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The moderation effect of AI Image Generator on the Relationship Between Evidences and Accurate Judgment

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A R T I C L E I N F O

Keywords:
AI, Image Generator, Text to Image generator, AI Image Generator, Evidences, Judgment, Accurate information, Information sensitivity.

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A B S T R A C T

This study examines AI picture generator's moderating influence on the correlation between evidence and sound judgment can be complicated and contingent on a number of variables. There are potential impacts that might have a negative impact on the accuracy of evidences. Risk of Bias or Misrepresentation, Subjectivity and Interpretation, Cognitive Overload or Dependency and User Proficiency with AI Tools are examined to test their effect on providing fake images generated by AI Image Generator tools. The study reveals that AI Image Generator has a strong impact on the relationship between evidences and accurate judgments. AI Image generators can enhance proving bias evidences which cannot be predicted from judgers and this might lead to unfair decisions. This paper investigates this moderation effect through an empirical study and a distributed survey. Manipulating the presence or absence of an AI image generator and examining how it interacts with different types of evidence to affect judgment accuracy are the main objectives. Understanding this moderation effect is essential for evaluating the impact of AI technologies on decision-making processes. It can also have implications for the ethical use of AI in various fields, including law, healthcare, and journalism, where accurate judgment based on evidence is crucial.

1. INTRODUCTION

AI image generators use artificial intelligence algorithms, particularly generative models, to create realistic or creative images. One popular type of generative model for image generation is the Generative Adversarial Network (GAN). GANs consist of two neural networks, a generator and a discriminator, that are trained simultaneously through a competitive process. GANs work as a generator network tool [1], [2]–[4]. This network takes random noise as input and generates images. In the beginning, the generated images may not resemble anything meaningful. The generator and discriminator are trained in a loop. The generator aims to produce images that are indistinguishable from real ones, while the discriminator gets better at telling the difference. GANs also plays the role of discriminator as it evaluates images, determining whether they are real (from the dataset) or fake (generated by the generator). The discriminator's goal is to become better at distinguishing real from fake images. Convergence, ideally, becomes so proficient at creating images that the discriminator can't reliably differentiate between real and generated images [5]–[7]. There are pre-trained models and frameworks available that make it easier to work with AI image generation. Some popular ones include StyleGAN and StyleGAN2. These models are known for generating high-quality, realistic images. They have been used for creating human faces, artwork, and more [8]–[11]. Deep Dream are developed by Google, Deep Dream uses a convolutional neural network to find and enhance patterns in images. It can create surreal and dreamlike images. Pix2Pix is a model is designed for image-to-image translation tasks. It can be used for tasks like turning sketches into realistic images, changing day scenes to night, and more. DALL-E is created by OpenAI, DALL-E is a GAN-based model that generates images from textual descriptions [12]. It can produce unique and imaginative visuals based on textual prompts. To use these models, users can explore open-source implementations available in popular deep learning frameworks like TensorFlow or PyTorch [13]–[16]. Keeping in mind that working with AI image generators may require some understanding of deep learning concepts and programming skills.

2. LITERATURE REVIEW

2.1 Image Generator

An image generator typically refers to a computer program or system that creates images either from scratch or based on certain inputs. These generators can be part of various applications, fields, or technologies. There are a few contexts in which image generators are commonly used. Computer graphics and gaming are used in the realm of computer graphics and gaming, image generators are often employed to create realistic or stylized visuals [17]–[20]. These generators can produce textures, 3D models, and entire scenes. They play a crucial role in rendering graphics for video games, simulations, and virtual environments. Machine learning and AI is employed as an image generator are used in the context of generative models, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) [21]–[23]. These models are capable of generating new images based on patterns and styles learned from existing datasets. GANs, for example, consist of a generator and a discriminator, which work in tandem to produce high-quality synthetic images. It is also needed in art and creativity where it is used in creative applications to produce art and design [24]. Various tools and software allow artists to use algorithms and parameters to generate unique visual compositions, patterns, and designs. In machine learning, particularly in computer vision tasks, image generators are used for data augmentation [25], [26]. Data augmentation involves creating new training examples by applying various transformations to existing images. This helps improve the generalization and robustness of machine learning models. As an addition, procedural content generation is enhanced with image generators [27]–[30]. For example, in game development and simulation, procedural content generation techniques use algorithms to create content dynamically. This can include landscapes, textures, and other visual elements. Image generators play a role in this process to produce diverse and realistic content [31]. Overall, the term "image generator" can encompass a wide range of applications, from artistic creation to technical and scientific uses. The specific functionality and purpose depend on the context in which the term is used [32]–[34].

