

# Artificial Intelligence Adoption in Forensic Science for City Security in the UAE

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## Abstract

The rapid adoption of Artificial Intelligence (AI) in forensic and security-related practices has transformed investigative processes, until now its effectiveness depends on organisational, ethical, and technological conditions. This study proposes and empirically tests an AI-TFPs (AI-Transformational Forensic Processes) framework to examine how AI integration, ethical and legal requirements, and technological advancements influence forensic outcomes through key mediating mechanisms: Adaptation and Learning, Iterative Evaluation, and Stakeholder Engagement. Using Partial Least Squares Structural Equation Modelling (PLS-SEM) and data collected from 403 professionals in the United Arab Emirates, the study evaluates both the measurement and structural models. The results confirm strong construct reliability, convergent validity, and discriminant validity. Structural model findings reveal that AI integration, ethical-legal requirements, and technological factors do not directly improve forensic outcomes. Instead, their effects are primarily transmitted through organisational adaptation and learning and stakeholder engagement. Adaptation and Learning emerge as the strongest predictor of forensic outcomes, followed by Stakeholder Engagement, while Iterative Evaluation shows no significant direct or mediating effect. The model demonstrates substantial explanatory power ( $R^2$ ), meaningful effect sizes ( $f^2$ ), strong predictive relevance ( $Q^2$ ), and acceptable model fit. Overall, the findings highlight that successful AI adoption in forensic contexts requires more than technological deployment where it depends on

continuous learning, ethical governance, and active stakeholder involvement. The study provides practical and theoretical insights for policymakers and law enforcement agencies seeking to enhance forensic effectiveness through responsible AI implementation.

**Keywords:** Artificial Intelligence Adoption, Forensic Science, Digital Transformation, United Arab Emirates (UAE)

## 1. Introduction

Artificial Intelligence (AI) has rapidly evolved into a transformative technology across multiple sectors, including healthcare, finance, manufacturing, and education. Scholars such as Haenlein and Kaplan (2021) and Jordan and Mitchell (2015) highlight its ability to enhance speed, accuracy, and efficiency in analysing complex datasets. In forensic science, AI is reshaping traditional investigative methods. For example, Choudhury, Basu, and Ghosh (2022) discuss its role in automating pattern recognition, while Ball (2018) emphasizes its contribution to digital evidence analysis. Similarly, Smith and Johnson (2020) note how predictive policing and decision-support systems are increasingly augmented by AI. This global adoption reflects a paradigm shift in approaches to public safety, justice, and governance, as argued by Cath et al. (2018) and further explored in criminology by Brantingham et al. (2021).

The United Arab Emirates (UAE) exemplifies this transformation. Strategic frameworks such as UAE Vision 2021 and the National AI Strategy 2031 (UAE Ministry of Artificial Intelligence, 2020) position the nation as a global hub for advanced technology. Alsharqi, AlMarashda, and Al Hammadi (2022) describe how innovation is embedded into governance structures, while Raed (2020) and Othman and Al Mahaddi (2023) highlight the emphasis on secure urban development. Within this context, integrating AI into forensic sciences becomes critical, offering opportunities to strengthen investigative capabilities and promote city security.

Despite these ambitions, adoption in UAE forensic practice remains uneven. Al-Ghamdi et al. (2019) report that many institutions have acquired AI-driven systems, yet Kumar and Raj (2023) show that integration into workflows and decision-making has not consistently achieved expected reliability. Organizational and behavioral barriers are equally significant; O'Neil et al. (2023) and Tian et al. (2022) identify trust, transparency, and institutional inertia as key inhibitors of effective assimilation.

Technology adoption research provides useful theoretical lenses. The Technology Acceptance Model (TAM) introduced by Davis (1989), later extended by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), emphasizes perceptions of usefulness and ease of use. The Innovation Diffusion Theory (IDT) articulated by Rogers (2003) explains how innovations spread across organizational settings. Yet, forensic contexts present unique challenges. Gilpin et al. (2018) argue that limited transparency undermines trust in AI outputs, while Leslie (2023) highlights ethical tensions that complicate ease of use and compatibility. Diffusion is also fragmented; Dwivedi et al. (2023) and Argote (2013) note that institutional adoption does not always translate into organizational learning or individual acceptance.

Existing studies often emphasize technological potential or ethical implications. For instance, Mavroeidis et al. (2022) examine opportunities and pitfalls of forensic AI, while Wang et al. (2020) focus on public safety applications in smart cities. However, fewer works, such as Chen et al. (2023) and Guttman et al. (2024), investigate the psychological and process mechanisms that convert AI capability into measurable performance improvements. Constructs derived from TAM (e.g., perceived usefulness, ease of use) and IDT (e.g.,

compatibility, complexity, observability) must be understood alongside organizational processes such as Adaptation & Learning (ADL), Stakeholder Engagement (SEG), and Iterative Evaluation (IEV).

In the UAE, this theoretical gap is particularly critical. National strategies emphasize readiness and infrastructure investment (UAE Government, 2024; UAE Ministry of Interior, 2022), yet the mediating role of human, organizational, and regulatory dimensions remains underexplored. Without a clear, theory-driven model linking adoption factors to institutional processes and performance, forensic AI initiatives risk becoming technically advanced but operationally ineffective.

Therefore, this study addresses the lack of an integrated theoretical and empirical model explaining how AI adoption factors grounded in TAM and IDT are operationalized through organizational processes to achieve measurable forensic outcomes in the UAE. By developing and validating a Structural Equation Model (SEM), the research contributes both to theoretical advancement and to practical strategies for AI adoption in forensic science, ultimately promoting city security and resilience.

## **2. Formulation of Conceptual Framework**

The conceptual framework for this study is designed to explain how Artificial Intelligence (AI) adoption in forensic science contributes to promoting city security in the United Arab Emirates (UAE). It is grounded in the Technology Acceptance Model (TAM), originally introduced by Davis (1989) and later extended by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), alongside the Innovation Diffusion Theory (IDT) developed by Rogers (2003). Together, these theories provide a foundation for integrating technological, ethical, and organizational dimensions that capture both the drivers and processes of AI assimilation in forensic practice.

