



# The Psychological Impact of the Use of AI in Digital Forensics on Criminal Investigators

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## ABSTRACT

As a transformative technology, Artificial Intelligence (AI) amplified the precision and efficiency of digital forensics investigations following its integration in the criminal investigations domain.

This study aimed at exploring the psychological impact of AI and digital forensics on criminal investigations in modern forensic psychology.

An online survey was conducted using Google Forms, in which forensic investigators were required to fill in a closed-ended survey. A total of 102 digital forensic investigators agreed to participate in this study and responded to the survey prompts.

The GAD-7 scale had a mean score of 9.20, confirming significant instances of “moderate” and “severe” anxiety among participants. The PSS mean score of 21.92 indicates at least “moderate stress” among the forensic investigators included in this study. The collected data confirms a positive linear relationship between AI usage and investigators’ psychological impact ( $r = .470$ ,  $p < .001$ ).

The adoption of AI in forensic procedures leads to the emergence of numerous psychological issues, such as anxiety and depression, among forensic specialists.

**Keywords:** Artificial Intelligence, Digital Forensics, Criminal Investigations, Forensic Psychology, Psychological Impact.



## Introduction

### Background and Context

The digital forensics field has expanded rapidly in recent years. According to Dunsin et al. (2024), digital forensics relies much on advancing technology to collect and analyze digital evidence used during criminal investigations. As Dunsin et al. (2024) noted, digital forensics primarily depends on the growing technology in collecting and analyzing digital evidence pertinent to any criminal investigation. While reviewing the scientific validation of digital evidence issues in the digital forensic area, Arshad et al. (2018) noted that digital forensic investigators must come up with and develop sound and efficient crime investigation strategies following the growing use of digital evidence in criminal investigations. The innovation of technology-intensive investigation tools also brings unseen psychological pressures toward investigators, and they have to change new methods quickly. Therefore, the application of digital forensics is gradually establishing itself as a rapidly growing subfield within the modern criminal investigations field. Furthermore, as tools with AI capabilities take a more significant role in establishing the administration of evidence, the psychological pressure of forensic specialists increases because of the requirement to understand the principles of deep learning and the stress of potential mistakes in intricate AI algorithms.

Digital forensics that relies on AI is still a relatively recent area, and for acquiring, analyzing, and processing large amounts of data, extensive computing is needed, making the process cumbersome and lengthy (Dunsin et al., 2024). Although deemed more accurate, machine-generated proofs have mostly replaced human fact-finding during the past two decades. Given that these judgments can vary for the same scientific evidence, just as they do for human experts, there are serious questions regarding the machine-generated findings or the legality of digital evidence. AI models may exhibit inherent biases or errors that could inadvertently mislead legal proceedings, amplifying concerns about AI reliability in the justice system. Like inadmissible and other out-of-court testimony, machine testimonies (sources) can cause closed-box issues for the legal system by causing fact-finders to draw inaccurate or partial conclusions. Additionally, investigators face increased cognitive strain from reconciling machine-generated insights with human intuition, heightening the potential for psychological stress. Skewed or disproportionate datasets, erroneous algorithms/code, and malfunctioning functional components of the system, such as operating systems and distributed platforms, are the most likely causes of errors or inaccurate interpretations of a machine-driven digital forensic analysis. However, the design, input, model, and environment can all play a role.

Some academics contend that the credibility of machines is heavily dependent on humans as people are in charge of creating and organizing all significant parts of a machine, such as its input, operational, and design modules. Therefore, a human being is the genuine declarant of any output that a machine can produce. Despite the advanced capacities of AI systems, human oversight remains crucial, as even minor errors in programming or operation can have profound consequences on investigation



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outcomes. A machine's creator or operator is not the only source of its utterances, even though they have some moral responsibility. All they are doing is repeating to the audience what a machine produced. In addition, as human and machine roles become interwoven in forensic tasks, investigators must navigate the psychological challenges of trusting complex systems whose workings they may not fully understand. Like an expert opinion, a machine-driven forensic inquiry results from "distributed cognition" between people and technology. There are several ways in which humans and machines are inseparable. This partnership reflects an ongoing integration of cognitive and technological resources, reinforcing the psychological complexity of modern forensic work.

### Problem Statement

As much as it is clear that AI presents numerous benefits in the contemporary digital forensics domain, current literature lacks sufficient research on the psychological effects that AI products have on forensic workers engaged in criminal investigations. AI's integration could lead to cognitive strain, as practitioners must balance traditional analytical skills with increasingly complex technological interfaces. It is, therefore, anticipated that as reliance on AI systems in key decision-making activities grows, forensic professionals may face increased mental workload, stress, and possibly changes in mental bias in their analytical flows. These issues act as the rationale for determining the potential of AI technology to cause changes in mental health implications and decision-making in forensic psychology. Addressing these potential impacts is crucial to safeguarding forensic experts' well-being and maintaining their work's integrity. To fill this gap, future studies should address the positive and negative impact of AI on all fields, including forensic analysis, hence avoiding a backlash of the technology to compromise the psychological health and work productivity of forensic analysts.

### Research Objectives

The present research will investigate the psychological and decision-making impacts of AI on forensic professionals, addressing the following objectives:

1. To assess the influence of AI on the mental well-being of forensic analysts.
2. To explore changes in decision-making processes and identify potential biases introduced by AI tools in digital forensics.
3. To examine how AI-based forensics might alter perceptions, behaviors, and professional judgment among forensic professionals in investigative contexts.

### Research Questions

To guide the research, this study will focus on the following primary questions:

- How does the use of AI in digital forensics impact the stress levels and cognitive biases of forensic professionals?
- What are the psychological implications associated with AI-driven decision-making in criminal investigations?



