PLS-SEM MODEL OF CRIME MITIGATION PERFORMANCE OF ABU DHABI POLICE PREDICTIVE POLICING

Hind Rashed Saleh Al Shamsi, Su'aidi Safei*

Institute of Technology Management and Entrepreneurship, Universiti Teknikal Malaysia Melaka, Malaysia

*Corresponding E-mail: suaidi@utem.edu.my

ABSTRACT

Objective: This study aimed to develop a Structural Equation Model (SEM) using Partial Least Square (PLS) of Crime Mitigation Performance of Abu Dhabi Police Predictive Policing.

Research Method: The model is developed and evaluated in SmartPLS software. A total of 316 valid responses from questionnaire survey were used for developing the model. The survey was conducted amongst employees of the Abu Dhabi Crime Scene Department. The model was evaluated at measurement component and structural component of the model.

Findings: It was found that at measurement component, all the evaluation criteria are achieved. Furthermore, the structural component also achieved the fitness criteria of the model. For hypothesis, it was found that there a significant connection between Collaborative Learning (CL) and Crime Mitigation Performance (CMP), with a p-value of 0.001, and Innovative Officer Performance (IOP) with an even more substantial p-value of 0.000. These factors evidently impact CMP. In contrast, Predictive Policing Adoption (PPA) and Specialised Technology Training (STT) lack statistical significance, with p-values of 0.509 and 0.972 respectively, suggesting chance-driven associations.

Originality: The developed PLS-SEM model of Crime Mitigation Performance of Abu Dhabi Police Predictive Policing.

Keywords: Crime Mitigation Performance, Police Predictive Policing

1. INTRODUCTION

To ensure further progress and sustained development, the UAE is poised to leverage Artificial Intelligence (AI) as a transformative tool. Embracing AI technology can amplify the ongoing transformation by fostering innovation, enhancing efficiency, and propelling the nation towards even greater economic diversification and competitiveness. Artificial intelligence (AI) has been demonstrated to be a very effective method for reducing complexity and making appropriate decisions quickly in order to achieve success (Almarashda et al. 2021). AI uses improved databases and more powerful computers to process data more quickly and with the right interpretation (Almarashda et al. 2022). Raheem & Tchantchane (2019) indicated in their research that as of October 2017, the UAE took a pioneering step by establishing its own dedicated AI ministry. The primary objective of this initiative is to propel the UAE government towards becoming one of the most effective, influential, and forward-thinking administrations, achieved through the strategic advancement and integration of AI technologies. Building upon this foundation, a recent study by PwC (PwC, 2018) highlights that the adoption of AI is projected to contribute significantly to the UAE's GDP growth, with an anticipated increase of $96 billion by 2030 (13.6% growth). Looking further ahead to 2035, various sectors are poised for substantial improvement and transformation. Specifically, the economics and financial sector is projected to witness a $37 billion enhancement, healthcare is anticipated to benefit by $22 billion, and the transport sector is expected to see a boost of $19 billion. These sectors are integral components of the UAE's economic framework and its trajectory for growth.

UAE government's use of AI is visible in driving operational efficiency, increasing labour productivity, and altering customer relations via AI-powered sales recommendations and fraud detection mechanisms (Shah & Shaheen, 2016). The UAE's 2017 AI plan emphasises the importance of AI in achieving a customer-centric approach, leading service agents to give successful solutions. Furthermore, AI has the potential for significant cost benefits, with estimates of billions of dollars in annual savings through automation (UAE AI plan, 2016). This strategy emphasises the possibility of reallocating resources in order to improve service quality and adapt to changing needs. Despite these developments, successful predictive policing technology adoption poses obstacles related to aligning with police personnel' experience (Ratcliffe et al., 2019). Predictive model opacity introduces mistakes that limit their applicability (Meijer & Wessels, 2019; Ferguson, 2019). Meijer and Wessels (2019) emphasise the need of officers understanding predictive algorithms in order to make the best decisions. This study intends to shed light on the scarcity of evidence on specialised AI and big data training for crime prevention (Ferguson, 2019). Collaborative learning, guided by educational psychology principles, is also important for improving officer performance (Kirschner et al., 2018).

The UAE government's commitment to innovation extends to public services, industrial growth, and the overall well-being of the country (UAE AI plan, 2016). The strategic integration of AI in public services, particularly predictive policing, intends to improve service delivery and overall quality (Dave & Sharma, 2019). AI technology is being used to improve citizen satisfaction in accordance with national visions such as UAE Vision 2021 and UAE Vision 2030. Exploring the function of training and collaborative learning becomes critical as Abu Dhabi Police continues to develop predictive policing (Abu Dhabi Police GHQ, 2020). The purpose of this research is to determine the relationship between crime mitigation performance and the elements that contribute to it, such as Predictive Policing Adoption, Specialized Technology Training, Innovative Officer Performance, and Collaborative Learning.

.

2. LITERATURE REVIEW

2.1 AI IN ORGANIZATIONS

AI is used in organizations to plan, organize, control, and lead. The movement of AI from research laboratories to organizations is not new. Early applications of AI in organizations were in the form of expert and knowledge management systems (Doukidis & Paul, 1990). These applications were designed primarily to aid in human decision-making (Duchessi, O'Keefe, and O'Leary, 1993). As such, these applications had little autonomy or agency of their own and were employed for a narrow set of tasks. However, the ability to capture, store, and rapidly process large data sets in real time has expanded the use and the degree of autonomy associated with AI in organizations. For example, AI is now being used to automatically search, filter, select, and recommend job applicants (Daugherty, Wilson, & Chowdhury, 2019). AI systems are not only automatically assigning workers to tasks but are also evaluating their work (Dhir & Chhabra, 2019; Hoshino, Slobodin, & Bernoudy, 2018). These work activities occur daily with minimal human intervention or awareness (Rosenblat, 2018).

The expanded use and increased autonomy of AI can be problematic. Previously, organizations underestimated the extent to which human biases could impact AI systems. For example, an early paper highlighted the advantage of AI to organizations by arguing that AI offers “more consistent decision making and greater reliability in decision processes” (Duchessi et al., 1993, p. 154). Although misguided, this rhetoric has not been entirely discarded. For example, as noted in a recent Harvard Business Review article, AI can be “potentially more impartial in its actions than human beings” (Kolbjørnsrud et al., 2016, p. 5). However, scholars generally now acknowledge that AI is far from less susceptible to human prejudices or biases (Daugherty et al., 2019).