Three independent variables which are Integration of AI (IAI), Ethical and Legal Requirements (ELR), and Technological Advancements and Challenges (TAC) that represent the influential factors shaping AI adoption. These constructs reflect the technical readiness, regulatory environment, and infrastructural capacity underpinning the UAE's national AI strategy, as emphasized in policy analyses by the UAE Ministry of Artificial Intelligence (2020) and strategic foresight studies such as Alsharqi, AlMarashda, and Al Hammadi (2022).

The framework introduces three mediating constructs that are Iterative Evaluation (IEV), Stakeholder Engagement (SEG), and Adaptation & Learning (ADL), to capture the organizational and behavioural mechanisms through which AI adoption translates into operational effectiveness. Continuous assessment and refinement of AI systems are highlighted by Chen et al. (2023) in their work on learning loops, while collaboration among law enforcement agencies, policymakers, and forensic professionals aligns with findings from Guttman et al. (2024) on human-in-the-loop AI in criminal justice.

The dependent variable, Forensic Outcomes (FOC), represents the ultimate measure of success, linking AI adoption to enhanced investigative capabilities and improved city security. Studies such as Mavroeidis et al. (2022) and Wang et al. (2020) demonstrate how

technological adoption in forensic and public safety contexts can yield measurable improvements in resilience and security. Direct and indirect pathways are hypothesized, suggesting that while adoption factors may exert immediate influence on forensic outcomes, their effectiveness is largely mediated by evaluation and engagement processes.

This formulation bridges the theory–practice gap by operationalizing TAM and IDT constructs within a forensic science context, thereby providing a structured framework for empirical validation. It ensures that the UAE’s investment in AI not only drives technological innovation but also enhances institutional capability, accountability, and resilience in safeguarding urban security, echoing the arguments of Leslie (2023) on balancing transparency and efficacy in forensic AI.

As illustrated in Figure 1, the proposed AI–TFPs conceptual framework positions AI adoption factors as antecedents that shape transformational forensic processes, which in turn lead to improved forensic outcomes. This framework underscores the strategic role of AI adoption in advancing forensic science practices and promoting city security within the UAE.

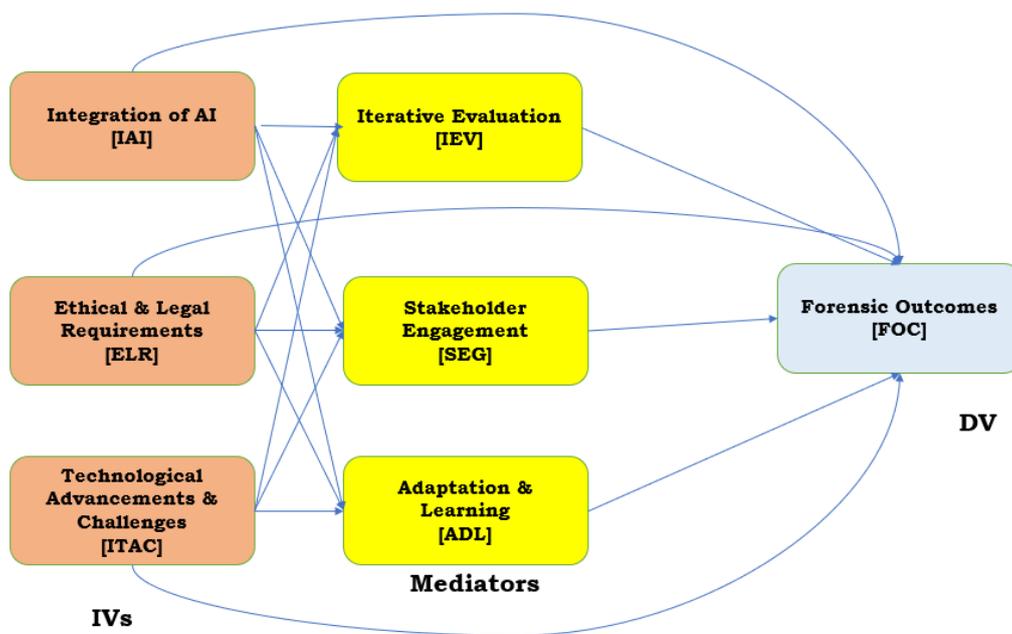


Figure 1. The conceptual framework

Based on the conceptual framework of *AI adoption factors* → *Transformational forensic processes* → *Forensic outcomes* (AI–TFPs) presented in Figure 1, the study formulates its hypotheses as outlined in Table 1 for the direct effects and Table 2 for the indirect effects.

Table 1. Direct effect hypotheses

<b>Variable</b>	<b>Code</b>	<b>Direct Path</b>	<b>Hypothesis Statement</b>
Integration of AI [IAI]	H1a	IAI → ADL	Integration of AI has a positive effect on Adaptation & Learning.
Ethical & Legal Requirements [ELR]	H1b	IAI → SEG	Integration of AI has a positive effect on Stakeholder Engagement.
	H1c	IAI → IEV	Integration of AI has a positive effect on Iterative Evaluation.
	H1d	IAI → FOC	Integration of AI has a positive effect on Forensic Outcomes.
Ethical & Legal Requirements [ELR]	H2a	ELR → ADL	Ethical & Legal Requirements have a positive effect on Adaptation & Learning.
	H2b	ELR → SEG	Ethical & Legal Requirements have a positive effect on Stakeholder Engagement.
	H2c	ELR → IEV	Ethical & Legal Requirements have a positive effect on Iterative Evaluation.
	H2d	ELR → FOC	Ethical & Legal Requirements have a positive effect on Forensic Outcomes.
Technological Advancements & Challenges [TAC]	H3a	TAC → ADL	Technological Advancements & Challenges have a positive effect on Adaptation & Learning.
	H3b	TAC → SEG	Technological Advancements & Challenges have a positive effect on Stakeholder Engagement.
	H3c	TAC → IEV	Technological Advancements & Challenges have a positive effect on Iterative Evaluation.
	H3d	TAC → FOC	Technological Advancements & Challenges have a positive effect on Forensic Outcomes.
Mediators → Outcome	H4	IEV → FOC	Iterative Evaluation has a positive effect on Forensic Outcomes.
	H5	SEG → FOC	Stakeholder Engagement has a positive effect on Forensic Outcomes.
	H6	ADL → FOC	Adaptation & Learning has a positive effect on Forensic Outcomes.