### Significance of the Study

This research has important implications for forensic psychology and the criminal justice field. Understanding the various psychological demands that arise from AI in forensic work can assist in implementing AI solutions that do not overwhelm users or take up much of their time, keeping technology integrated into forensic work at optimal levels. Thus, outlining AI's possible psychological and decision-making impacts in the given research will contribute to a better understanding of numerous-sided issues that AI creates for forensic practice. The outcomes of this study point out an avenue for future research to establish the impact of integrating technological strengths into forensic science while still retaining humane methods that are opposed to the acceptable mode of implementing AI in the field. Moreover, these insights could contribute to developing training programs that prepare forensic workers for the mental and technical demands of AI-driven analysis. Also, it could be applied to create meaningful policies about the mental health of forensic practitioners within the new age characterized by AI methodology. In this way, the study will provide a groundwork for subsequent research on sustainable and ethical considerations of AI application in forensic psychology.

### Literature Review

#### AI and Digital Forensics in Criminal Investigations

Integrating artificial intelligence (AI) within digital forensics represents one of the most transformative shifts in modern criminal investigations. According to the study conducted by Jarrett and Choo (2021), AI technologies are implemented gradually and seamlessly during the different steps of Forensic Science to improve pattern recognition, predictive analysis, and the optimization of data analysis. AI is useful in forensic investigations in analyzing large data sets, identifying patterns within such data, and providing deep insights, which ordinarily could take much time to produce manually (Ahmed Alaa El-Din, 2022). These capabilities are beneficial in today's investigations, where a large volume of digital evidence may include surveillance videos and records, communication records and logs, and forensic DNA profiles that must be processed and analyzed as soon as possible.

Today, AI-based approaches have revealed advancements in various investigative procedures. For example, sophisticated, intelligent models can make very accurate predictions of crime incidence, help in linking related cases, and give credible biometric identification (Ateş et al., 2020). Further, Embarak et al. (2024) observed that deep learning and natural language processing have significantly enhanced efficiency in evidence interpretation: a process that may take several weeks in normal circumstances where analysts comb through the evidence text for relationships that may take up to weeks to identify can now be done within minutes. Similar to facial recognition and voice analysis programs, other automatic systems can process large amounts of data instantly, which would be incredibly helpful in solving criminal cases.



As vital as it is, several limitations exist to using AI in digital forensics. From the study of Ngiam and Khor (2019), AI tools are handy in data analysis because they rely on the quality of data and the algorithms used in data analysis. It is up to question whether these systems have inherited prejudicial biases from the data and training techniques or if the results are flawed when applied to forensics (Sanclemente, 2022). This raises something like skepticism about the predictability of AI because, in its essence, forensic science is based on accuracy and objectivity. Deeks (2019) said that most AI algorithms work secretly as ‘black boxes.’ Although the algorithms give an outcome to the forensic analysts, they do not show the thought process, denying transparency and being ethically unsound. The limitations of AI thus highlight the importance of human oversight in forensic investigations to ensure accuracy and accountability.

### Psychological Impact of AI on Professionals

The deployment of AI systems in high-stakes environments is increasing, prompting many researchers to explore the psychological effects of AI on professionals. Mainly, the work of Nizamani et al. (2024) has been devoted to the AI effects on cognition load, decision-making trade-offs, and mental strain in occupational activities that require high levels of the brain. According to cognitive load theory, cognitive resources are scarce, which implies that employing sophisticated AI systems may impose more cognitive demands on forensic professionals to understand, verify, and cross-check the algorithms’ outcomes, not to mention the need to be keen on possible AI errors (Chang, 2024). In forensic psychology, where precise decision-making is crucial, such an increased cognitive demand and overload can increase the risk of decision fatigue, especially as the professionals are thrown into an overload of data churned out by the AIs that have to be sifted and analyzed with utmost efficiency.

Decision fatigue, defined as a decline in decision quality due to continued efforts in decision-making, is quite relevant to forensic analysts. Busey et al. (2022) also show that applying AI decisions increases forensic professionals’ decision fatigue because they must consider their judgment against the AI results when the outcomes are questionable or uncertain. This generally causes a reduction in the precision and, often, the soundness of decisions being made, which can compromise the rigor of forensic conclusions. The enormity of this fatigue effect, coupled with decreased accuracy and deteriorated judgment, presents the possibility of more heuristically driven, or rule of thumb, approaches to assessing forensic data.

The third forensic implication of AI usage is psychological stress. Wang et al. (2023) found that technology-induced stress affects many professionals who closely work with AI systems because they are likely to reach high-stress levels, especially when they are working on serious matters such as crime scenes. This stress is often exacerbated by AI’s capacity to interpret and the possibilities of original biases within AI algorithms. To avoid potentially excluding minorities and other bias-prone groups from false suspicion, forensic analysts may experience significant psychological stress when striving for AI high accuracy (Almazrouei et al., 2024). Additionally, AI decision-making processes lack transparency, contributing to frustration and





helplessness feelings among professionals who may struggle to justify or fully comprehend AI-derived outcomes.

### Decision-Making Processes in Forensic Psychology

According to Vredeveldt et al. (2024), the formal decision-making models common for forensic professionals can be described as systematic, highly structured, and evidence-based, using heuristics that guarantee a high probability of correct decisions. Nonetheless, with the development of artificial intelligence, many of these decision-making processes are being supported, thus posing the following critical question: How does AI intervene in forensic judgment, and can AI tech potentially introduce biases?

The dual-process model, which posits that decision-making occurs through both intuitive (System 1) and analytical (System 2) processes, is particularly relevant in forensic psychology. Edmond et al. (2017) explain that digital forensic analysts may be expected to use analytical thinking given that many of their tasks are highly critical and complex. Nevertheless, using AI might move decision understanding to more intuitive best practices, especially if the contributors develop pride in AI results. Such change may result in dependency on AI-driven results, even though the possibility of performing a manual check shows that there are discrepancies and mistakes. In addition, as identified by Rastogi et al. (2022), confirmation bias may be augmented through AI systems because professionals could only pay attention to the AI outcomes that fit best with their prejudices or assumptions.