Examining fairness, or the lack thereof, in AI is becoming recognized as an increasingly important topic of investigation across many research communities. The ACM Conference on Fairness, Accountability, and Transparency (FAT), which started in 2018, is one example of this recognition. Scholars from diverse fields such as management, law, information, data science, medical science, and public policy are questioning and examining issues of AI fairness (Jarrahi, 2018; Siau & Wang, 2018; Veale & Brass, 2019; Vellido, 2019; Žliobaitė, 2017). However, without a theoretical and systematic approach, researchers and designers lack a road map for crafting interventions likely to help promote fairer AI.

AI refers to a cluster of technologies enabling machines to operate with sophisticated intelligence and replicate human capabilities such as sensing, understanding, and executing tasks. These machine capacities are augmented by the ability to learn from experiences and adapt over time. Essentially, AI empowers machines to reason within their surroundings and respond to the circumstances influencing them. The application of AI systems is progressively expanding across industries, gaining in prominence due to their increasing capabilities. In contemporary terms, AI stands as a fully developed technology. Recent AI systems and technologies possess fundamental abilities to discern and engage with various human expressions, emotions, tones, and interactions (Microsoft, 2017). Although the history of AI has seen periods of advancement followed by extended frustration, the present landscape is marked by an unprecedented wave of technological innovation spanning multiple sectors, fueling the growth of AI initiatives. Two pivotal factors propelling this growth are the proliferation of digitized data within the global economy and the widespread accessibility of computing power, coupled with reduced costs for data storage offered through cloud services.

Artificial intelligence (AI) is an encompassing term that encompasses a range of technologies aimed at accomplishing tasks typically associated with human intelligence. Coined by John McCarthy in 1955 (McCarthy, 1989), it is defined as "the science and engineering of creating intelligent machines."

2.2 AI ASSIST GOVERNMENT FUNCTIONS

The integration and application of AI within government operations encompass the design, structuring, implementation, and assessment of cognitive computing and machine learning. This integration aims to enhance the management of public agencies, elevating both service quality and the government's capacity to provide these services (Liebowitz, 2001). Huang and Rust (2018) conducted a recent study illustrating how AI and advanced cognitive systems enable U.S. public agencies to liberate their workforce from repetitive tasks through the implementation of chatbots and natural language processing. The study highlights "Emma," a U.S. chatbot designed to assist visitors in navigating the U.S. Citizenship and Immigration Services (USCIS) website by addressing millions of customer queries. Emma can type responses in both English and Spanish while also providing spoken responses in English.

Furthermore, Hamet and Tremblay (2017) emphasized in their research the acceleration of process speed and transactions as a key benefit of AI adoption in governments. AI efficiently predicts and prioritizes structured and repetitive tasks, optimizing the delegation of responsibilities between humans and machines. The study cites Hong Kong as an example, where the Immigration Department streamlined its visa application process through AI. By training an AI system to classify applications and automatically transfer them to visa officers for final review, the department increased processing speed and efficiency by 40%. In the realm of government innovation and creativity, Prpic and Melton (2017) pointed out that AI expedites the creativity and innovation cycle, particularly within the context of public policy decision frameworks. Cognitive systems excel in multifaceted and challenging decision-making scenarios, owing to their ability to handle vast amounts of data and establish connections with enhanced effectiveness and efficiency.

In the UAE, governmental leaders recognize the substantial potential of AI technology. As a result, the public sector has embarked on a comprehensive initiative to adopt AI across various domains. Within this context, government implementers embrace AI as a central agent for cognitive computing, robotics, and machine learning. These technologies aim to amplify human capabilities, particularly in addressing simple and complex tasks, thereby augmenting employee abilities, productivity, and performance as highlighted in a recent study by Brougham and Haar (2018). This involves intelligent learning from vast and diverse datasets, transcending heterogeneous systems in near-real-time, and engaging in natural language processing interactions.

2.3 ADOPTION OF AI TECHNOLOGY IN POLICING IN THE UAE

You might perceive AI as an innovative, futuristic, and revolutionary endeavor, but its impact is now extending deeply and substantially, particularly within the realm of government. While cognitive and reasoning technologies cannot replace the intricate strategic planning and management crucial for various important public administrators, we are entering an era of automated intelligence, wherein tasks once believed to demand human decision-making are being automated. In this context, this section illustrates how AI can effectively and seamlessly facilitate different governmental and citizen services:

1. Streamlining Administrative Tasks: The integration of AI introduces promising prospects for automation, leading to significant reductions or even eliminations of repetitive administrative tasks. AI-powered 'BOTS' can amalgamate diverse activities into automated processes, particularly those with repetitive characteristics. This ranges from processing invoices and form filling to routine data entry and comprehensive budget reporting. By freeing up time through such automation, the government can function more efficiently, allowing employees to focus on impactful work, enhancing overall performance, productivity, and responsiveness to citizens' needs.
2. Tackling Backlogs: Excessive backlogs and prolonged waiting times can be immensely frustrating for both citizens and government personnel. The adept use of cognitive technologies enables efficient navigation through data backlogs and the completion of end-to-end business procedures on a considerable scale. Complex cases can be directed to human specialists, ensuring more effective and timely resolution.
3. Enhancing Predictive Capabilities: AI, coupled with machine learning and language processing technologies, exhibits the capacity to identify and analyze patterns intelligently. Through trial and error, these systems develop distinctive predictive abilities, especially concerning future potential events. Governments can leverage wearable and smart monitors based on AI and machine learning to monitor injuries' significance and urgency, aiding medical professionals in treatment planning. Simultaneously, the Department of Energy employs self-learning weather forecasting technology, utilizing machine learning systems and specialized sensor data, along with cloud-motion physics derived from sky cameras and satellite data, to enhance solar forecasting accuracy by approximately 30 percent.

The UAE was formerly ranked as the 21st happiest country globally and the foremost in the Arab world, as indicated by the UN World Happiness Report (Helliwell, Layard, & Sachs, 2017). The UAE maintains its pursuit of claiming the top spot worldwide in this aspect. Furthermore, the integration of AI technologies is anticipated to play a facilitating role in achieving the happiness objective. By enhancing services through digitalization, technological advancements, and innovation, AI is poised to minimize time, costs, and efforts associated with service provision. This shift always ensures the availability of creative services. As explained by Halaweh (2018), AI applications and comprehensive systems can be integrated into various facets of people's lives. This integration goes beyond merely improving the provision of crucial services; it also elevates the overall quality of life for individuals. This is achieved through the provision of services that are more precise, self-reliant, easily accessible, and boundless. These services are no longer dependent solely on human capacities and skills, thus reducing the occurrences of biases, errors, and misunderstandings that could arise from human interactions.