Table 2. Indirect effect hypotheses

Variable	Code	Indirect Path	Hypothesis Statement
Integration of AI [IAI]	H7a	IAI → ADL → FOC	Adaptation & Learning mediates the relationship between IAI and Forensic Outcomes.
	H7b	IAI → SEG → FOC	Stakeholder Engagement mediates the relationship between IAI and Forensic Outcomes.
	H7c	IAI → IEV → FOC	Iterative Evaluation mediates the relationship between IAI and Forensic Outcomes.
Ethical & Legal Requirements [ELR]	H7a	ELR → ADL → FOC	Adaptation & Learning mediates the relationship between ELR and Forensic Outcomes.
	H7b	ELR → SEG → FOC	Stakeholder Engagement mediates the relationship between ELR and Forensic Outcomes.
	H7c	ELR → IEV → FOC	Iterative Evaluation mediates the relationship between ELR and Forensic Outcomes.
Technological Advancements & Challenges [TAC]	H7a	TAC → ADL → FOC	Adaptation & Learning mediates the relationship between TAC and Forensic Outcomes.
	H7b	TAC → SEG → FOC	Stakeholder Engagement mediates the relationship between TAC and Forensic Outcomes.
	H7c	TAC → IEV → FOC	Iterative Evaluation mediates the relationship between TAC and Forensic Outcomes.

### 3. Data Collection

The data used to model the conceptual framework with SmartPLS software were collected from 403 respondents across the United Arab Emirates (UAE). The target population comprised professionals directly engaged in the adoption, implementation, and oversight of AI-enabled forensic science systems. This included forensic practitioners and analysts, law enforcement officers, technical and data specialists, policy and governance officials, and academic researchers. Such diversity ensured that perspectives were captured across the AI adoption chain, from technology design and deployment to operational integration and regulatory enforcement (Chen et al., 2023; Guttman et al., 2024).

Institutional coverage reflected the UAE's leadership under the National AI Strategy 2031 and We the UAE 2031 vision. Respondents were drawn from major forensic and law enforcement agencies such as the Ministry of Interior's Forensic Science and Criminology Directorate, Abu Dhabi Police Forensic Evidence Department, Dubai Police Forensic Laboratory, and Sharjah Police Crime and Evidence Unit. Academic partners, including Khalifa University and UAE University, also contributed, reinforcing the study's connection to ongoing AI research and training in forensic applications. This institutional diversity aligns with foresight studies on AI diffusion in the UAE's public sector (Alsharqi et al., 2022) and reflects the federal AI ethics frameworks outlined by the UAE Ministry of Artificial Intelligence (2020).

A purposive sampling technique was employed to intentionally select respondents with relevant expertise and direct exposure to AI-based forensic systems, supplemented by snowball sampling to access professionals in secure or restricted forensic departments. The appropriateness of purposive sampling in specialist contexts has been emphasized by Etikan et al. (2016), while snowballing has been recognized as a practical necessity in security-sensitive environments (Israel & Hay, 2006). Participation criteria required (a) direct or indirect involvement in AI-based forensic processes, (b) employment within UAE-based law enforcement, forensic, or academic institutions, and (c) a minimum of one year of professional experience in the forensic or related technological field. This approach maximized representativeness while respecting confidentiality protocols inherent to government and security agencies, consistent with ethical guidance provided by Bryman (2016) and Creswell and Creswell (2018).

The demographic profile of the sample further underscores its diversity. Most respondents were male (63%), reflecting the predominance of men in law enforcement and forensic professions, while females accounted for 37%. Age distribution was balanced, with the largest group aged 30–39 years (34%), followed by 40–49 years (29%), 20–29 years (20%), and 50 years or older (18%), representing both early-career and experienced professionals. Professionally, law enforcement officials (34%) and government/policy officials (31%) formed the largest subgroups, complemented by forensic experts and technicians (23%) and researchers (11%). Geographically, respondents were concentrated in Dubai (40%) and Abu Dhabi (29%), with smaller proportions from Sharjah (17%) and other Emirates (14%). These demographic patterns mirror institutional realities described in studies of AI integration in law enforcement (Al-Ghamdi et al., 2019) and reinforce the UAE's strategic investment in forensic and security applications (Raed, 2020; Kumar & Raj, 2023).

Hence, the target population, institutional coverage, sampling strategy, and demographic distribution demonstrate that the study sample is sufficiently diverse and representative. This enhances the robustness and generalizability of the findings, providing a strong empirical basis for modelling the conceptual framework in SmartPLS, consistent with methodological guidance on PLS-SEM applications (Hair et al., 2022; Henseler et al., 2016).

#### **4. Validation of Conceptual Framework**

To empirically validate the proposed conceptual framework, this study applied Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS software. PLS-SEM was selected because of its proven suitability for analysing complex models that incorporate multiple constructs, mediating variables, and relatively modest sample sizes, while also accommodating non-normal data distributions (Chin, 1998; Hair et al., 2022; Henseler et al., 2016). As illustrated in Figure 2, the modelling process was implemented in two sequential stages:

- Validation of the Measurement Model – to ensure construct reliability, convergent validity, and discriminant validity.
- Validation of the Structural Model – to assess the strength and significance of hypothesised relationships, explanatory power ( $R^2$ ), effect sizes ( $f^2$ ), and predictive

relevance ( $Q^2$ ).

Following these validations, hypotheses testing was performed to examine both direct and indirect effects. This systematic approach ensures rigorous evaluation of the conceptual framework, providing robust evidence on how AI adoption factors, organisational processes, and mediating mechanisms collectively shape forensic outcomes in the UAE context.