2.2. Harnessing AI in Image Generating

AI image generation involves the use of algorithms and models, particularly generative models, to create realistic and visually appealing images. One popular approach for image generation is the use of Generative Adversarial Networks (GANs), although other models like Variational Autoencoders (VAEs) and autoregressive models can also be employed. Here is a simplified overview of how GANs work as image generators. Generator Network is the generator is a neural network that takes random noise or a seed as input and produces an image as output [35]–[37]. In the initial stages, the generator output may not resemble anything meaningful. It essentially starts with generating random images. Discriminator Network is another neural network trained to distinguish between real images from a dataset and fake images generated by the generator [38]. It receives both real and generated images as input and outputs a probability score indicating whether the input image is real or fake. During training process, the generator aims to produce images that are indistinguishable from real images, while the discriminator learns to become better at distinguishing between real and fake images [1], [39], [40]. The generator's objective is to fool the discriminator into classifying its generated images as real. The discriminator's objective is to correctly classify real and fake images. Adversarial process that is a generator and discriminator are trained in an adversarial manner, meaning they are in a constant competition. As the training progresses, the generator becomes better at creating realistic images, and the discriminator becomes more discerning. Equilibrium is another way of how GANs work as image generators [2], [3], [41], [42]. Ideally, this adversarial process reaches a point where the generator produces images that are so realistic that the discriminator can no longer distinguish them from real images. At this point, the system has reached a kind of equilibrium, and the generated images are considered successful outputs [6], [7], [43], [44]. Fine-tuning and Hyperparameter Adjustment is essential in AI enrolment of image generation. The training process involves adjusting hyperparameters, such as learning rates and network architectures, to achieve the desired balance between generator and discriminator [45]. Once the GAN is trained, you can use the generator to generate new images by providing random noise or seeds as input. It is important to note that GANs are just one type of generative model, and other architectures like VAEs operate differently but also aim to generate realistic images. Additionally, advancements in AI research continue to introduce new models and techniques for image generation [8], [9], [46], [47].

2.3. Types of Evidences

In the context of legal and investigative processes, evidence is information or objects that are presented in a court of law to support or refute a legal argument. There are various types of evidence, broadly categorized into two main groups: direct evidence and circumstantial evidence. Evidences can be presented within direct and indirect categories. Direct evidence includes eyewitness testimony that are statements made by individuals who directly observed an event, documentary evidence which are written or recorded documents, such as contracts, letters, or emails, physical evidence that are tangible items, including weapons, clothing, or other objects related to a crime, and finally video and audio recordings of events that can provide direct visual or auditory information. Circumstantial Evidence can be forensic Evidence that are scientific analysis of physical materials, such as DNA, fingerprints, or ballistics, trace evidence which are small bits of physical evidence, such as hair, fibres, or soil, and digital evidence. Digital evidence is information stored or transmitted in electronic form, like computer files, emails, or social media posts. Another type is character evidence that can be either character witnesses, which are individuals who testify about the character of a person involved in a legal case or prior acts or conduct that is evidence of a person's previous behaviour to establish a pattern of conduct [10], [14], [48], [49]. The evidence related to this research is demonstrative evidence such as charts, graphs, models, simulations, maps or diagrams. charts and graphs are visual aids that help explain complex information [16], [50]–[52]. models or simulations can be in physical or digital representations used to demonstrate how an event might have occurred. Maps and diagrams are also visual representations of locations or scenes. It is important to note that the admissibility of evidence can be subject to rules and procedures established by the legal system, and not all types of evidence may be considered valid in every situation. Additionally, the weight and credibility of evidence can vary, and the interpretation of evidence is often a critical aspect of legal proceedings. However, AI text to image generator is able today to provide evidences that can be easily used to proof what is not true. If judges receive digitalized evidences, then they need to deal with it [17], [53]–[55]. The doubt is about the extent to which these digitalized evidences may affect the accuracy of judging in case they were fake.