Fresh research findings on AI's effects on the forensic decision-making process show that users may suffer from AI-generated results that differ from their conclusions. This conflict may compromise confidence in one's knowledge and the AI, which in turn affects decision-making at the final stage (Vredeveldt et al., 2024). Hence, the impact that AI can have on forensic decision-making is both deep and multifaceted, which means that training initiatives to teach the professionals how to approach the analysis of results provided by such systems critically from the best vantage point whilst retaining their objectivity.

### The Ethical Implications of AI in Forensic Contexts

Due to the widespread use of AI solutions in forensic psychology, ethical issues are core to its use in criminal justice. Algorithm fairness is captured from a range of ethical issues in the Akter et al. (2022) study as a critical issue since algorithms might result in biased outcomes for particular groups based on the bias present in the training data set. In the forensic setting, algorithmic bias can cause biased decisions and this is enhanced through facial recognition as well as predictions regarding policing (Kordzadeh & Ghasemaghaei, 2022). Such biases pose a question about the neutrality of using artificial intelligence in the courts of law.

The second primary ethical concern that relates to AI in forensics is transparency. According to Deeks (2019) who pointed out that algorithms work as "black boxes," their working is not fully transparent. That opacity undermines the work of forensic professionals in their attempt to prove the results generated by AI (Tortora, 2024). It



also reduces their authoritarian control over the interpretative side of forensic analysis. Hence, the independence of forensic analysts could be compromised, and sometimes, the conclusions presented could be accepted without enough scrutiny by AI.

Another layer to the above subject of accountability is the conduct of forensic investigations applying AI. Data interpretation in conventional forensic practices involves human beings responsible for their conclusions, and there are established ways of checking and correcting errors (Edmond et al., 2015). According to Slota et al. (2023), the line of accountability, including decision-making, is defused whenever AI is involved because professionals within the premises holding such posts and the developers of the smart AI system get to share responsibilities. Such an approach poses several questions: Who is to blame when wrongful convictions stem from AI mistakes? Ethical frameworks for AI in forensic psychology are therefore necessary to solve the problems of quality, responsibility, and impartiality of the use of AI tools in forensic practice.

## Methodology

### Research Design

The present research adopted a cross-sectional survey design, in which participants' data was collected at a single point in time, focusing on immediate psychological responses to AI use. This design also enabled efficient data collection from a larger sample, which is crucial for robust statistical analysis. According to Kruger et al. (2024), the quantitative methodology enhances research's objectivity and reliability of the findings; thus, suitable for examining relationships and drawing inferences about the psychological dimensions of AI use in criminal forensic contexts. The choice of considering a quantitative approach was appropriate to help quantify the collected information and test objectives.

### Sample Size and Target Population

Before the sampling process is conducted for any research activity, it is essential to identify the target population. In this case, the target population was forensic investigators attributed to different forensic investigation bodies. To prevent the issues of unguided generalization, a statistical approach was employed to determine sample size selection. After performing power analysis, it was deemed appropriate to involve a minimum sample size of 100 participants, given an estimated medium effect size (Cohen's  $d = 0.5$ ), a power level of 0.80, and an alpha level of 0.05 (Serdar et al., 2021). This sample size ensured sufficient statistical power for multiple regression and correlation analyses. An expert sampling technique was used, as the study required specific expertise in AI-driven forensics. This approach enabled selecting individuals whose experiences aligned with the study's aims. One of the inclusion criteria for the participants was to be a member of at least one forensics professional body. This condition was adopted to ensure the inclusion of only qualified and practicing forensic investigators in the present research. Participants' age and work



experience in the digital forensics investigations domain were not significant factors to consider when recruiting participants. Participants were contacted via email and received an information sheet outlining the study's purpose, inclusion criteria, and confidentiality measures.

### Data Collection and Techniques for Data Analysis

The present research targeted forensic investigators with varying experience levels in digital forensics as the survey participants. Participants were recruited using online platforms to reduce the overall research costs that could have otherwise skyrocketed with traveling, printing, and other administration expenses, given the large target sample size. Therefore, a Google Form was created, and the closed-ended questionnaires were distributed to the recruited personnel. The initial section of the survey captured demographic data, including age, gender, level of education, marital status and years of professional experience.

Freely available validated psychological scales assessed stress levels and anxiety levels. The Generalized Anxiety Disorder 7-item (GAD-7) scale was used to measure the participants' anxiety levels. The GAD-7 has demonstrated strong internal consistency, with Cronbach's alpha values consistently exceeding 0.85 in previous studies, and it has been validated for use in both clinical and non-clinical populations. At the same time, the Perceived Stress Scale (PSS), with its 10 items, gauged participants' perceptions of stress by assessing feelings of control over work-related stressors. The PSS has been widely validated, with Cronbach's alpha ranging from 0.74 to 0.91, and its 10-item version has been adapted to assess the stress perceptions of professionals in high-stakes environments. This tool was instrumental in measuring the psychological strain potentially exacerbated by AI use.

A custom instrument assessed participants' perceptions of AI's role in forensic work, using various Likert-like scales to measure attitudes toward AI reliability, ethical concerns, and accountability in AI-driven forensic analysis. The customized AI perception scale was developed following established guidelines for scale creation, including item clarity, face validity, and pilot testing among a small subset of forensic professionals to ensure relevance and comprehensibility. The internal consistency of this scale was evaluated using Cronbach's alpha, which yielded a value of 0.81, indicating good reliability.