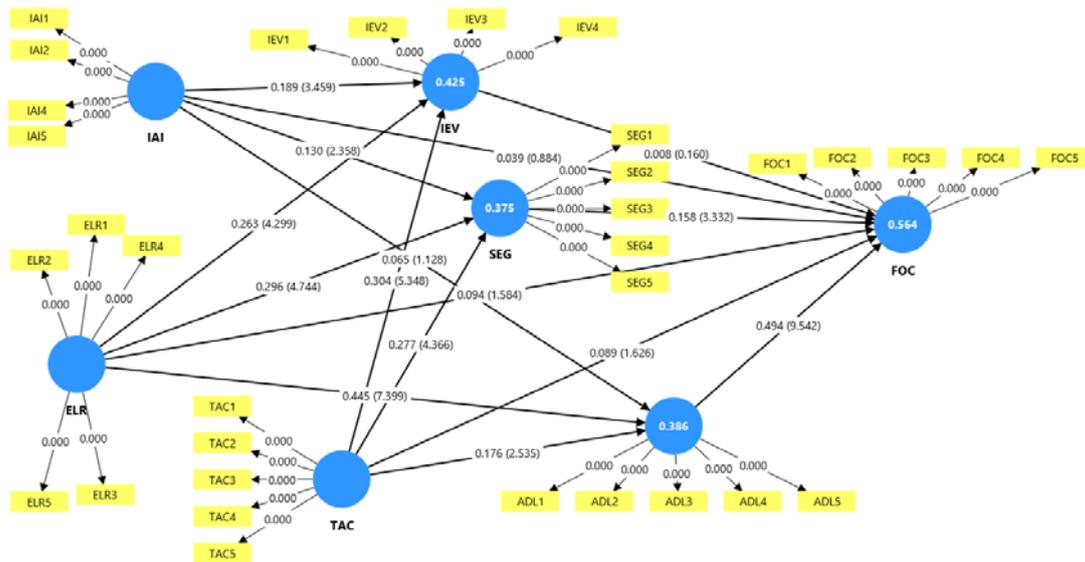


Figure 2. PLS-SEM Model of the framework

#### 4.1 Validation of Measurement Model

The measurement model was assessed to ensure that the constructs were reliable and valid before testing structural relationships. Reliability was evaluated using Cronbach’s alpha and Composite Reliability (CR), both exceeding the recommended threshold of 0.70, confirming internal consistency (Nunnally & Bernstein, 1994). Convergent validity was established via Average Variance Extracted (AVE) values, all above 0.50, demonstrating that each construct adequately captured the variance of its indicators (Fornell & Larcker, 1981). Discriminant validity was verified using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, confirming that the constructs were distinct (Henseler et al., 2016). Detailed results are presented in the following sub-sections.

##### 4.1.1 Reliability and Validity of Constructs

Table 3 shows the reliability and validity results for the seven *AI adoption factors* → *Transformational forensic processes* → *Forensic outcomes* (AI–TFPs) constructs. Cronbach’s alpha values ranged from 0.78 (IAI) to 0.89 (FOC), exceeding 0.70 (Nunnally & Bernstein, 1994), while CR values ranged from 0.75 (IAI) to 0.92 (FOC), also above the recommended minimum. AVE values ranged from 0.58 (FOC) to 0.70 (IEV), confirming convergent validity (Fornell & Larcker, 1981).

Table 3. Reliability and validity of constructs

Construct	Cronbach's $\alpha$	CR	AVE
IAI – Integration of AI	0.78	0.75	0.66
ELR – Ethical & Legal Requirements	0.82	0.87	0.66
TAC – Technological Advancements & Challenges	0.80	0.86	0.66
IEV – Iterative Evaluation	0.81	0.80	0.70
SEG – Stakeholder Engagement	0.79	0.85	0.67
ADL – Adaptation & Learning	0.85	0.89	0.67
FOC – Forensic Outcomes	0.89	0.92	0.58

Overall, the measurement model meets the required standards of reliability and validity, providing a robust foundation for structural model analysis.

#### 4.1.2 Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratio.

##### 4.1.2.1 Fornell–Larcker Criterion

As shown in Table 4, the square roots of the Average Variance Extracted (AVE) values (bold diagonal) exceed the inter-construct correlations, thereby confirming discriminant validity (Fornell & Larcker, 1981). Some correlations are relatively high such as the relationship between Adaptation & Learning (ADL) and Forensic Outcomes (FOC) is 0.714, while Ethical and Legal Requirements (ELR) and Technological Advancements and Challenges (TAC) correlate at 0.671. These values reflect theoretical linkages among constructs but remain below the  $\sqrt{\text{AVE}}$  thresholds, thus satisfying the criterion for discriminant validity.

Table 4. Fornell–Larcker criterion

	<b>ADL</b>	<b>ELR</b>	<b>FOC</b>	<b>IAI</b>	<b>IEV</b>	<b>SEG</b>	<b>TAC</b>
ADL	0.788						
ELR	0.603	0.767					
FOC	0.714	0.567	0.835				
IAI	0.423	0.593	0.426	0.659			
IEV	0.490	0.579	0.456	0.507	0.700		
SEG	0.622	0.559	0.587	0.453	0.512	0.734	
TAC	0.510	0.671	0.515	0.532	0.581	0.545	0.739

Note. Diagonal =  $\sqrt{\text{AVE}}$ ; Off-diagonal = inter-construct correlations.

##### 4.1.2.2 Heterotrait–Monotrait Ratio

Table 5 shows that all HTMT values are below the conservative threshold of 0.85 (Henseler et al., 2015), ranging from 0.575 to 0.833. The highest ratio (ELR–TAC = 0.833) indicates

close conceptual proximity but confirms that constructs are empirically distinct.

Table 5. HTMT ratios

	ADL	ELR	FOC	IAI	IEV	SEG	TAC
ADL							
ELR	0.720						
FOC	0.815	0.660					
IAI	0.581	0.807	0.587				
IEV	0.644	0.765	0.575	0.789			
SEG	0.758	0.677	0.688	0.644	0.683		
TAC	0.623	0.833	0.613	0.739	0.781	0.678	

Hence, both Fornell–Larcker and HTMT analyses confirm that the AI–TFPs constructs are empirically distinct. Some pairs (such as ELR–TAC, ADL–FOC, IAI–ELR) exhibit strong conceptual relationships, consistent with theoretical expectations, but do not compromise discriminant validity.

#### 4.2 Validation of Structural Model

The structural model was evaluated to examine the hypothesised relationships.  $R^2$  values demonstrated substantial explanatory power, particularly for Forensic Outcomes (FOC), while  $f^2$  effect sizes highlighted the relative influence of each predictor. Positive  $Q^2$  values confirmed predictive relevance, and model fit indices (SRMR,  $d_{ULS}$ ,  $d_G$ , Chi-square, NFI) indicated an acceptable correspondence between the data and the model (Hair et al., 2022; Henseler et al., 2016). Detailed results are presented in the sub-sections below.