In the UAE, particularly in the city of Dubai renowned for its smart city initiatives, AI has been strategically implemented to serve as a proficient intermediary connecting the city's government with its citizens. This utilization of AI has led to the delivery of exceptional governmental public services. Expanding its AI adoption from domains like transportation, environment, renewable energy, and education, Dubai's government is now introducing AI systems to provide a range of public services to its residents.

One notable implementation is the use of "Rammas" chatbots by the Dubai Electricity and Water Authority (DEWA). Starting in January 2017, they leveraged a Google AI platform within their Customer Happiness Centers. This AI platform adeptly recognizes, comprehends, and responds to written inquiries in both Arabic and English. A significant feature of this system is its ability to learn and adapt based on the questions posed by the authority's customers. This initiative has considerably minimized the need for physical visits while enriching customer knowledge and interactions.

Autonomous Vehicles: Sheikh Mohammed bin Rashid Al Maktoum, the ruler of Dubai, has set a target for 25 percent of the emirate's vehicles to be self-guided or autonomous by 2030. This strategic endeavour aims not only to reduce the volume of cars on the roads, but also holds the potential to decrease the frequency of vehicle accidents. Additionally, the transition to having 25 percent of vehicles as driverless is projected to yield savings of up to $6 billion and generate various economic impacts by cutting down travel time.

2.4 CRIME MITIGATION PERFORMANCE

Challenges in implementing predictive policing technology revolve around aligning police officers' expertise (Ratcliffe et al., 2019). The opacity of predictive models leads to errors, hindering effectiveness (Meijer & Wessels, 2019; Ferguson, 2019). Meijer & Wessels emphasize understanding predictive algorithms for optimal decisions. Ferguson aims to illuminate the limited evidence of specialized AI and big data training for crime prevention. Enhancing officer performance through collaborative learning, grounded in educational psychology, is vital (Kirschner et al., 2018). Rapid technological advancement, especially in Artificial Intelligence (AI), disrupts sectors and challenges established norms. AI excels in real-time data processing and knowledge accumulation (Krasadakis, 2018).

The UAE reshapes industries, particularly in healthcare, utilizing AI innovatively (Halaweh, 2018; Wehbe & Svetinovic, 2018). Strategic AI deployment across domains in the UAE leads to notable progress (Halaweh, 2019). Bessen (2018) highlights AI's potential in streamlining processes, optimizing resources, and improving citizen services. It introduces intricate roles, affecting workforce augmentation. AI addresses data challenges, improves cognitive processes, and advances predictive capabilities, aiding informed policy decisions (Bessen, 2018). In the UAE, AI significantly enhances business efficiency, employee productivity, and customer experiences. Technology-driven practices like sales recommendations and fraud detection transform customer interactions (Shah & Shaheen, 2016). The UAE's 2017 AI strategy focuses on a customer-centric approach, guiding service representatives to provide effective solutions. It envisions substantial cost-saving through automation, reallocating resources for better service quality and adapting to evolving needs (UAE AI strategy, 2016). The UAE government extends innovation beyond business to public services and national well-being (UAE AI strategy, 2016). AI integration in predictive policing

accelerates service delivery and enhances quality (Dave & Sharma, 2019), aligning with the UAE's 2021 and 2030 visions for citizen satisfaction.
Given the ongoing implementation of predictive policing across the Abu Dhabi Police, investigating the role of training and collaborative learning takes on pivotal importance (Abu Dhabi Police GHQ, 2020). This study endeavours to uncover the relationship between crime mitigation performance and other contributing factors, such as Predictive Policing Adoption, Specialized Technology Training, Innovative Officer Performance, and Collaborative Learning. Through this research, insights into enhancing the effectiveness of AI-driven crime mitigation strategies can be gained, contributing to the broader evolution of law enforcement practices

2.4.1 PREDICTIVE POLICING

Predictive policing applies data analytics to anticipate crime trends, aiding law enforcement in staying ahead of criminals (Perry et al., 2014). This proactive era of policing, driven by artificial intelligence and big data, involves predicting crimes, offenders, and victims (Ekblom, 2013; Meijer and Wessels, 2019; Richardson et al., 2019). It surpasses traditional crime analysis methods (Perry et al., 2014). Real-time analysis of criminal responses forms the basis of predictive policing, utilizing AI to allocate resources to high-risk areas (Ekblom, 2013; Meijer and Wessels, 2019). It enhances police operations by targeting specific locations and factors contributing to crime risk, with minimal human intervention.

2.4.2 INNOVATIVE OFFICER

Innovation is defined as the application of fresh approaches and concepts to effectively enhance performance (Stanko, 2020). Particularly within an officer's duties, the importance of innovative performance has been highlighted, especially in reducing injuries during physical interventions and problematic arrests (Weisburd and Braga, 2019). Police innovation takes on diverse forms and encompasses strategic, tactical, and operational dimensions of crime prevention efforts (Vera Jiménez et al., 2020). It has also proven crucial in improving police-community relations, maintaining law and order, and contributing to crime prevention and successful arrests (Vera Jiménez et al., 2020; Liaw et al., 2019).

2.4.3 SPECIALISED TECHNOLOGY TRAINING

The need for training in predictive policing arises from the recognition that anticipated benefits often dwindle in both controlled experiments and real-world situations (Meijer and Wessels, 2019). To fully harness the enhanced potential of predictive policing, it becomes crucial to provide human agents with training to address inherent limitations. Among the various challenges associated with predictive policing, the central issue revolves around the lack of synchronization between technological tools and police personnel (Ekblom, 2013; Meijer and Wessels, 2019; Richardson et al., 2019). A critical emphasis lies in the requirement to embrace and prepare for efficient system utilization, as highlighted by Richardson et al. (2019). This challenge underscores the core research gap in the current study and corresponds with what Ensign et al. (2017) denote as the "runaway feedback" loop in predictive policing. As rapid technological progress broadens the potential applications of predictive technology (Shapiro, 2017), law enforcement officers must effectively engage with these systems to grasp their capabilities and how they can enhance their operational duties (Meijer and Wessels, 2019).