The independent variable, "AI Tool Usage in Criminal Investigations," was measured using a customized scale with several prompts, including measures of the frequency of using the AI tools and the level of confidence that participants exhibited while using the tool. Two questions used to measure AI usage are: (a) How frequently do you use AI or digital forensic tools in your investigations? (daily, weekly, monthly, rarely, never) and (b) What level of confidence do you have in interpreting AI-generated data? (very confident, somewhat confident, neutral, somewhat unconfident, and very unconfident). The customized scale for AI tool usage underwent expert validation, where experienced forensic professionals reviewed the items to confirm content relevance. Test-retest reliability was calculated during the pilot phase,





resulting in a reliability coefficient of 0.77, indicating a good stability of responses over time.

The dependent variables were measured using multiple customized and previously created but freely available scales as provided in the appendices section. The survey link that led to the Google Form with survey prompts was distributed to the recruited participants using email. The link was open for ten days to allow respondents to answer the questions at their convenience within the stipulated period. To encourage full participation, the questionnaire was designed to be concise, with a maximum completion time of 15–20 minutes, as pre-tested in a pilot study.

Prior to the start of the data collection process, participants were allowed to withdraw from taking part in this study without any explanation or consequence since all respondents agreed to be involved in the research voluntarily. Informed consent was obtained digitally, where participants confirmed their understanding of the study objectives, the confidentiality of their responses, and their right to withdraw at any stage without penalty.

### Data Analysis Techniques and Procedure

The data sheet was imported into the IBM SPSS v30 program for statistical analysis after the preliminary steps of cleaning the data and preparing it for presentation and analysis using the pre-selected analysis tools. The demographic profiles of the participants were compiled, descriptive and inferential statistical analyses were carried out on several data segments.

### Ethical Considerations

The current research was completed based on the ethical principles guiding human conduct to ensure that all the rights of the identified potential participants are safeguarded and protected. Strict adherence to the ethical principles in the contemporary research domain was strategic in encouraging the target population to participate in the present research. All potential participants were advised to read the consent form in Section 1 of the survey tool, highlighting the study's purpose and objectives. The participants would not be entitled to any form of pay or gift because the participation was voluntary, and the research was not for profit because it was for academic purposes. After reading and agreeing to the research attributes, participants were required to agree to the informed consent form before accessing the survey prompts; otherwise, not agreeing to the provided consent form instructions led to the end of the survey session without taking part.

Additionally, ethical approval was sought from the relevant organs, given that the present research involved human subjects in the data collection process. Furthermore, participants had the option of withdrawing from the current research without having to provide any explanation to justify their decisions. Participants did not provide their names to enhance the confidentiality of the responses. Collected data was to be used only to complete the proposed study, and all the gathered information and analysis results had to be stored using multiple security features on a password-enabled laptop to prevent data access from unauthorized third parties.



### Limitations of Methodology

While the cross-sectional design was beneficial for capturing a snapshot of AI's psychological impacts, it limited causal inferences. Future studies may benefit from longitudinal approaches to examine changes in psychological effects over time. Additionally, self-reported data may introduce response biases, as participants could underreport stress or fatigue due to professional stigma. Nonetheless, the use of validated psychological scales aimed to minimize such biases and enhance the reliability and validity of the findings.

### Results and Findings

#### Demographic Profile

The sample consisted of 102 participants, of which 101 provided valid responses for gender. Among them, 42 participants (41.2%) identified as male, accounting for 41.6% of valid responses, while 59 participants (57.8%) identified as female, representing 58.4% of the valid responses. There was one missing response, constituting 1.0% of the sample, making up a total of 102 responses (see Table 1).

**Table 1**

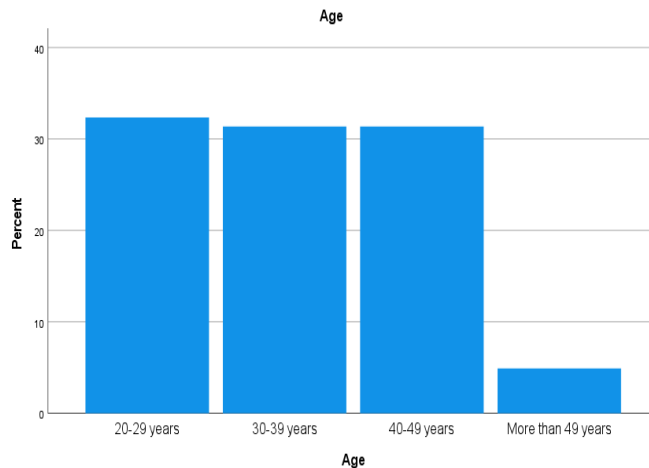
Participants' gender

	Frequency	Percent
Male	42	41.2
Female	59	57.8
Total	101	99.0

The age distribution of the 102 participants indicates that most respondents are between 20 and 49 years old. Specifically, 33 participants (32.4%) fall within the 20-29 age range, 32 participants (31.4%) are aged 30-39, and another 32 (31.4%) are in the 40-49 age group. Only a small portion, 5 participants (4.9%), are over 49 years old (see Figure 1).



**Figure 1**  
Participants' age



The data on participants' highest level of education reveals that the majority held a bachelor's degree, comprising 57.8% of the total sample (n=59). This was followed by individuals with a master's degree, representing 31.4% (n=32), while participants with a PhD constituted 10.8% (n=11). These findings underscore the predominance of professionals with undergraduate and postgraduate qualifications in the sample, indicating a well-educated cohort. The cumulative percentages highlight that 89.2% of respondents had at least a master's degree, reflecting a high level of academic attainment among participants engaged in forensic investigations (see Table 2).