##### 4.2.1 Coefficient of Determination ( $R^2$ )

As shown in Table 6, the model explains a moderate to substantial proportion of variance in the endogenous constructs. Specifically, the predictor constructs account for 38.6% of the variance in Adaptation and Learning (ADL), 42.5% in Iterative Evaluation (IEV), and 37.5% in Stakeholder Engagement (SEG). Most notably, 56.4% of the variance in Forensic Outcomes (FOC) is explained by the combined effects of Integration of AI, Ethical and Legal Requirements, Technological Advancements and Challenges, as well as the mediating processes (ADL, IEV, and SEG).

According to Chin (1998),  $R^2$  values between 0.33 and 0.67 indicate moderate explanatory power, while values above 0.67 reflect substantial explanatory strength. In this study, the  $R^2$  values for ADL, IEV, and SEG fall within the moderate range, whereas the  $R^2$  for FOC reflects a moderate-to-substantial level of explained variance. This suggests that the proposed AI–TFPs model demonstrates strong predictive capability for forensic outcomes and adequately captures the key mechanisms underlying the mediating constructs.

Furthermore, the relatively high  $R^2$  value for FOC supports the theoretical assumption that AI

adoption factors, together with organisational learning, iterative evaluation, and stakeholder engagement processes, play a critical role in shaping effective forensic outcomes. Overall, the findings indicate that the model provides a robust explanatory framework for understanding how AI-related factors influence forensic performance (Hair et al., 2022).

Table 6. Coefficient of determination ( $R^2$ )

Construct	R-square
ADL	0.386
FOC	0.564
IEV	0.425
SEG	0.375

Table 6 indicates that the model achieves satisfactory explanatory power across all endogenous constructs, with particularly strong performance in predicting Forensic Outcomes (FOC), thereby confirming the relevance and adequacy of the proposed structural model.

#### 4.2.2 Effect Size ( $f^2$ )

Table 7 presents the effect size ( $f^2$ ) results for the AI-TFPs model, indicating the relative contribution of each exogenous construct to the endogenous variables. Adaptation and Learning (ADL) exhibit the strongest effect on Forensic Outcomes (FOC) ( $f^2 = 0.286$ ), which corresponds to a medium-to-large effect size according to Cohen (1988). This finding highlights ADL as the most influential determinant of forensic performance within the model.

Ethical and Legal Requirements (ELR) demonstrate small effects on ADL ( $f^2 = 0.152$ ), Iterative Evaluation (IEV) ( $f^2 = 0.057$ ), and Stakeholder Engagement (SEG) ( $f^2 = 0.066$ ), while their effect on FOC is negligible ( $f^2 = 0.008$ ). Similarly, Technological Advancements and Challenges (TAC) show small effects on ADL ( $f^2 = 0.026$ ), IEV ( $f^2 = 0.064$ ), and SEG ( $f^2 = 0.084$ ), but only a negligible influence on FOC ( $f^2 = 0.008$ ). Integration of AI (IAI) exerts very small effects across all constructs (e.g., ADL = 0.004; FOC = 0.002), suggesting a limited direct contribution within this model.

Both IEV and SEG also have minimal effects on FOC ( $f^2 = 0.000$  and  $f^2 = 0.029$ , respectively), indicating that their influence on forensic outcomes is relatively weak compared to ADL. These results reinforce the methodological guidance of Hair et al. (2022), who emphasize that  $f^2$  values provide critical insight into the relative importance of predictors in PLS-SEM models.

Table 7. Effect Size ( $f^2$ ) (N = 403)

	ADL	ELR	FOC	IAI	IEV	SEG	TAC
ADL			0.286				
ELR	0.152		0.008		0.057	0.066	
FOC							
IAI	0.004		0.002		0.038	0.017	
IEV			0.000				
SEG			0.029				
TAC	0.026		0.008		0.084	0.064	

Overall, the results indicate that Adaptation and Learning is the primary driver of forensic outcomes, whereas ELR and TAC mainly affect the mediating constructs rather than FOC directly. This pattern underscores the central role of continuous learning and organisational adaptation in enhancing forensic effectiveness, while ethical, legal, and technological factors shape the process more indirectly.

#### 4.2.3 Predictive Relevance ( $Q^2$ )

The predictive relevance of the AI-TFPs model was assessed using the PLS-Predict procedure in SmartPLS. This method generates case-level predictions for the endogenous constructs and compares them with a naïve linear benchmark model, providing a robust test of out-of-sample predictive power (Hair et al., 2022). As recommended in methodological guidelines,  $Q^2$  values greater than zero indicate that the model has predictive relevance, while negative values suggest a lack of predictive capability (Chin, 1998; Henseler et al., 2016).

 Table 8. Predictive relevance ( $Q^2$ ) (N = 403)

Construct	$Q^2_{\text{predict}}$	RMSE	MAE
ADL	0.371	0.797	0.618
FOC	0.347	0.811	0.651
IEV	0.409	0.773	0.619
SEG	0.362	0.803	0.637

Table 8 shows that all  $Q^2_{\text{predict}}$  values exceed zero (ADL = 0.371; IEV = 0.409; SEG = 0.362; FOC = 0.347), indicating that the model demonstrates predictive relevance for all endogenous constructs (Stone, 1974; Geisser, 1974). According to Hair et al. (2019),  $Q^2$  values between 0.15 and 0.35 reflect medium predictive relevance, while values above 0.35 indicate large predictive relevance. On this basis, IEV exhibits the strongest predictive capability, followed by ADL, SEG, and FOC, all of which fall within the medium-to-high range.

The RMSE and MAE values further confirm stable predictive accuracy across constructs,

with no evidence of systematic prediction bias. Collectively, these findings suggest that the AI–TFPs model not only explains variance effectively, as shown by the  $R^2$  results (Chin, 1998), but also produces reliable out-of-sample predictions. This enhances the practical usefulness of the model for understanding how AI adoption factors and mediating processes influence forensic outcomes in real-world settings (Hair et al., 2019; Henseler et al., 2016).

#### 4.2.4 Model Fit

To evaluate the overall fit of the AI–TFPs model, several goodness-of-fit indices were examined, including the Standardised Root Mean Square Residual (SRMR), squared Euclidean distance ( $d_{ULS}$ ), geodesic discrepancy ( $d_G$ ), Chi-square, and Normed Fit Index (NFI). These indices are widely recommended in the PLS-SEM literature for assessing model fit beyond variance explanation (Hair et al., 2022; Henseler et al., 2016). The results for both the saturated and estimated models are presented in Table 9.