2.4. Judgement Accuracy

The accuracy of judgment based on fake evidence is inherently compromised, as the evidence itself is not genuine or reliable. Judgment and decision-making rely on the quality and authenticity of the information available. When fake evidence is introduced, it distorts the basis on which decisions are made, leading to potentially incorrect conclusions and actions [19], [21], [54], [56]. In legal contexts, using fake evidence is considered unethical and can lead to serious consequences, including legal penalties. In other areas of life, such as personal relationships or professional settings, relying on false information can damage trust, credibility, and relationships. It is essential to emphasize the importance of integrity, honesty, and adherence to ethical principles when making judgments or decisions. Valid and reliable evidence is crucial for accurate and fair assessments in various domains of life. If there are suspicions or concerns about the authenticity of evidence, it is important to investigate thoroughly and ensure that decision-making processes are based on truthful and reliable information [23], [25], [26], [57].

2.5. AI and Text to Image Generator

- AI, like any tool, can be used for both positive and negative purposes. While AI itself doesn't have intentions, humans can misuse AI to create fake evidence. AI technologies, including deep learning algorithms, can generate realistic-looking images, videos, audio, and text [1]. These capabilities have legitimate uses, such as in creative industries or for enhancing certain aspects of media production. However, when misused, AI-generated content can be employed to create misleading or entirely fabricated evidence. This raises ethical concerns and poses challenges for legal and forensic systems [2]–[4]. It's essential for society to develop mechanisms to detect and mitigate the misuse of AI in generating fake evidence. Many organizations and researchers are actively working on developing tools to detect AI-generated content, commonly referred to as deepfakes. Additionally, legal and ethical frameworks are being discussed and implemented to address the potential misuse of AI in creating deceptive evidence. It is crucial to stay vigilant, educate people about the existence of such technologies, and continually develop methods to identify and counteract their misuse. Potential impacts can be in enhanced Visualization and understanding. A strong moderation effect can be hypothesized [5]–[8]. AI image generator may enhance the presentation of evidences, providing visual aids that aid in better comprehension. This could lead to improved understanding of the information, potentially resulting in more accurate judgments, or perhaps the opposite. This study examines the moderation effect of using AI image generator on the relationship of digitalized evidence on the levels of accuracy in depending on digitalized evidences to make judgements. Three main factors are examined [9]–[11], [13].

1. Risk of Bias or Misrepresentation

The first Hypothesis expects that there is a negative moderation effect of using AI image generator on the relationship between digital evidences and judgment accuracy [14]–[17]. If the AI image generator introduces bias or misrepresents the evidences, it can negatively impact the accuracy of judgment. Users may rely too heavily on generated visuals, leading to inaccurate interpretations.

2- Subjectivity and Interpretation:

Hypothesis 2 suggests that there are varied moderation effects of using AI image generator on the relationship between digital evidences and judgment accuracy [18]–[21]. The impact of AI image generation could vary based on the subjectivity of the evidences. In some cases, generated images might help clarify ambiguous information, while in other cases, they might introduce additional subjectivity [22], [23], [25], [26].