**Table 2**  
Participants' level of education

		Frequency	Percent
Valid	Bachelor's degree	59	57.8
	Master's degree	32	31.4
	PhD	11	10.8
	Total	102	100.0

The marital status distribution of the participants indicates that a significant majority, 75.5% (n=77), were married, while 24.5% (n=25) identified as single. This distribution demonstrates that the sample predominantly comprised married individuals. The cumulative percentage shows that all participants' marital statuses were accounted for, providing a comprehensive demographic overview (see Table 3).

**Table 3**

Participants' Marital status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Single	25	24.5	24.5	24.5
	Married	77	75.5	75.5	100.0
	Total	102	100.0	100.0	

The sample data on years of experience in criminal investigations shows that among the 101 valid responses, 24 participants (23.5%) have less than 1 year of experience, 33 participants (32.4%) have 1-5 years of experience, and 36 participants (35.3%) have 6-10 years of experience, making this the largest group. Only 8 participants (7.8%) reported having more than 10 years of experience. This distribution reveals that the majority of the forensic investigators involved in this study have between 1 and 10 years of experience, with a cumulative percentage reaching 92.1% at the 6-10 years' mark (see Table 4).

**Table 4**

Participants' years of experience in criminal investigations

	Frequency	Percent
Less than 5 years	24	23.5
1-5 year	33	32.4
6-10 years	36	35.3
More than 10 years	8	7.8
Total	101	99.0

**Reliability Test**

The internal consistency of the scales used to collect in this study were assessed using Cronbach's Alpha.

**Table 5**

Internal consistency of the GAD-7 scale

Cronbach's Alpha			
Based on			
Cronbach's Alpha	Standardized Items	N of Items	
.832	.832	7	

**Table 6**

Internal consistency of the PSS scale

Cronbach's Alpha Based on		
Cronbach's Alpha	Standardized Items	N of Items
.813	.813	10

**Table 7**

Internal consistency of the Self-made survey tools

Cronbach's Alpha Based on		
Cronbach's Alpha	Standardized Items	N of Items
.771	.773	12

The analysis for the tools used yielded a Cronbach's Alpha of at least 0.77, indicating a good reliability of the scales used in this study. The Cronbach's Alpha based on standardized items was  $> 0.7$ , confirming the robustness of the internal consistency.

**Generalized Anxiety Disorder 7-item (GAD-7)**

Based on the GAD-7 scoring guidelines, participants in this study show a range of anxiety levels. Specifically, among the 100 valid responses, 11 participants fall in the "minimal anxiety" range (0–4), indicating low levels of anxiety. A larger portion, consisting of 42 participants, scored between 5 and 9, categorizing them with "mild anxiety." Another 38 participants group scored between 10 and 14, indicating "moderate anxiety," while 9 participants scored between 15 and 21, placing them in the "severe anxiety" category (see Table 8 and Figure 2).

**Table 8**

GAD-7 anxiety distribution

	Frequency	Percent
.00	4	3.9
1.00	3	2.9
2.00	2	2.0
3.00	2	2.0
5.00	2	2.0
6.00	1	1.0
7.00	21	20.6
8.00	10	9.8
9.00	8	7.8
10.00	11	10.8
11.00	8	7.8
12.00	7	6.9
13.00	8	7.8

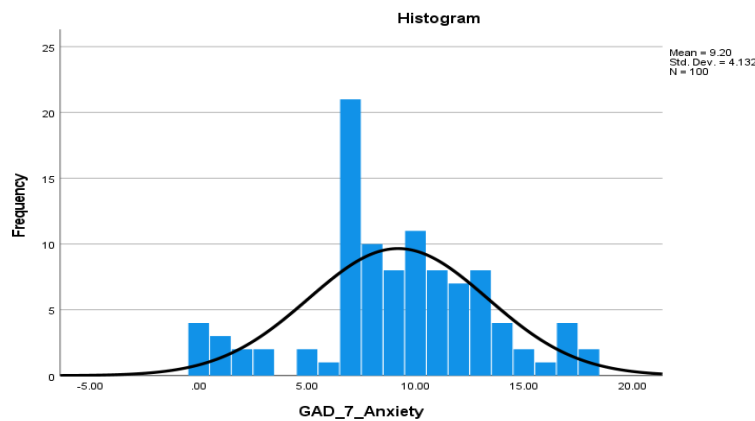




14.00	4	3.9
15.00	2	2.0
16.00	1	1.0
17.00	4	3.9
18.00	2	2.0
Total	100	98.0

**Figure 2**

GAD-7 anxiety severity distribution



The GAD-7 Anxiety scores for 100 valid respondents range from 0 to 18, with a mean value around the 50th percentile of 9. The standard deviation is 4.13, showing some variability around the mean, and the variance is 17.071. The data shows slight negative skewness (-0.199), indicating a minor tail towards lower scores, while kurtosis (0.122) suggests a relatively normal distribution. At the 25th percentile, scores are at 7, while the 75th percentile is 12, showing that the majority of participants scored between these values. The cumulative percent distribution shows that 21% of participants scored 7, with scores generally distributed across the scale, and only a small percentage scoring at the extreme ends. There were two missing responses, accounting for 2% of the total sample (see Table 9).

**Table 9**

GAD-7 anxiety severity descriptive statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
GAD_7_Anxiety	100	9.2000	4.13167	-.199	.241	.122	.478



The ANCOVA analysis for GAD-7 anxiety severity showed that the model significantly explained variations in anxiety levels, with 28.7% of the variance accounted for by the predictors. Among the demographic factors, gender had a significant effect on anxiety levels, as did age. Specifically, gender differences were observed, with anxiety levels differing between male and female participants, with females reporting higher levels of anxiety. Age also played a significant role, with younger professionals experiencing higher levels of anxiety compared to their older counterparts. However, factors such as education level, marital status, and professional experience did not show significant differences in anxiety levels. These results suggest that gender and age are key variables that contribute to variations in anxiety levels among forensic professionals (see Table 10).