Table 9. Model fit indices

Index	Saturated Model	Estimated Model
SRMR	0.071	0.079
$d_{ULS}$	2.799	3.527
$d_G$	0.860	0.900
Chi-square	1899.089	1936.905
NFI	0.719	0.714

The SRMR values were 0.071 for the saturated model and 0.079 for the estimated model, both of which are below the recommended threshold of 0.08 (Henseler et al., 2016; Hu & Bentler, 1999). This indicates an acceptable level of model fit.

The  $d_{ULS}$  (2.799 saturated; 3.527 estimated) and  $d_G$  (0.860 saturated; 0.900 estimated) values are reported for reference, with lower values reflecting a closer fit between the empirical and model-implied covariance matrices. Although no strict cut-off criteria exist for these indices, the observed values fall within acceptable ranges for complex PLS-SEM models (Hair et al., 2019).

The Chi-square statistics are relatively high (1899.089 saturated; 1936.905 estimated), which is common in large-sample studies and therefore not unexpected. The NFI values (0.719 saturated; 0.714 estimated) fall below the conventional threshold of 0.90 (Bentler & Bonett, 1980), indicating modest incremental fit. However, NFI is known to underestimate model fit in complex PLS-SEM models and should be interpreted with caution (Hair et al., 2022).

Overall, the SRMR results provide strong evidence of adequate model fit, while the remaining indices suggest that the AI–TFPs model achieves a satisfactory approximation of the empirical data. Although the NFI values are below ideal levels, this outcome is consistent with prior PLS-SEM research involving complex, multi-construct models and does not

undermine the robustness of the findings (Henseler et al., 2016; Hair et al., 2019)..

#### 4.3 Results of Hypotheses Testing

The hypotheses were tested using the validated measurement and structural models. The results are presented in two parts: direct effect hypotheses and indirect (mediating) effect hypotheses, as discussed in the following sub-sections.

##### 4.3.1 Direct Effects

This sub-section presents the results of the direct relationships between the independent variables [Integration of AI (IAI), Ethical and Legal Requirements (ELR), and Technological Advancements and Challenges (TAC)], the mediating variables [Adaptation and Learning (ADL), Iterative Evaluation (IEV), and Stakeholder Engagement (SEG)], and the dependent variable, Forensic Outcomes (FOC).

The direct effects were assessed using bootstrapping procedures in SmartPLS, a resampling technique widely recommended for estimating path coefficients ( $\beta$ ), t-values, and p-values in PLS-SEM (Hair et al., 2022; Henseler et al., 2016). These statistics indicate the strength, direction, and significance of each hypothesised relationship. A significance level of  $p < .05$  was used to determine whether a hypothesis was supported, consistent with conventional thresholds in SEM research (Chin, 1998).

The results of the direct relationships are summarised in Table 10, which reports the estimated path coefficients, associated t-statistics, and p-values. Collectively, these findings provide empirical evidence on how AI adoption factors and organisational processes exert direct influence on forensic outcomes in the UAE context.

Table 10. Results of direct effects relationships

Hypothesis	Structural Path	$\beta$ (O)	t-value	p-value	Decision
H1a	IAI → FOC	0.039	0.884	0.377	Not supported
H1b	IAI → ADL	0.065	1.128	0.259	Not supported
H1c	IAI → IEV	0.189	3.459	0.001	Supported
H1d	IAI → SEG	0.130	2.358	0.018	Supported
H2a	ELR → FOC	0.094	1.584	0.113	Not supported
H2b	ELR → ADL	0.445	7.399	0.000	Supported
H2c	ELR → IEV	0.263	4.299	0.000	Supported
H2d	ELR → SEG	0.296	4.744	0.000	Supported
H3a	TAC → FOC	0.089	1.626	0.104	Not supported
H3b	TAC → ADL	0.176	2.535	0.011	Supported
H3c	TAC → IEV	0.304	5.348	0.000	Supported
H3d	TAC → SEG	0.277	4.366	0.000	Supported
H4	IEV → FOC	0.008	0.160	0.873	Not supported
H5	SEG → FOC	0.158	3.332	0.001	Supported
H6	ADL → FOC	0.494	9.542	0.000	Supported

Table 10 presents the results of the hypothesis testing for the direct structural relationships in the AI-TFPs model. The table reports the path coefficients ( $\beta$ ), t-values, p-values, and the corresponding decisions for each hypothesised relationship. The findings show that Integration of AI (IAI) does not have a significant direct effect on Forensic Outcomes (FOC) ( $\beta = 0.039$ ,  $p = 0.377$ ) or Adaptation and Learning (ADL) ( $\beta = 0.065$ ,  $p = 0.259$ ). However, IAI has a significant positive effect on Iterative Evaluation (IEV) ( $\beta = 0.189$ ,  $p = 0.001$ ) and Stakeholder Engagement (SEG) ( $\beta = 0.130$ ,  $p = 0.018$ ), supporting H1c and H1d. This suggests that AI integration primarily strengthens evaluative and collaborative processes rather than directly influencing forensic outcomes.

Similarly, Ethical and Legal Requirements (ELR) do not significantly influence Forensic Outcomes directly ( $\beta = 0.094$ ,  $p = 0.113$ ). In contrast, ELR has strong and significant effects on ADL ( $\beta = 0.445$ ,  $p < 0.001$ ), IEV ( $\beta = 0.263$ ,  $p < 0.001$ ), and SEG ( $\beta = 0.296$ ,  $p < 0.001$ ), indicating that regulatory and ethical considerations play a critical role in shaping organisational learning, evaluation practices, and stakeholder involvement. For Technological Advancements and Challenges (TAC), no significant direct effect on FOC is observed ( $\beta = 0.089$ ,  $p = 0.104$ ). However, TAC significantly influences ADL ( $\beta = 0.176$ ,  $p = 0.011$ ), IEV ( $\beta = 0.304$ ,  $p < 0.001$ ), and SEG ( $\beta = 0.277$ ,  $p < 0.001$ ), suggesting that technological factors mainly affect forensic outcomes indirectly through internal processes.

