment of law enforcement requirements, expectations and priorities. Royal United Services Institute for Defence and Security Studies.

Dave, D., Goyal, G. R., & Sharma, J. (2019). Solution of dynamic economic power dispatch problem using AI techniques. Journal of Emerging Technologies and Innovative Research (JETIR), 6(1), 1942-1948.

Ekblom, P., 2013. How to police the future: Scanning for scientific and technological innovations which generate potential threats and opportunities in crime, policing and crime reduction. In Crime science (pp. 27-55). Willan.

Ferguson, A. G., 2016. Policing predictive policing. Wash. UL Rev., 94, 1109.

Ferguson, A. G., 2019. Predictive Policing Theory. (December 31, 2019). Chapter 24: The Cambridge Handbook of Policing in the United States (ed. Tamara Rice Lave & Eric J. Miller), Cambridge Univ. Press

Hair Jr, J. F., Babin, B. J., & Anderson, R. E. (2010). A global p-erspect-ivie. Kennesaw: Kennesaw State University.

Hair, J.F., Gabriel, M. and Patel, V., 2014. AMOS covariance-based structural equation modeling (CB-SEM): Guidelines on its application as a marketing research tool. Brazilian Journal of Marketing, 13(2), pp.44-55.

Harrison, B., 2019. Command college–foresight as a foundation to police executive development. On the Horizon, 27(1), pp.24-34.

Johnston, R., Jones, K. and Manley, D., 2018. Confounding and collinearity in regression analysis: a cautionary tale and an alternative procedure, illustrated by studies of British voting behaviour. Quality & quantity, 52(4), pp.1957-1976.

Kirschner, P. A., Sweller, J., Kirschner, F., and Zambrano, J., 2018. From cognitive load theory to collaborative cognitive load theory. International Journal of Computer-Supported Collaborative Learning, 13(2), pp.213-233.

Larsen, H.L., Blanco, J.M., Pastor, R.P. and Yager, R.R. Eds., 2017. Using Open Data to Detect Organized Crime Threats: Factors Driving Future Crime. Springer.

Le, N.T., Loll, F. and Pinkwart, N., 2013. Operationalizing the continuum between well-defined and ill-defined problems for educational technology. IEEE Transactions on Learning Technologies, 6(3), pp.258-270.

Malek C., 2018. AI will help police fight crime more efficiently, Abu Dhabi forum hears. Retrieved from: https://www.thenational.ae/uae/government/ai-will-help-police-fight-crime-more-efficiently-abu-dhabi-forum-hears-1.711149

Meijer, A. and Wessels, M., 2019. Predictive policing: Review of benefits and drawbacks. International Journal of Public Administration, 42(12), pp.1031-1039.

MENA Herald, 2018. Dubai Police launch Future Societies 5.0: world's smartest force announce 2019 AI summit that will promote safer, happier policing across the world. Available at: https://www.menaherald.com/en/business/events-services/dubai-police-launch-future-societies-50-world%E2%80%99s-smartest-force-announce

Mohler, G.O., Short, M.B., Malinowski, S., Johnson, M., Tita, G.E., Bertozzi, A.L. and Brantingham, P.J., 2015. Randomized controlled field trials of predictive policing. Journal of the American statistical association, 110(512), pp.1399-1411.

Perry, W.L., McInnis, B., Price, C.C., Smith, S. and John, S., 2014. Hollywood, Predictive Policing: Forecasting Crime for Law Enforcement.

Ramahi, N., 2018. Cameras with facial recognition software will identify wrongdoers in Dubai. Retrieved from: https://www.thenational.ae/uae/cameras-with-facial-recognition-software-will-identify-wrongdoers-in-dubai-1.699321

Ratcliffe, J.H., Taylor, R.B. and Fisher, R., 2019. Conflicts and congruencies between predictive policing and the patrol officer's craft. Policing and Society, 30(6), pp.639-655.

Richardson, R., Schultz, J.M. and Crawford, K., 2019. Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice. NYUL Rev. Online, 94, pp.15-55.

Saunders, J., Hunt, P. and Hollywood, J.S., 2016. Predictions put into practice: a quasi-experimental evaluation of Chicago's predictive policing pilot. Journal of Experimental Criminology, 12(3), pp.347-371.

Scheuer, O., Loll, F., Pinkwart, N. and McLaren, B.M., 2010. Computer-supported argumentation: A review of the state of the art. International Journal of Computer-supported collaborative learning, 5(1), pp.43-102.

Shaheen, S., & Shaheen, H. (2016). Emotional intelligence in relation to psychological well-being among students. The International Journal of Indian Psychology, 3(4), 206-213.

Shouk, A. A., 2019a. UAE the safest country in the world. Retrieved from: https://gulfnews.com/uae/uae-the-safest-country-in-the-world-1.62729939

Shouk. A. A., 2019b. AI and smart data ends crime in Palm Jumeirah, Emirates Hills. Retrieved from: https://gulfnews.com/uae/crime/ai-and-smart-data-ends-crime-in-palm-jumeirah-emirates-hills-1.65006123

Stanko, E.A., 2020. Learning versus Training: Thoughts about the Origins of the Home Office Innovation Fund Project 'Developing an Evidence-Based Police Degree Holder Entry Programme'2016–18. Policing: A Journal of Policy and Practice, 14(1), pp.43-51.

Teasley, S.D. and Roschelle, J., 1993. Constructing a joint problem space: The computer as a tool for sharing knowledge. Computers as cognitive tools, pp.229-258.

Tomsic, A. and Suthers, D.D., 2006. Discussion tool effects on collaborative learning and social network structure. Journal of Educational Technology & Society, 9(4), pp.63-77.

Vera Jiménez, J. C., Fernández, F., Ayuso Vilacides, J., and Lorente Acosta, J. A., 2020. Evaluation of the police operational tactical procedures for reducing officer injuries resulting from physical interventions in problematic arrests. The case of the Municipal Police of Cádiz (Spain).

Weisburd, D. and Braga, A.A. eds., 2019. Police innovation: Contrasting perspectives. Cambridge University Press.

Zaman, K., Usman, B., Sheikh, S.M., Khan, A., Kosnin, A.B.M., Rosman, A.S.B., Ismail, S., Ali, D.F. and Hishan, S.S., 2019. Managing crime through quality education: A model of justice. Science & Justice, 59(6), pp.597-605.