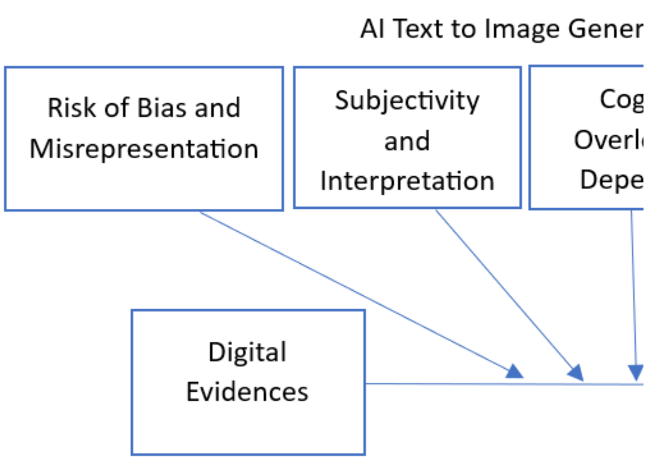
3. Cognitive Overload or Dependency:

Hypothesis 3 expects a negative moderation effect of the dependency on the complexity of the generated images, there's a risk of cognitive overload. If the visuals are too intricate or distracting, they may impede rather than aid accurate judgment. Additionally, users might become overly reliant on the generated images.

The use of AI generator is investigated from two perceptions that are ethical considerations and user proficiency with AI tools [1], [3], [5], [7], [11], [19], [22], [26]. Ethical considerations are expected to have a negative moderation effect. If the AI image generator is not ethically designed, there could be unintended consequences, such as the creation of misleading visuals or the perpetuation of stereotypes. This may distort the relationship between evidences and accurate judgment. User proficiency with AI tools is another factor. Varied Moderation Effects is expected to be existing on the relationship. Users' familiarity and proficiency with AI tools may influence the moderation effect. Those who understand how to interpret and use generated images effectively may experience a positive impact, while others might struggle, leading to a negative effect. In conclusion, the moderation effect of an AI image generator on the relationship between evidences and accurate judgment is contingent on the quality of the generated visuals, user proficiency, ethical considerations, and the nature of the evidences. A thoughtful and well-designed implementation of AI image generation is crucial to ensure a positive impact on judgment accuracy. The following framework displays the five hypotheses of this research.

The five hypotheses (H1 to H5) of this research examines the following research questions (Q1 to Q5):
Q1: Does risk of bias or misrepresentation affect the relationship between digital evidence and judgment accuracy?
H1: There is a negative moderation effect of risk of bias or misrepresentation in using AI image generator on the relationship between digital evidences and judgment accuracy

Figure 1: Conceptual Framework



Q2: Does subjectivity and interpretation of evidences affect the relationship between digital evidence and judgment accuracy?
H2: There are varied moderation effects of using subjectivity and interpretation AI image generator on the relationship between digital evidences and judgment accuracy.

Q3: Does cognitive overload and dependency of AI text generator effect the relationship between digital evidence and judgment accuracy?
H3: There is a negative moderation effect of cognitive overload and dependency of generated images on the relationship between digital evidence and judgment accuracy.

Q4: Do ethical considerations of using AI image generators affect the relationship between digital evidence and judgment accuracy?
H4: There is a negative moderation effect of ethical considerations in using AI image generator on the relationship between digital evidence and judgment accuracy.

Q5: Does user proficiency with AI tools of AI image generator affect the relationship between digital evidence and judgment accuracy?
H5: There are varied moderation effects of user proficiency with AI tools on the relationship between digital evidence and judgment accuracy.

3. METHODOLOGY

The explanatory method (survey) of research employing a combination of quantitative and qualitative approach is the analysis and assessment employed in this research design to address the research issues. Since we employed a small sample size for a large population quickly, the deployment strategy used in this research article is cross-sectional. Only university students in the United Arab Emirates made up the small random sample. This sample size will be illustrated in the next poll, which will use an internet survey as the frequency technique. More precisely, ten academic sources were examined in the research paper. The study made use of digital libraries of scholarly journals, books, and primary materials, such Google Scholar, EBSCO, and others. These academic publications were closely scrutinized to identify various stressors and how they affected academic performance around the globe in order to gain a knowledge of the relationship between stress and academic performance. The review of abstracts was done in order to determine how different sample sizes were interpreted in the previous research projects. This approach was useful in determining the relationship between stress and academic achievement. More specifically, the correlation between the variables was shown using the information from these academic sources. In order to determine whether there is a negative association between stress and academic performance, the sources were analysed rigorously and the correlation between stress and academic success was assessed.