2.4.4 COLLABORATIVE LEARNING

Collaboration is still necessary for achieving shared learning goals inside collaborative environments, particularly in Predictive Policing (Teasley and Roschelle, 1993). It serves as a forum for exchanging ideas and encouraging innovation towards common goals (Scheuer et al., 2010). Collaboration in the current technological environment can take place either face-to-face or through technological systems (Le et al., 2013). Tasks or challenges may arise from shared learning activities in collaborative projects, varied in clarity as either well-defined or open-ended. Participants in the cooperation can take on certain roles to meet the task or challenge depending on the nature of the problem (Le et al., 2013; Scheuer et al., 2010). While cooperation is essential for identifying urgent solutions, its long-term influence results in enhanced group adaptability as a result of accumulated experience through time (Kirschner et al., 2018). Because of its synergistic link with other social structures, collaborative learning has demonstrated its usefulness in cultivating a productive work environment in the field of law enforcement (Tomsic and Suthers, 1993). Furthermore, Zaman et al. (2006) emphasise that law enforcement officials should recognise the potential for joint educational programmes to reduce crime and improve overall work efficiency.

3. CONCEPTUAL MODEL

The pervasive role of AI across diverse domains, including reinforcement learning (Al-Emran, 2015a), robotics (Al-Emran, 2015b), NLP (Al-Emran, Zaza, and Shaalan, 2015), data mining (Saa, Al-Emran, and Shaalan, 2019), and IoT (Al-Emran, Malik, and AlKa-bi, 2020), is undeniable. Within this context, the Technology Adoption Model (TAM) serves as a prominent approach to identify critical success factors (CSFs) for AI implementation across industries, encompassing sectors such as law enforcement (Alharbi & Drew, 2014; Phatthana and Mat, 2011). However, despite excess of research on AI's performance, there exists a gap concerning its specific application in enhancing police predictive policing. This study bridges this gap by exploring the potential of AI implementation in augmenting Police Predictive Policing operations in the UAE. It investigates into the perceptions of employees regarding challenges and potential threats associated with integrating AI within the organizational framework (Abdullah and Ward, 2016; Al-Emran and Teo, 2019). Drawing upon preceding discussions, the foundational literature substantiates the conceptual model presented in Figure 1.

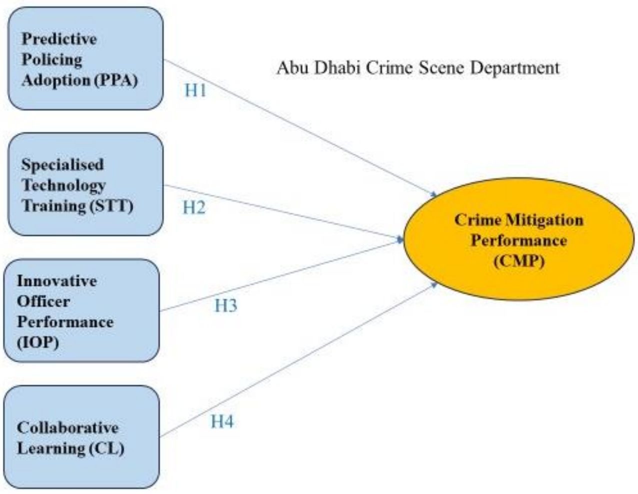

Figure 1: Conceptual framework

Figure 1 shows the conceptual model which consists of five basic independent constructs namely Predictive Policing Adoption (PPA) Specialised Technology Training (STT), Innovative Officer Performance (IOP), Collaborative Learning (CL), and dependent construct that is Crime Mitigation Performance (CMP). The hypothesis that can be drawn from the conceptual model is as presented in table 1

Table 1: Hypothesis from the conceptual model

Code	**Hypothesis Descriptions**
H1	Predictive Policing Adoption has a positive impact on Innovative Officer Performance
H2	Innovative Officer Performance has a positive impact on Crime Mitigation Performance in the Abu Dhabi Police GHQ
H3	Specialized Technology Training significantly moderates the impact of Predictive Policing Adoption on Crime Mitigation Performance in Abu Dhabi Police GHQ
H4	Collaborative Learning significantly mediates the impact of Innovative Officer Performance on Crime Mitigation Performance in Abu Dhabi Police GHQ

4. MODELLING OF CONCEPTUAL MODEL

A Structural Equation Model (SEM) is an advanced extension of regression analysis that model's relationships between observed and latent variables, incorporating factors like measurement models and direct/indirect paths. SEM is a powerful statistical methodology used to analyse complex relationships between variables. Two prominent approaches within SEM are the covariance-based approach and the variance-based approach. For covariance-based, it tests predefined theories using covariance and fit indices. Best for established models and hypothesis testing. However, for variance-based (commonly known as partial least square, PLS) which focuses on predicting relationships, suited for complex models or less-defined theories. Emphasizes explaining variance and can handle smaller samples (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). Since this study does not has predefined theory, hence it adopted variance-based or PLS approach in developing the SEM model based on the conceptual model. Further, PLS-SEM is being used more frequently in scientific and business research because it is a reliable method of data analysis. SEM can be used for a variety of purposes, including risk analysis, forecasting models, and decision support systems (Memon et al. 2023a).

4.1 MODEL DEVELOPMENT

Data used to develop the model is derived from a questionnaire survey from employees of the Abu Dhabi Crime Scene Department. The questionnaires were distributed aligned with the department's demographic profile using a probability sampling technique, ensuring equal participation opportunities for all members, as recommended by Saunders et al. (2016). With the collected data, the model was developed and evaluated in SmartPLS software as in figure 2.

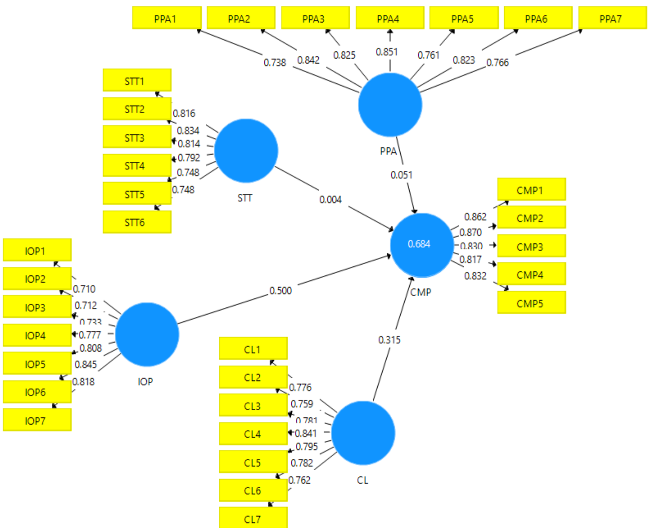

Figure 2: the generated model

4.2 EVALUATION OF MEASUREMENT COMPONENT

4.2.1 CONSTRUCT'S RELIABILITY AND VALIDITY

Construct reliability and validity are important research principles that ensure the robustness and credibility of measurement tools and theoretical frameworks. They analyse the consistency, stability, and accuracy of conceptions employed to measure variables and phenomena as a group. The recommended cut-off values for the reliability and validity measures are as follows (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). For Cronbach's Alpha, a value of 0.7 or greater is regarded acceptable in most cases, but higher values are recommended in more robust investigations. For rho_A (Rho A), a value of 0.7 or greater is typically recognised as demonstrating excellent internal consistency, like Cronbach's Alpha. For composite Reliability, values of 0.7 or greater are deemed acceptable, with higher values preferred and finally, for Average Variance Extracted (AVE), : values of 0.5 or above are suggested. The generated construct reliability and validity values from the model after conducting PLS Algorithm process are as in table 2.