**Table 10**

Analysis of Covariance Between Anxiety Levels and Demographic Factors

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	481.653 <sup>a</sup>	5	96.331	7.395	.000	.287
Intercept	.182	1	.182	.014	.906	.000
Gender	154.407	1	154.407	11.853	.001	.114
Age	233.339	1	233.339	17.912	.000	.163
Education	34.233	1	34.233	2.628	.108	.028
Marriage	.730	1	.730	.056	.813	.001
Experience	29.193	1	29.193	2.241	.138	.024
Error	1198.470	92	13.027			
Total	10056.000	98				
Corrected Total	1680.122	97				

a. Dependent Variable: GAD 7 Anxiety Severity

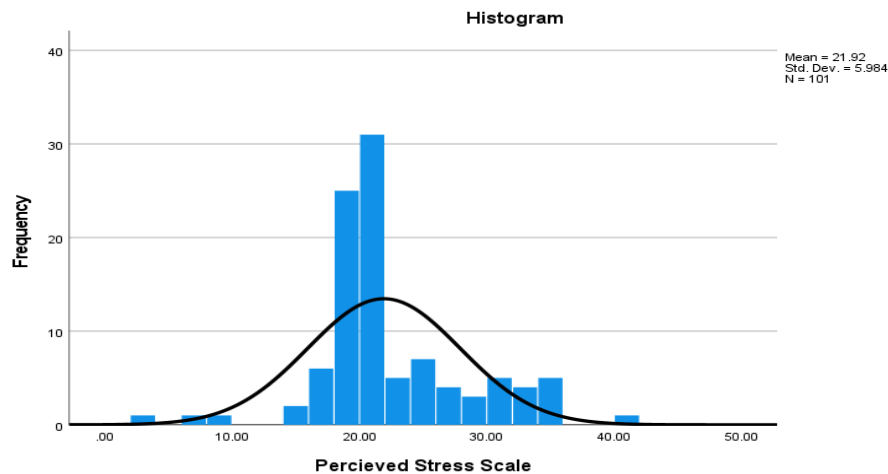
b. R Squared = .287 (Adjusted R Squared = .248)

### Perceived Stress Scale

The PSS scores among the 101 valid responses show that the majority of participants' experience moderate stress, with 77 respondents (76.2%) scoring between 14 and 26. A smaller portion, 21 participants (20.8%), reported high perceived stress, with scores ranging from 27 to 40. Only 3 participants (3%) fell into the low-stress category, scoring between 0 and 13. This distribution indicates that most participants perceive a moderate level of stress, while a notable minority experiences high stress.

**Figure 3**

Perceived stress scale participants' scores



The PSS scores for 101 participants reveal an average score of 21.92, with a mode of 20, suggesting that many participants clustered around this value. The standard deviation of 5.98 and variance of 35.81 indicate moderate variability in stress levels among respondents. The skewness of 0.436 points to a slight positive skew, meaning a small number of participants reported higher stress scores, while the kurtosis of 1.287 suggests a somewhat peaked distribution. The scores range from a minimum of 3 to a maximum of 40, capturing a wide spectrum of perceived stress levels in the sample population, with only one missing response (see Table 11).

**Table 11**

Perceived stress scale scores descriptive analysis

N	Valid	101
	Missing	1
Mean		21.9208
Mode		20.00
Std. Deviation		5.98445
Variance		35.814
Skewness		.436
Std. Error of Skewness		.240
Kurtosis		1.287
Std. Error of Kurtosis		.476
Minimum		3.00
Maximum		40.00

The ANCOVA analysis revealed a statistically significant effect of the model on perceived stress levels (PSS scores),  $F(5, 93) = 5.996$ ,  $p < .001$ ,  $\eta^2 = .244$ , indicating that approximately 24.4% of the variance in PSS scores was explained by the predictors. Among the demographic variables, age showed a significant effect on stress levels,  $F(1, 93) = 24.312$ ,  $p < .001$ ,  $\eta^2 = .207$ , accounting for a notable portion



of the variance. Professional experience also had a significant, albeit smaller, effect,  $F(1, 93) = 4.810$ ,  $p = .031$ ,  $\eta^2 = .049$ . Conversely, gender, education level, and marital status did not significantly contribute to variations in stress levels ( $p > .05$ ). The adjusted  $R^2$  value of .203 suggests that the model provides a reasonable fit to the data. These findings highlight age and experience as key factors influencing perceived stress among forensic professionals ( see Table 12).

**Table 12**

Analysis of Covariance Between Stress Levels and Demographic Factors

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	867.171 <sup>a</sup>	5	173.434	5.996	.000	.244
Intercept	294.420	1	294.420	10.180	.002	.099
Gender	2.116	1	2.116	.073	.787	.001
Age	703.173	1	703.173	24.312	.000	.207
Education	30.386	1	30.386	1.051	.308	.011
Marriage	26.124	1	26.124	.903	.344	.010
Experience	139.122	1	139.122	4.810	.031	.049
Error	2689.819	93	28.923			
Total	51429.000	99				
Corrected Total	3556.990	98				

a. Dependent Variable: Perceived Stress Scale

b. R Squared = .244 (Adjusted R Squared = .203)

**Correlational Analysis**

Bivariate Pearson correlation was conducted to determine linear relationships between the AI usage in the digital forensic investigations and the psychological impact on the investigators. The results documented in Table 13 indicate that the Pearson correlation coefficient for the two variables is .470, which is significant ( $p < 0.001$  for a two tailed test) based on the 101 complete observations. This data confirms that AI usage and investigators' psychological impact have a statistically significant linear relationship ( $r = .470$ ,  $p < .001$ ) and the direction of the relationship is positive; thus, the variables tend to increase together. These findings indicate that the more AI is used in the digital forensics domain, the more digital forensic investigators suffer psychologically.