4. DATA COLLECTION AND ANALYSIS

Through the use of an online survey and a quantitative technique, this research was able to provide answers to some questions. This study work uses a survey deployment method and a cross-sectional frequency method. Only courts in the United Arab Emirates made up the small random sample. Furthermore, as this study is descriptive in nature, descriptive analysis will be employed in our quest to find answers to our research questions. Number of samples: n = 50

There are two types of Sampling Methods used in this research. Non-Probability Sampling Method: In this method, participants are chosen based on a set of criteria; not every person is given the opportunity to take part in the study. This approach might be prejudiced. The non-probability sampling approach includes the following four techniques: judgment sampling, quota sampling, snowball sampling, and convenience sampling.

Methods for Probability Sampling: Everyone has the same probability of getting chosen, and there are no special requirements. Additionally, four strategies are used in this: strata, cluster, simple random, and systematic.

From the 50 respondents that participated, the results of data analysis for the five hypotheses revealed the following information:

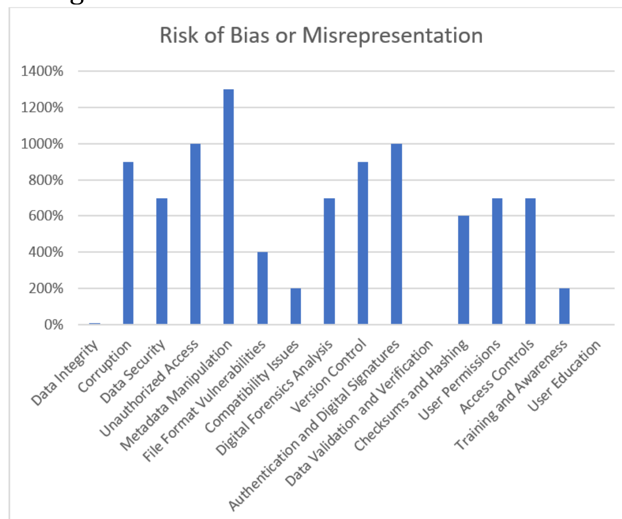
The concept of "risk of bias" of the first question of this research in the context of digital files typically refers to the potential for inaccuracies, errors, or manipulations that may affect the reliability and trustworthiness of the information contained in those files. This variable was examined by analysing the following factors in Table 1 that have considerations regarding the risk of bias in digital files.

Table 1. Risk of Bias or Misrepresentation

Risk of Bias or Misrepresentation	
Data Integrity	7%
Corruption	9%
Data Security	7%
Unauthorized Access	10%
Metadata Manipulation	10%
File Format Vulnerabilities	4%
Compatibility Issues	2%
Digital Forensics Analysis	7%
Version Control	9%
Authentication and Digital Signatures	13%
Data Validation and Verification	0%
Checksums and Hashing	6%
User Permissions	7%
Access Controls	7%
Training and Awareness	2%
User Education	0%

16% of the respondents find that data integrity and corruption of digital files can become corrupted due to various reasons such as hardware malfunctions, software issues, or transmission errors. Corrupted files may lead to data loss or misinterpretation. 17% believe that data security and unauthorized access were considered. If digital files are not adequately protected, there is a risk of unauthorized access. This could lead to intentional or unintentional modifications, deletions, or additions to the content, resulting in biased information. 10% of respondents find that metadata manipulation of metadata in digital files often contain metadata, which includes information about the file itself. Manipulating metadata can potentially mislead users about the origin, creation date, or other essential details of the file. Another component is the file format vulnerabilities that resulted in 4% of responses, where 2% only believed that compatibility issues of some file formats may have vulnerabilities that can be exploited by malicious actors. Using outdated or insecure file formats may expose the files to risks. 7% of participants answers agreed that digital forensics analysis and assessing the risk of bias may involve digital forensics to determine whether files have been tampered with or altered. This process requires specialized knowledge and tools. 9% reflected the factor of version control where and agreed that ensuring proper version control is essential to prevent confusion and potential bias. Knowing which version of a file is the most recent and authentic is crucial for reliability. The highest rate, that is 13%, reveals that most of the participants find that authentication and using digital signatures can help verify the authenticity and integrity of digital files. A valid digital signature provides assurance that the file has not been altered since it was signed. The findings of surveys find that data validation and verification of checksums and hashing is not considered as a risk of bias or misrepresentation. Implementing checksums or hashing algorithms can help validate the integrity of digital files. By comparing the checksum or hash value before and after transmission or storage, one can identify any changes. User permissions and access controls properly managing user permissions reduces the risk of unauthorized changes. Limiting access to only those who need it can mitigate the potential for bias. 2% was the result of training and awareness factors. Educating users about the importance of data integrity and security can help prevent unintentional errors that may introduce bias. To mitigate the risk of bias in digital files, it is essential to implement a combination of technical safeguards, security measures, and best practices for data management. Regular audits, monitoring, and updates to security protocols are also crucial to address emerging threats. The following Cart presents the risks rates of bias or misrepresentation in AI generators.