Table 2 result of construct reliability and validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CL	0.897	0.898	0.919	0.617
CMP	0.898	0.900	0.924	0.709
IOP	0.888	0.896	0.912	0.598
PPA	0.907	0.912	0.926	0.643
STT	0.881	0.885	0.91	0.628

Table 2 presents measures of internal consistency and reliability for five constructs: CL, CMP, IOP, PPA, and STT. It includes Cronbach's Alpha, rho_A, Composite Reliability, and Average Variance Extracted (AVE) values for each construct. These measures evaluate the consistency of items within constructs, the reliability of constructs in structural equation modelling, and the variance captured by construct indicators. Higher values across these measures indicate strong internal consistency, reliability, and variance capture within the constructs.

4.2.2 DISCRIMINANT VALIDITY

Discriminant validity is a crucial principle in research that guarantees measurement tools distinguish across unrelated constructs efficiently. It ensures that the measurements accurately represent distinct concepts and are not impacted by external circumstances. Discriminant validity protects against ambiguity in results and misinterpretation of links between constructs by evaluating them using statistical approaches such as correlation analysis and confirmatory factor analysis. Researchers improve the credibility and robustness of their study findings by demonstrating discriminant validity (Hair Jr, J.F. et. al., 2014; Hair Jr, J.F. et.al., 2017).

Table 3 results of discriminant validity

Construct	CL	CMP	IOP	PPA	STT
CL	**0.786**				
CMP	0.778	**0.842**			
IOP	0.848	0.807	**0.774**		
PPA	0.714	0.645	0.732	**0.802**	
STT	0.757	0.69	0.816	0.787	**0.793**

Table 3 displays correlation coefficients among five constructs: CL, CMP, IOP, PPA, and STT. The coefficients indicate the strength and direction of the relationships between pairs of constructs. Higher coefficients suggest stronger correlations. These correlations provide insights into how the constructs are interconnected, aiding in understanding their potential associations and supporting the validity of measurement instruments and theoretical relationships in research.

4.2.3 CHECKING THE PRESENCE OF MULTICOLLINEARITY

Collinearity statistics pertain to the correlation among independent variables in a regression model, indicating a linear relationship. When correlated variables coexist within the same model, their individual abilities to predict the dependent variable are compromised. While the term "collinearity" refers broadly to variable correlations, "multicollinearity" focuses on the correlation between independent variables in regression analysis. However, multicollinearity's presence is problematic as it can lead to unstable results and unreliable coefficient estimates within regression models. To address multicollinearity, employing strategies like feature selection and regularization becomes crucial to enhance model stability and interpretability.

Table 4 presents the Variance Inflation Factor (VIF) values for independent variables in the model. VIF is used to assess multicollinearity, which occurs when predictor variables are highly correlated with each other, leading to instability in parameter estimates. The VIF values in this table show the extent of multicollinearity for each independent variable. Lower VIF values generally indicate lower levels of multicollinearity and less correlation among the predictor variables (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017).

Table 4 Results of multicollinearity

Independent variables	VIF	Independent variables	VIF
CL1	2.172	PPA1	2.025
CL2	2.051	PPA2	2.814
CL3	2.282	PPA3	2.478
CL4	2.966	PPA4	2.942
CL5	2.444	PPA5	2.005
CL6	2.086	PPA6	2.524
CL7	1.84	PPA7	1.779
CMP1	2.647	STT1	2.187
CMP2	2.8	STT2	2.489
CMP3	2.195	STT3	2.101
CMP4	2.137	STT4	2.111
CMP5	2.168	STT5	1.959
IOP1	2.043	STT6	2.016
IOP2	2.212		
IOP3	1.725		
IOP4	2.231		
IOP5	2.67		
IOP6	2.612		
IOP7	2.331		

Table 4 presents VIF values for several independent variables across different constructs, such as CL (construct 1), PPA (construct 2), CMP (construct 3), and STT (construct 4). The values for each independent variable range from approximately 1.7 to 2.8, suggesting that multicollinearity is not of substantial concern, as the VIF values are within an acceptable range.

4.2.4 VALIDATING MEASUREMENT MODEL

Construct Cross-Validated Redundancy (CCR) and Construct Cross-Validated Communality (CCC) are part of the process of validating the measurement model in structural equation modelling (SEM). Validating the measurement model involves assessing how well the latent constructs represent the observed variables. These metrics play a crucial role in this validation process by providing insights into the quality of the relationships between the latent constructs and the observed variables. They help ensure that the latent constructs are effectively capturing the information present in the observed data and that they are not redundant or overlapping (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). By examining CCR and CCC, researchers can gain confidence in the accuracy and reliability of the measurement model, which is a fundamental step in conducting meaningful and accurate structural equation modelling analyses.

4.2.4.1 CONSTRUCT CROSS VALIDATED REDUNDANCY (CCR)

CCR is a metric in structural equation modelling that assesses the extent to which observed variables are explained by the underlying latent constructs. Lower values indicate that the latent constructs effectively capture the variability in the observed variables, implying minimal redundancy. This metric helps evaluate the efficiency of the measurement model and ensures that latent constructs provide meaningful explanations for the observed data. Interpretation should consider model complexity, research objectives, and comparison with other relevant measures. The cutoff value for CCR is not standardized and varies based on factors like model complexity and research context. Lower values are desirable as they suggest efficient representation of observed variables by latent constructs, minimizing redundancy. Results of CCR generated from blindfolding process of the model are as in table 5.