**Table 13**

Correlations between AI usage and participants' psychological impact

		Psychological Impact	AI Tool Usage in Criminal Investigations
Psychological Impact	Pearson Correlation	1	.470**
	Sig. (2-tailed)		.000
	N	101	101
AI Tool Usage in Criminal Investigations	Pearson Correlation	.470**	1
	Sig. (2-tailed)	.000	
	N	101	102

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

**Regression Analysis**

Linear regression analysis was conducted to examine the relationship between the independent and the dependent variables from the model summary, ANOVA, and coefficients' results. The model summary for AI usage and the psychological impact among digital forensic investigators is shown in Table 14. The R value is .470. and the R square value is 22.1% of the independent variable.

**Table 14**

Model Summary for Independent Variables on Dependent Variable

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.470 <sup>a</sup>	.221	.213	.40475

a. Predictors: (Constant), AI Tool Usage in Criminal Investigations

b. Dependent Variable: Psychological Impact

As shown in Table 15, the regression model predicts statistically the investigators' psychological impact while using AI to perform forensic investigations. Furthermore, the ANOVA table shows F value of 93.60, which indicates a high variation between sample means relative to the variation with the samples. As a result, the p-value is low to confirm that the regression model statistically predicts the dependent variable.

**Table 15**

ANOVA Between AI Usage and Psychological impact

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.609	1	4.609	28.135	.000 <sup>b</sup>
	Residual	16.219	99	.164		
	Total	20.828	100			

a. Dependent Variable: Psychological Impact

b. Predictors: (Constant), AI Tool Usage in Criminal Investigations

Table 16 shows the coefficients obtained after conducting regression analysis on the independent and dependent variables involved in the current research.





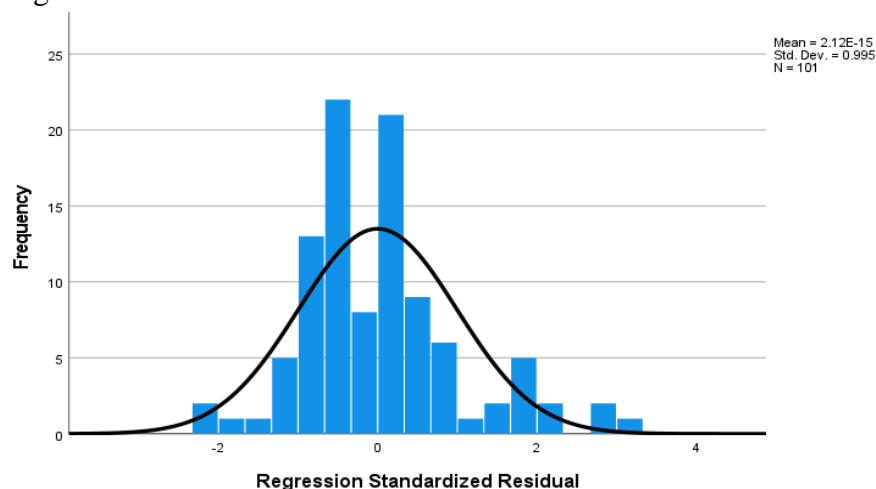
As presented in the table,  $p < 0.001$ , thus, they are statistically significantly different from zero, prompting the rejection of the null hypothesis and confirming that the use of AI in forensic investigations impacts the investigators psychologically.

**Table 16**  
Coefficients Table

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.105	.117		18.053	.000
	AI Tool Usage in Criminal Investigations	.236	.044	.470	5.304	.000

a. Dependent Variable: Psychological Impact

**Figure 4**  
Regression standardized residual



## Discussion

Computerized forensic technologies are revolutionizing methods of crime scene investigation and analysis. They can work with large amounts of data and find patterns that are hardly discernible by human personnel. Still, such efficiency is attained at a psychological expense, as our research reveals a positive and moderate association between AI application and cognitive strain among forensic investigators. As the present research shows, the application of complex AI solutions at work may be pushing the Limits of the human mind, which expects analysts to trust, understand, and confirm the results provided by AI systems. The ability to integrate AI analysis while maintaining a fusion of analytical and investigative work puts a strain on the mental agility of a worker.



While bias is a factor that cannot influence the judgment made when doing forensic work, integrating the use of AI tools brings bias into the process. All AI algorithms have inherent biases that depend on the data chosen as training and developmental material. In the present research, there was a direct relationship between the degree of AI reliance and the extent of cognitive bias. As the investigators work with the materials generated by AI algorithms, they may unconsciously change their conclusions according to the algorithm's suggestions. Such an occurrence threatens accurate decisions and leads to using AI as the sole tool for problem-solving, disregarding human instinct and logical reasoning. In addition, while accuracy is an essential strength of AI, this work reveals that it can skew investigations toward machine-generated results over human analysis, an issue regarding the fairness and the validity of digital forensics methods.

Another astonishing aspect of this research is that AI-based forensic tools psychologically impact investigators. They had higher scores on the GAD-7 and PSS scales. This stress arises from several factors, including the severity of criminal cases and the need to operate within criminal investigation systems augmented by artificial intelligence without adequate disclosure of functions. Essentially, investigators are tasked with interpreting AI results under tremendous pressure, given that the options for interpreting AI results are often scarce within a given time constraint. This pressure can lead to unhappiness and anxiety as investigators appear to be always on the edge, adversely impacting their health and morale.