Figure 2. Risks rates of bias or misrepresentation in AI generators



The second hypothesis investigates subjectivity and interpretation of digital evidence. Subjectivity and interpretation play crucial roles in the analysis of digital evidence. Digital evidence refers to electronic data that can be used as evidence in legal proceedings. This type of evidence is often found in the form of computer files, emails, text messages, social media posts, and other digital artifacts. The subjectivity and interpretation of digital evidence can impact how it is collected, analysed, and presented in legal contexts. Table 3 presents the responses rates of participants.

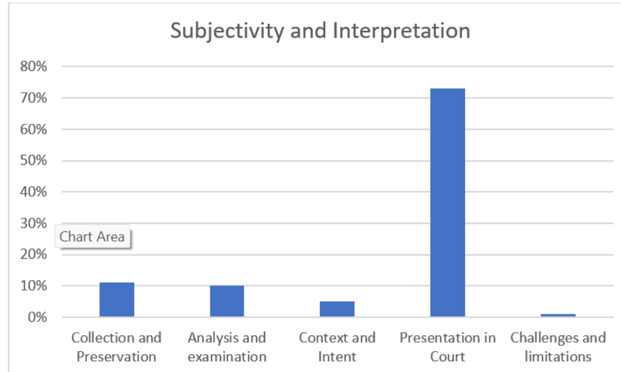
Table 3. Components of Subjectivity and Interpretation

Subjectivity and Interpretation	
Collection and Preservation	11%
Analysis and examination	10%
Context and Intent	5%
Presentation in Court	73%

Collection and Preservation got a response rate of 11%. Collection and preservation Subjectivity and the process of collecting digital evidence can be influenced by the subjective decisions made by investigators. The choice of what to collect, how to collect it, and when to collect it can be subjective. Collection and preservation Interpretation besides the interpretation of what constitutes relevant evidence can vary among investigators. Different individuals may prioritize different data sources or artifacts based on their interpretation of the case. 10% rates of responses of analysis and examination was found. Interpreting the meaning of digital artifacts, such as emails, files, or messages, can be subjective. Investigators may need to interpret the context, intent, or significance of the data. The interpretation of digital evidence may require expertise in various areas, such as computer forensics, cybersecurity, or data analysis. Different experts may reach different conclusions based on their interpretation of the evidence. 5% of participants only agreed on the context and intent as a component. Understanding the context in which digital evidence was created or used requires subjective judgment.

For example, the intent behind a particular communication or the purpose of certain files may be open to interpretation. Investigators must interpret the significance of digital evidence in the context of the overall case. This involves connecting dots and making inferences based on their understanding of the situation. A surprising result was in the findings that is 73% is the rate in which the presentation in court factor affects the relationship between evidences and accuracy judgment. Presenting digital evidence in court involves making subjective decisions about which pieces of evidence to emphasize and how to present them. This can impact the overall narrative of a case. Legal professionals, including judges and jurors, may need to interpret the digital evidence presented to them. The way evidence is framed and explained can influence their understanding and decision-making. Figure 3 displays the analysis of the second variable.