Regarding the mediating constructs, Iterative Evaluation (IEV) does not significantly predict FOC ( $\beta = 0.008$ ,  $p = 0.873$ ), leading to the rejection of H4. In contrast, both Stakeholder Engagement (SEG) ( $\beta = 0.158$ ,  $p = 0.001$ ) and Adaptation and Learning (ADL) ( $\beta = 0.494$ ,  $p < 0.001$ ) have significant positive effects on Forensic Outcomes, supporting H5 and H6. Among all predictors, ADL demonstrates the strongest effect on FOC. Overall, the results indicate that forensic outcomes are primarily driven by organisational learning and stakeholder engagement, while AI integration, ethical/legal requirements, and technological challenges influence outcomes mainly through these mediating processes rather than through direct effects.

#### 4.3.2 Indirect (Mediating) Effects

To examine the mediating effects of Adaptation and Learning (ADL), Stakeholder Engagement (SEG), and Iterative Evaluation (IEV) on the relationships between Integration of AI (IAI), Ethical and Legal Requirements (ELR), Technological Advancements and Challenges (TAC), and Forensic Outcomes (FOC), bootstrapping procedures were employed. Bootstrapping is widely recommended in PLS-SEM for testing indirect effects and mediation, as it provides robust estimates of path coefficients and confidence intervals without relying on normal distribution assumptions (Preacher & Hayes, 2008; Hair et al., 2022; Henseler et al., 2016).

The results of the indirect effects are presented in Table 11, which reports the bootstrapped path coefficients, t-values, and p-values for each mediating pathway. These findings highlight the extent to which organisational processes [ADL, SEG, and IEV] serve as critical mechanisms through which AI adoption factors influence forensic outcomes in the UAE context.

Table 11. Results of indirect (Mediating) hypothesis testing

Hypothesis	Indirect Path	$\beta$ (O)	t-value	p-value	Decision
H7c	IAI $\rightarrow$ IEV $\rightarrow$ FOC	0.001	0.151	0.880	Not supported
H7a	IAI $\rightarrow$ ADL $\rightarrow$ FOC	0.032	1.116	0.264	Not supported
H7b	IAI $\rightarrow$ SEG $\rightarrow$ FOC	0.020	1.884	0.060	Marginally supported
H7a	ELR $\rightarrow$ ADL $\rightarrow$ FOC	0.220	5.649	0.000	Supported
H7b	ELR $\rightarrow$ SEG $\rightarrow$ FOC	0.047	2.560	0.010	Supported
H7c	ELR $\rightarrow$ IEV $\rightarrow$ FOC	0.002	0.154	0.877	Not supported
H7a	TAC $\rightarrow$ ADL $\rightarrow$ FOC	0.087	2.478	0.013	Supported
H7b	TAC $\rightarrow$ SEG $\rightarrow$ FOC	0.044	2.797	0.005	Supported
H7c	TAC $\rightarrow$ IEV $\rightarrow$ FOC	0.002	0.158	0.875	Not supported

Note.  $\beta$  = standardized indirect effect; significance assessed at  $p < 0.05$ .

Table 11 shows that the indirect effects of Integration of AI (IAI) on Forensic Outcomes through ADL ( $\beta = 0.032$ ,  $p = 0.264$ ) and IEV ( $\beta = 0.001$ ,  $p = 0.880$ ) are not significant. However, the indirect effect of IAI through Stakeholder Engagement (SEG) is marginally significant ( $\beta = 0.020$ ,  $p = 0.060$ ), suggesting a weak mediating role of SEG in linking AI integration to forensic outcomes. In contrast, Ethical and Legal Requirements (ELR) exhibit significant indirect effects on Forensic Outcomes through ADL ( $\beta = 0.220$ ,  $p < 0.001$ ) and SEG ( $\beta = 0.047$ ,  $p = 0.010$ ), indicating strong mediation via organisational learning and stakeholder involvement. The indirect pathway through IEV is not significant ( $\beta = 0.002$ ,  $p = 0.877$ ), suggesting that iterative evaluation does not mediate the ELR–FOC relationship.

Similarly, Technological Advancements and Challenges (TAC) show significant indirect effects on Forensic Outcomes through ADL ( $\beta = 0.087$ ,  $p = 0.013$ ) and SEG ( $\beta = 0.044$ ,  $p = 0.005$ ). The indirect effect via IEV is not significant ( $\beta = 0.002$ ,  $p = 0.875$ ), indicating that TAC influences forensic outcomes primarily through learning and stakeholder engagement rather than through evaluative processes. Overall, these findings demonstrate that Adaptation and Learning and Stakeholder Engagement play critical mediating roles in translating AI-related, ethical, legal, and technological factors into improved forensic outcomes. In contrast, Iterative Evaluation does not function as a significant mediator in the proposed model.

## 5. Practical Implications for AI Adoption in Forensic Settings

The findings of this study provide important practical insights for law enforcement agencies and policymakers seeking to implement artificial intelligence in forensic environments. The validated AI–TFPs framework demonstrates that effective AI adoption in forensics is not achieved through technological integration alone. Instead, forensic outcomes are primarily shaped by organisational adaptation and learning and stakeholder engagement, which act as critical mechanisms translating AI-related, ethical, legal, and technological factors into meaningful performance improvements.

First, the results indicate that Adaptation and Learning (ADL) is the most influential driver of

forensic outcomes. This finding underscores the need for law enforcement agencies to invest in continuous capability development rather than viewing AI as a plug-and-play solution. Practical measures include structured training programmes for forensic analysts and investigators, interdisciplinary learning between technical and legal professionals, and the institutionalisation of feedback mechanisms that enable organisations to learn from AI-assisted forensic applications. Agencies should prioritise human–AI collaboration, ensuring that personnel understand both the capabilities and limitations of AI systems in evidentiary contexts.

Second, Stakeholder Engagement (SEG) plays a significant role in enhancing forensic outcomes and mediating the effects of AI integration and regulatory requirements. This highlights the importance of building trust and collaboration among key stakeholders, including prosecutors, judges, defence experts, regulators, and the wider public. Law enforcement agencies should adopt transparent communication strategies regarding the use of AI in forensic investigations, engage judicial actors early in the implementation process, and encourage inter-agency cooperation to harmonise standards and practices. Such engagement is essential for ensuring the credibility, admissibility, and societal acceptance of AI-supported forensic evidence.