Table 5 Results of CCR after blindfolding process

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
CL	2786	2786	
CMP	1990	1046.436	0.474
IOP	2786	2786	
PPA	2786	2786	
STT	2388	2388	

Table 5 presents information about the Sum of Squares Explained (SSO), Sum of Squares Error (SSE), and the Q^2 coefficient for different constructs. The SSO represents the variability explained by the model, while SSE indicates the unexplained variability. The Q^2 coefficient quantifies the proportion of variability explained by the model relative to the unexplained variability. For instance, in the case of the CMP construct, it explains approximately 47.4% (0.474) of the variability, with 1046.436 units of SSE. The table offers insights into the model's effectiveness in explaining variance across different constructs.

4.2.4.2 CONSTRUCT CROSS VALIDATED COMMUNALITY (CCC)

CCC is an evaluation measure in structural equation modelling. It gauges the extent to which a latent construct accounts for variance in an observed variable, while considering model generalizability across different datasets. The cutoff value for CCC is context-dependent, with higher values indicating better performance. Its interpretation hinges on research goals and field-specific standards. Comparing values with other measures is crucial for assessing the construct's ability to explain observed variable variance effectively. Results of CCC generated from blindfolding process of the model are as in table 6.

Table 6 Results of CCC after blindfolding process

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
CL	2786	1442.031	0.482
CMP	1990	880.895	0.557
IOP	2786	1493.499	0.464
PPA	2786	1338.212	0.52
STT	2388	1255.545	0.474

Table 6 displays data related to the Sum of Squares Explained (SSO), Sum of Squares Error (SSE), and the Q^2 coefficient for different constructs. The SSO represents the total variability explained by the model, while the SSE indicates the unexplained variability. The Q^2 coefficient measures the proportion of variability explained by the model relative to the unexplained variability. For instance, in the case of the CMP construct, the model explains around 55.7% (0.557) of the variability, with an SSE of 880.895 units. The table provides insights into the effectiveness of the model in explaining variance across various constructs.

4.3 EVALUATION OF MEASUREMENT COMPONENT

4.3.1 FIGURES AND TABLES

Path coefficients quantify the strength and direction of relationships between latent variables or observed variables. These coefficients indicate the change in the dependent variable for a unit change in the independent variable, while accounting for other variables in the model. It provides valuable insights into the impact and significance of different factors within the complex relationships modelled by PLS (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). Table 7 provides insights into how different factors relate to Crime Mitigation Performance. The path coefficients quantify the strength and direction of these relationships, indicating the extent to which changes in the independent variables influence changes in Crime Mitigation Performance.

Table 7 Path coefficient or strength

Relationship	Path coefficients
Collaborative Learning (CL) -> Crime Mitigation Performance (CMP)	0.315
Innovative Officer Performance (IOP) -> Crime Mitigation Performance (CMP)	0.500
Predictive Policing Adoption (PPA) -> Crime Mitigation Performance (CMP)	0.051
Specialised Technology Training (STT) -> Crime Mitigation Performance (CMP)	0.004

Table 7 indicate that for the Collaborative Learning (CL) factor, the path coefficient is 0.315. This suggests that a unit increase in Collaborative Learning is associated with a 0.315 unit increase in Crime Mitigation Performance (CMP). The Innovative Officer Performance (IOP) factor has a path coefficient of 0.500. This implies that a unit increase in Innovative Officer Performance corresponds to a more substantial 0.500 unit increase in Crime Mitigation Performance. Predictive Policing Adoption (PPA) is associated with a path coefficient of 0.051. This relatively small coefficient suggests that there is a minor increase in Crime Mitigation Performance for each unit increase in Predictive Policing Adoption. The Specialised Technology Training (STT) factor exhibits the smallest path coefficient of 0.004. This indicates that any changes in Crime Mitigation Performance due to variations in Specialised Technology Training are minimal.

4.3.2 HYPOTHESIS TESTING

Hypothesis testing in PLS modelling entails evaluating relationships between variables through the analysis of generated p-values. A relationship is deemed significant if its associated p-value is below 0.05, signifying a strong statistical relevance. The computation of these p-values involves the application of bootstrapping within the SmartPLS software. Bootstrapping, a robust resampling technique, establishes the dependability of model outcomes by constructing numerous datasets via random sampling with replacement (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). Non-parametric bootstrapping was applied to test the hypothesis (Rahman et al. 2022). Table 8 presents the outcomes of bootstrapping that examined relationships among the policing elements and their potential influence on Crime Mitigation Performance

Table 8 significant level of the model's relationships

Relationship	**P Values**	**Significant level**
Collaborative Learning (CL) -> Crime Mitigation Performance (CMP)	0.001	Significant
Innovative Officer Performance (IOP) -> Crime Mitigation Performance (CMP)	0.000	Significant
Predictive Policing Adoption (PPA) -> Crime Mitigation Performance (CMP)	0.509	Not Significant
Specialised Technology Training (STT) -> Crime Mitigation Performance (CMP)	0.972	Not Significant

Table 8 shows the relationship between Collaborative Learning (CL) and Crime Mitigation Performance (CMP) demonstrates a notably low p-value of 0.001. This compellingly suggests that the connection between CL and CMP is statistically significant. Thus, Collaborative Learning is very likely to impact Crime Mitigation Performance in a meaningful way. Innovative Officer Performance (IOP) boasts an even more striking p-value of 0.000, which emphasizes an exceptionally robust statistical significance. The data strongly indicates that Innovative Officer Performance has a profound impact on Crime Mitigation Performance. On the other hand, Predictive Policing Adoption (PPA) exhibits a p-value of 0.509. This figure surpasses conventional significance thresholds, implying that the relationship between PPA and CMP is not statistically significant. In other words, the data does not provide a convincing case for an impactful association. Similarly, Specialised Technology Training (STT) shows a notably high p-value of 0.972. This outcome underscores that any potential effects of Specialised Technology Training on Crime Mitigation Performance are likely due to chance rather than a substantive relationship.

4.3.3 VALIDATING STRUCTURAL MODEL

In PLS, model fit is typically evaluated through various metrics and techniques. One common approach is examining the goodness-of-fit measures, such as the goodness-of-fit index (GoF) or the coefficient of determination (R^2). The Goodness of Fit (GoF) index is used to assess the model's overall validity and explanatory power (Memon et. Al. 2023b, Khahro et al. 2021). These metrics assess the proportion of variance in the endogenous constructs that is explained by the model, providing insight into the overall explanatory power.

4.3.3.1 R SQUARE

The coefficient of determination, often denoted as R^2, is a statistical measure used to assess the proportion of the variance in the dependent variable that can be explained by the independent variables in a regression model. It determines the predictive relevancy of the model (Almansoori et al. 2021). In other words, it quantifies the goodness of fit of the regression model to the observed data. R^2 takes values between 0 and 1, where: $R^2 =0$ indicates that the independent variables do not explain any of the variance in the dependent variable. $R^2 =1$ indicates that the independent variables perfectly explain all the variance in the dependent variable (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). The generated R^2 values for the model are as in table 9.