The psychological effect of AI on forensic investigators is not limited to workload but also encompasses the concept of accountability. They noted that errors can occur in the analysis, which is performed with the help of Artificial Intelligence, and there is often ambiguity as to who is responsible for such errors; therefore, it creates moral and ethical issues for forensic psychologists. Such workers may be under pressure to assume responsibility for conclusions made by the machines, leading to increased stress levels and the likelihood of unhappiness at the workplace. With AI tools potentially becoming more closely integrated with forensic work, structures that offer guidance on responsibility matters need to be put in place to lessen some psychological stresses on investigators.

AI is now prevalent in forensic investigations. It brings a concept of distributed cognition; the human and machine resources work hand in hand. This partnership, however, requires a specific brainwork configuration in that it cannot be a one-sided affair. Criminal investigators have to filter raw data with the help of an AI and consider the advisory even though it may differ from the logic used by professionals. Concerning practical implications, it is asserted that the presented results show that the continued interaction between human and machine cognition may cause cognitive dissonance as forensic professionals may develop discomfort from opposing beliefs and sources of information. Distributed cognition also increases the risk of cognitive overload since investigators have to close work and filter numerous sources of information to build a coherent story for each case.

These findings demonstrate that this cognitive load can cause mental exhaustion that, in turn, decreases the likelihood of investigator impartiality and attentiveness during



the investigation. This reliance on AI entails a major cognitive transition that is not self-explanatory, resulting in agitation and, at times, even inefficiency presented by investigators who feel they are not entirely in charge of their work. Because AI is quite psychologically demanding in delivering augmented digital forensic services, ways of addressing the ramifications on workers in forensic areas must be considered. One of the ways forward could be designing awareness training that combines AI literacy and stress management. There are possibilities that this training can assist the investigators in comprehending the algorithms used by AI, accurately deciphering the results produced by a machine, and identifying the prejudice present in the AI instrumentations. Investigating AI can help investigators develop AI competence and manage the perceived lack of control associated with psychological strain.

In addition, the actual design of AI forensic tools might be improved by reducing the cognitive load. In addition, the problem of cognitive load can be mitigated by enhancing the usability of AI forensic tools. The integration of transparency and readability in systems to enable investigators to understand more clearly how specific results were reached instead of enclosed, black box results would help to decrease uncertainty and stress. Transparency that avoids allowing the machine to put the investigator in a box could be attained by explainable AI (XAI) models, where the basis for the output is explained so that the investigator is confident to make correct conclusions. Another approach is integrating health support for troubled mental personalities within forensic companies. Screenings for feelings of stress, anxiety, and possible burnout, as well as readily available psychological diagnoses of individuals working with AI regularly in forensic sciences, could aid in the employee's early detection of the listed feelings of distress. Significantly, our study points to the fact that even a moderate level of mental health support would result in enhanced job satisfaction and productivity provided to the investigators managing the complexities introduced by the digital forensic mechanization tools.

### Limitations of the Study

Despite providing significant insights in the use of AI in digital forensics domain, the present research is associated with multiple limitations. Firstly, the sample size was relatively small and geographically limited, potentially affecting the generalizability of the findings. Secondly, the included participants did report enough work experience in the digital forensics domain since more than 50% of the participants had less than five years' experience, resulting in a possibility of the results changing with a more experienced participant who use AI tools in performing digital forensics. Therefore, there is a need for future studies to screen and include only experienced participants, such as at least 10 years in the active digital forensics domain to enhance the results' validity. Thirdly, causality cannot be firmly established, although we identified correlations between AI use and psychological outcomes. Another limitation of this study is the weak intensity of the correlations between the variables, despite their statistical significance. While the relationships between demographic factors (such as age and gender) and anxiety levels or perceived stress were found to be significant, the correlation coefficients were relatively low. This suggests that



although these variables are statistically related, the strength of these relationships may not be substantial enough to make strong inferences regarding their impact on anxiety or stress. Additionally, the regression analysis revealed that the predictors explained less than 30% of the variance in the dependent variables, which indicates that the model had a minimal contribution in explaining the observed anxiety and stress levels. This result points to the possibility that other unmeasured factors may be influencing these variables. Finally, this study relied on self-reported measures, which might have introduced the biasness when participants documented their stress experience.

### Future Research Directions

In future research, new research should focus on the long-term psychological impact of AI in the forensic workspace. Such studies could help gain further insights into the effects of continuous engagement with AI tools on the mental health and cognition of the user. Also, further research could be done on the mediating role of demographic characteristic variables like Age and years of experience in the psychological influence of AI in digital forensics. Such an approach would also improve feasibility since we would be comparing specific subgroups to identify who is more resilient or prone to AI-related stress so that targeted programs could be designed.

Perhaps a more productive area for future research is the study of the segregated functionalities of AI, more specifically, the potential impact of predicting algorithms and face recognition on people's psychological state. With knowledge of which artificial intelligence functionalities contribute to the overall cognitive load or create biases, forensic organizations could devise learning protocols for their specific personnel and policies that would reduce these dangerous effects. Future research could benefit from identifying additional factors, such as organizational influences, work-related stressors, or personal coping mechanisms, which might provide a more comprehensive understanding of the psychological impacts on forensic professionals.

### Conclusion

Adopting AI in forensic procedures enhances investigative efficiency results and the emergence of numerous psychological issues in forensic specialists. This paper's results support the need to tackle these issues to enhance the capacity of forensic analysts to do their tasks efficiently without excessive burden in terms of cognition or emotion. With the advancement in AI, adopting human-centered approaches to applying AI in forensic settings has become pertinent. Ensuring the professionalization of forensic investigators through training them about how the AI was built and designed and providing mental health support for handling anxiety of job loss to forensic AI will be essential in developing an effective partnership and collaboration framework between humans and AI in forensic psychological practice. Thus, if the mentioned problems are solved in advance, forensic organizations will be able to boost the application of AI in improving investigative procedures and ensuring its personnel's well-being and professional standing.



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