Third, the study reveals that Ethical and Legal Requirements (ELR) and Technological Advancements and Challenges (TAC) influence forensic outcomes indirectly through learning and engagement processes. This finding suggests that ethical compliance and technological readiness should be treated as enabling conditions rather than as direct performance drivers. Agencies should establish robust AI governance frameworks, clarify accountability structures, and align AI tools with existing legal and evidentiary standards. Addressing issues such as data quality, system interoperability, and explainability is crucial for supporting effective learning and stakeholder confidence.

Interestingly, Iterative Evaluation (IEV) did not exhibit a significant direct or mediating effect on forensic outcomes. This suggests that evaluation mechanisms, such as audits and performance reviews, are insufficient when implemented in isolation. For evaluation to be impactful, its outputs must be actively integrated into organisational learning initiatives and stakeholder dialogue. Law enforcement agencies should therefore reposition evaluation as a supportive process that informs training, policy refinement, and engagement strategies rather than as a standalone compliance activity.

To support practical implementation, this study proposes an AI–TFPs implementation roadmap (Table 12), which outlines a staged, process-oriented approach for law enforcement agencies. The roadmap emphasises ethical–legal readiness, organisational learning, stakeholder engagement, and supportive evaluation as sequential and mutually reinforcing elements of responsible AI adoption. By following this roadmap, agencies can move beyond technology-centric strategies and adopt a socio-technical approach that enhances forensic effectiveness while maintaining legal integrity and public trust.

Table 12. AI–TFPs implementation roadmap in forensic settings

Implementation Stage	Key Constructs (AI–TFPs)	Empirical Insight	Practical Actions for Law Enforcement Agencies	Expected Impact on Forensic Outcomes
Stage 1: Ethical–Legal Readiness	Ethical and Legal Requirements (ELR)	ELR has no direct effect on forensic outcomes but exerts strong indirect effects through Adaptation and Learning and Stakeholder Engagement	<ul style="list-style-type: none"> <li>• Establish AI governance frameworks and accountability mechanisms</li> <li>• Ensure compliance with evidentiary, privacy, and human rights laws</li> <li>• Provide ethics and legal training for forensic personnel</li> </ul>	Enhances organisational readiness, legitimacy, and acceptance of AI-supported forensic evidence
Stage 2: Organisational Adaptation and Learning	Adaptation and Learning (ADL)	ADL is the strongest predictor of forensic outcomes ( $\beta = 0.494$ , $p < 0.001$ )	<ul style="list-style-type: none"> <li>• Implement continuous AI skills training and certification</li> <li>• Foster human–AI collaboration in forensic analysis</li> <li>• Institutionalise learning loops from AI deployment experiences</li> </ul>	Direct and substantial improvement in accuracy, reliability, and effectiveness of forensic outcomes
Stage 3: Stakeholder Engagement and Trust Building	Stakeholder Engagement (SEG)	SEG significantly influences forensic outcomes directly and mediates AI-related effects	<ul style="list-style-type: none"> <li>• Engage prosecutors, judges, defence experts, and regulators early</li> <li>• Promote transparency in AI use and limitations</li> <li>• Facilitate inter-agency and cross-sector collaboration</li> </ul>	Strengthens trust, evidentiary credibility, and judicial acceptance of AI-assisted forensic outputs
Stage 4: Iterative Evaluation (Support Function)	Iterative Evaluation (IEV)	IEV shows no significant direct or mediating effect on	<ul style="list-style-type: none"> <li>• Use audits and evaluations to inform training and</li> </ul>	Supports continuous improvement when

		forensic outcomes	policy refinement	integrated with
			<ul style="list-style-type: none"> <li>• Avoid treating evaluation as a standalone compliance exercise</li> <li>• Align evaluation results with learning and engagement processes</li> </ul>	learning and stakeholder engagement
Stage 5: Technology Integration as an Enabler	Integration of AI (IAI); Technological Advancements and Challenges (TAC)	IAI and TAC influence forensic outcomes indirectly through ADL and SEG	<ul style="list-style-type: none"> <li>• Select AI tools aligned with organisational capacity and legal requirements</li> <li>• Address interoperability, data quality, and system reliability issues</li> <li>• View AI as a socio-technical system rather than a standalone solution</li> </ul>	Ensures sustainable and effective AI adoption without overreliance on technology alone

## 6. Conclusion

This study examined how artificial intelligence adoption influences forensic outcomes through key organisational and stakeholder-based processes within the UAE context. By developing and empirically validating the AI-TFPs framework using PLS-SEM, the research provides robust evidence that the impact of AI in forensic settings is largely indirect, operating through Adaptation and Learning and Stakeholder Engagement rather than through direct technological effects.

The findings demonstrate that Integration of AI, Ethical and Legal Requirements, and Technological Advancements and Challenges do not independently improve forensic outcomes. Instead, their effectiveness depends on the extent to which law enforcement organisations are able to absorb new knowledge, adapt practices, and engage relevant stakeholders. Among all constructs, Adaptation and Learning emerged as the strongest predictor of forensic outcomes, highlighting the central role of organisational capacity in realising the benefits of AI. Stakeholder Engagement also played a significant role, reinforcing the importance of trust, transparency, and collaboration in AI-supported forensic practices. In contrast, Iterative Evaluation did not significantly influence forensic outcomes,

suggesting that evaluation processes must be embedded within broader learning and engagement systems to be effective.

The validated model demonstrated strong explanatory power, meaningful effect sizes, positive predictive relevance, and acceptable overall model fit, confirming the robustness of the proposed framework. Theoretically, this study contributes to the AI and forensic management literature by shifting the focus from direct technology–performance relationships to process-based and socio-technical mechanisms. It extends existing AI adoption research by empirically demonstrating how organisational learning and stakeholder engagement function as critical mediators in high-stakes, legally sensitive contexts such as forensic science.

From a practical perspective, the study highlights that successful AI adoption in forensic settings requires more than technological investment. Law enforcement agencies must prioritise continuous learning, ethical governance, and stakeholder collaboration to ensure that AI systems enhance forensic accuracy, reliability, and legitimacy. Policymakers should support these efforts by funding training initiatives, developing clear regulatory frameworks, and fostering cross-institutional cooperation.

Future research could extend this framework to other national or institutional contexts, employ longitudinal designs to capture learning dynamics over time, or examine additional mediating factors such as leadership, organisational culture, and public trust. As AI continues to transform forensic practices, the AI–TFPs framework offers a comprehensive, evidence-based foundation for understanding and guiding responsible, effective, and sustainable AI adoption in law enforcement.

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