Table 9 Generated model's R square values

Dependent construct	**R Square**	**R Square Adjusted**
CMP	0.684	0.681

Table 9 displays R^2 and adjusted R^2 values for the CMP construct in a regression model. The R^2 value of 0.684 indicates that about 68.4% of the variance in CMP is explained by the model's independent variables. Adjusted R^2, at 0.681, considers model complexity and offers a more balanced assessment of explanatory power.

4.3.3.2 MODEL FIT

Model fit assessment involves evaluating how closely a statistical model corresponds to observed data. Fit indices like SRMR, d_ULS, and d_G measure discrepancies between predicted and actual values, with lower values indicating better alignment. Chi-Square assesses goodness of fit by comparing observed and expected frequencies, while NFI gauges the model's improvement over a null model. The Standardized Root Mean Residual (SRMR) suggests that a value below 0.08 is generally acceptable for fit, with values closer to 0.05 or lower indicating better alignment. The Discrepancy Function for Unweighted Least Squares (d_ULS) and Geodesic Discrepancy (d_G) should ideally have lower values, around 2 or lower, signifying a favourable fit. The Chi-Square test's cut-off involves seeking a non-significant p-value, although this varies with sample size and model complexity. The Normed Fit Index (NFI) ranges from 0 to 1, with higher values being better; an NFI value above 0.9 is often considered indicative of a strong fit (Hair Jr, J.F. et.al., 2014; Hair Jr, J.F. et.al., 2017). Generated values of model fit after PLS Algorithm process are as in table 10.

Table 10 generated values of model fit after PLS Algorithm process

Indices	Saturated Model	Estimated Model
SRMR	0.064	0.064
d_ULS	2.159	2.159
d_G	1.112	1.112
Chi-Square	2346.865	2346.865
NFI	0.772	0.772

Table 10 presents the comparison between a Saturated Model and an Estimated Model based on several fit indices. Both models have the same values for each fit index, indicating that the Estimated Model aligns closely with the Saturated Model. The Standardized Root Mean Residual (SRMR) is 0.064 for both models, indicating a good fit. The discrepancy function (d_ULS) and the Geodesic discrepancy (d_G) also match at 2.159, reflecting a consistent fit. The Chi-Square value is identical for both models at 2346.865. The Normed Fit Index (NFI) is also the same at 0.772, indicating a relatively good fit for both models. Overall, the Estimated Model demonstrates a strong resemblance to the Saturated Model across these fit indices, suggesting that the Estimated Model is a valid representation of the data.

5. CONCLUSIONS

This paper presents a study on developing a PLS-SEM Model of Crime Mitigation Performance of Abu Dhabi Police Predictive Policing. The model is based on five basic independent constructs namely Predictive Policing Adoption (PPA) Specialised Technology Training (STT), Innovative Officer Performance (IOP), Collaborative Learning (CL), and dependent construct that is Crime Mitigation Performance (CMP). The data used to develop the model was derived from questionnaire survey amongst the employee of Abu Dhabi Police Crime Department. The model was developed and evaluated using SmartPLS software. The model was evaluated at measurement component and structural component of the model. It was found that at measurement component, all the evaluation criteria are achieved. Furthermore, the structural component also achieved the fitness criteria of the model. For hypothesis, it was found that there a significant connection between Collaborative Learning (CL) and Crime Mitigation Performance (CMP), with a p-value of 0.001, and Innovative Officer Performance (IOP) with an even more substantial p-value of 0.000. These factors evidently impact CMP. In contrast, Predictive Policing Adoption (PPA) and Specialised Technology Training (STT) lack statistical significance, with p-values of 0.509 and 0.972 respectively, suggesting chance-driven associations. Findings from this study, significantly contribute to the Abu Dhabi Police Predictive Policing for considerations.

ACKNOWLEDGEMENT

The authors would like to thank UTeM for allowing to conduct and publish this work.

REFERENCES

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. Computers in human behavior, 56, 238-256.

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

Abu Saa, A., Al-Emran, M., & Shaalan, K. (2019). Factors affecting students' performance in higher education: a systematic review of predictive data mining techniques. Technology, Knowledge and Learning, 24, 567-598.

Al-Emran, M. (2015). Hierarchical reinforcement learning: a survey. International journal of computing and digital systems, 4(02).

Al-Emran, M., & Teo, T. (2020). Do knowledge acquisition and knowledge sharing really affect e-learning adoption? An empirical study. Education and information technologies, 25(3), 1983-1998.

Al-Emran, M., Malik, S. I., & Al-Kabi, M. N. (2020). A survey of Internet of Things (IoT) in education: Opportunities and challenges. Toward social internet of things (SIoT): Enabling technologies, architectures and applications: Emerging technologies for connected and smart social objects, 197-209.

Al-Emran, M., Zaza, S., & Shaalan, K. (2015). Parsing modern standard Arabic using Treebank resources. In 2015 International Conference on Information and Communication Technology Research, ICTRC 2015. https://doi.org/10.1109/ICTRC.2015.7156426

Alharbi, S., & Drew, S. (2014). Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems.

Almansoori, M. T. S., Rahman, I. A., Memon, A. H., & Nasaruddin, N. A. N. (2021). Structural Relationship of Factors Affecting PMO Implementation in the Construction Industry. Civil Engineering Journal, 7(12), 2109-2118

Almarashda, H. A. H. A., Baba, I. B., Ramli, A. A., & Memon, A. H. (2022). User Expectation and Benefits of Implementing Artificial Intelligence in the UAE Energy Sector. Journal of Applied Engineering Sciences, 12(1).

Almarashda, H. A. H. A., Baba, I. B., Ramli, A. A., Memon, A. H., & Rahman, I. A. (2021). Human Resource Management and Technology Development in Artificial Intelligence Adoption in the UAE Energy Sector. Journal of Applied Engineering Sciences, 11(2)

Artificial Intelligence Office, UAE | United Arab Emirates. (n.d.). https://ai.gov.ae/wp-content/uploads/2021/07/UAE-National-Strategy-for-Artificial-Intelligence-2031.pdf

Bessen, J. (2018). Artificial intelligence and jobs: The role of demand. In The economics of artificial intelligence: an agenda (pp. 291-307). University of Chicago Press.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization, 24(2), 239-257.

Daugherty, P. R., Wilson, H. J., & Chowdhury, R. (2018). Using artificial intelligence to promote diversity. MIT Sloan Management Review.

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.

Dhir, K., & Chhabra, A. (2019). Automated employee evaluation using fuzzy and neural network synergism through IoT assistance. Personal and Ubiquitous Computing, 23, 43-52.

Doukidis, G. I., & Paul, R. J. (1992). A survey of the application of artificial intelligence techniques within the OR society. Artificial intelligence in operational research, 9-21.

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, 27-55.

Ensign, D., Friedler, S.A., Neville, S., Scheidegger, C. and Venkatasubramanian, S., (2018). Runaway feedback loops in predictive policing. In Conference on Fairness, Accountability and Transparency, 160-171.

Ferguson, A. G. (2019). Predictive Policing Theory. 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. and Krey, N. (2017). Covariance-based structural equation modeling in the Journal of Advertising: Review and recommendations. Journal of Advertising, 46(1), 163-177.

Hair Jr, J.F., Sarstedt, M., Hopkins, L. and Kuppelwieser, V.G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. European business review, 26(2), 106-121.

Hair Jr, J.F., Sarstedt, M., Ringle, C.M. and Gudergan, S.P., (2017). Advanced issues in partial least squares structural equation modeling. SAGE publications.

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), 44-55.

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).

Halaweh, M. (2018). Cash on delivery (COD) as an alternative payment method for e-commerce transactions: Analysis and implications. International Journal of Sociotechnology and Knowledge Development (IJSKD), 10(4), 1-12.

Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. Metabolism, 69, S36-S40.

Helliwell, J. F., Layard, R., & Sachs, J. D. (2017). World happiness report 2017. Sustainable Development Solutions Network.
Hoshino, R., Slobodin, A., & Bernoudy, W. (2018). An automated employee timetabling system for small businesses. In Proceedings of the AAAI Conference on Artificial Intelligence, 32(1).
Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of service research, 21(2), 155-172.
Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business horizons, 61(4), 577-586.
Khahro, S. H., Memon, A. H., Memon, N. A., Arsal, A., & Ali, T. H. (2021). Modeling the factors enhancing the implementation of green procurement in the Pakistani construction industry. Sustainability, 13(13), 7248
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.
Kolbjørnsrud, V. (2018). Collaborative organizational forms: on communities, crowds, and new hybrids. Journal of Organization Design, 7(1), 11.
Krasadakis, G. (2018). Artificial Intelligence: the impact on employment and the workforce: How is AI replacing jobs? Which roles and industries will be most impacted? How can societies get prepared?. Which roles and industries will be most impacted? How can societies get prepared.
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), 258-270.
Liaw, J.O.H., Wong, W., Singh, I.S.T., Ridzuan, A.A., Moiden, A.H., Mohaiyadin, N.M. and Rahiman, A.S.A. (2019). The Review of Effectiveness Integration Programs to Reduce Crime in Malaysia. International Journal of Academic Research in Business and Social Sciences, 9(1), 1353-1361.
Liebowitz, J. (2001). Knowledge management and its link to artificial intelligence. Expert systems with applications, 20(1), 1-6.
McCarthy, J. J. (1989). Linear order in phonological representation. Linguistic inquiry, 20(1), 71-99.
Meijer, A. and Wessels, M. (2019). Predictive policing: Review of benefits and drawbacks. International Journal of Public Administration, 42(12), 1031-1039.
Memon, A. H., Memon, A. Q., Soomro, M. A., Memon, M. A., & Khan, J. S. S. (2023a). Structural model of cost overrun factors affecting Pakistani construction projects. Mehran University Research Journal Of Engineering & Technology, 42(2), 108-123.
Memon, A. H., Memon, A. Q., Khahro, S. H., & Javed, Y. (2023b). Investigation of Project Delays: Towards a Sustainable Construction Industry. Sustainability, 15(2), 1457
Microsoft annual report (2017). Microsoft 2017 Annual Report. (n.d.). https://www.microsoft.com/investor/reports/ar17/index.html
O'Keefe, R. M., & O'Leary, D. E. (1993). Expert system verification and validation: a survey and tutorial. Artificial Intelligence Review, 7, 3-42.
Perry, W.L., McInnis, B., Price, C.C., Smith, S. and John, S., 2014. Hollywood, Predictive Policing: Forecasting Crime for Law Enforcement.
Phatthana, W., & Mat, N. K. N. (2011). The Application of Technology Acceptance Model (TAM) on health tourism e-purchase intention predictors in Thailand. In 2010 International conference on business and economics research (Vol. 1, pp. 196-199).
Prpic, J., Melton, J., Taeihagh, A., & Anderson, T. (2017). MOOCs and crowdsourcing: Massive courses and massive resources. arXiv preprint arXiv:1702.05002.

PwC. (2018). Workforce of the future: The competing forces shaping 2030. Retrieved from: https://www.pwc.com.au/people-business/assets/workforce-of-the-future.pdf

Raheem, K., & Tchantchane, A. (2019). IoT Importance in Construction Industry: Dubai. Accelerating the Sustainable Development Goals through Digital Transformation, 78.

Rahman, I. A., Al Ameri, A. E. S., Memon, A. H., Al-Emad, N., & Alhammadi, A. S. M. (2022). Structural relationship of causes and effects of construction changes: case of UAE construction. Sustainability, 14(2), 596

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, 15-55.

Rosenblat, A. (2018). Uberland: How algorithms are rewriting the rules of work. Univ of California Press.

Saunders, M., Lewis, P. and Thornhill, A. (2016) Research Methods for Business Students. 7th Edition, Pearson, Harlow.

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, N. S., & Shaheen, S. (2016). Artificial Intelligence (AI), Genomics and Personalized Medicine. Biotechnological Research, 2(4), 173-175.

Shapiro, A., 2017. Reform predictive policing. Nature, 541(7638), pp.458-460.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. Cutter business technology journal, 31(2), 47-53.

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.

Veale, M., & Brass, I. (2019). Administration by algorithm? Public management meets public sector machine learning. Public management meets public sector machine learning.

Vellido, A. (2019). Societal issues concerning the application of artificial intelligence in medicine. Kidney Diseases, 5(1), 11-17.

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).

Wehbe, Y., Al Zaabi, M., & Svetinovic, D. (2018). November. Blockchain AI Framework for Healthcare Records Management: Constrained Goal Model. In 2018 26th Telecommunications Forum (TELFOR), 420–425.

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.

Žliobaitė, I. (2017). Measuring discrimination in algorithmic decision making. Data Mining and Knowledge Discovery, 31(4), 1060-1089