Figure 3. Subjectivity and Interpretation of AI Generators



The third variable is examining two components: the cognitive overload and dependency of AI generators. They are two important aspects to consider when dealing with artificial intelligence (AI) technologies like text generators. This study explores each concept with many variables.

Cognitive overload refers to the mental strain or burden on an individual's cognitive resources when they are exposed to too much information or complexity, leading to difficulty in processing and retaining information. AI Text Generators and Cognitive Overload has three components.

1. Information Overload: AI text generators can produce vast amounts of information in a short period. If users are bombarded with excessive information, they may experience cognitive overload, making it challenging to extract meaningful insights.
2. Complexity of Output: The complexity of AI-generated text may vary, and if the output is too intricate or technical, it can overwhelm users, especially those without a strong background in the subject matter.
3. Filtering and Distilling Information: Users may find it difficult to filter through AI-generated content to identify relevant and accurate information, leading to cognitive strain.

Generation Strategies of Cognitive overload is also examined by testing the following three variables:

1. User-Friendly Interfaces: Design interfaces that present information in a clear and organized manner, helping users process the generated content without feeling overwhelmed.
2. Customization Options: Provide users with options to customize the output, such as setting the level of detail or filtering specific types of information.
3. Guided Interactions: Implement guided interactions to help users navigate through the

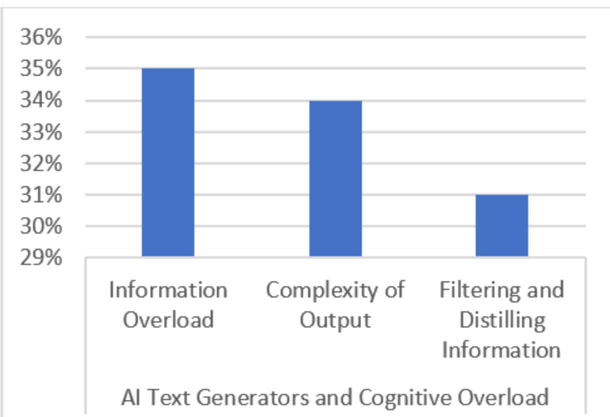
generated content with prompts, summaries, or step-by-step breakdowns.

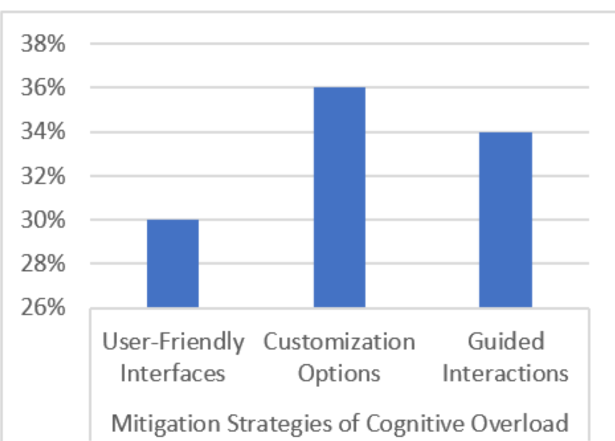
Tables 3a presents the data analysis of the Cognitive overload component and Figure 3a.

Table 3a. Rates of Cognitive Overload and Generation Strategies

AI Text Generators and Cognitive Overload	Information Overload	35%
	Complexity of Output	34%
	Filtering and Distilling Information	31%
Generation Strategies of Cognitive Overload	User-Friendly Interfaces	30%
	Customization Options	36%
	Guided Interactions	34%

Figure 3a. Cognitive Overload and Mitigation Strategies of AI Generators





Dependency on AI text generators refers to reliance on these tools for generating content or making decisions, sometimes to the extent that individuals may neglect critical thinking or the development of their own skills.

AI Text Generators and Dependency:

1. Loss of Critical Thinking: Excessive reliance on AI text generators may lead to a decline in critical thinking skills, as users may accept generated content without questioning its accuracy or validity.
2. Reduced Creativity: Relying heavily on AI-generated content might hinder the development of creative thinking and expression, as users may become accustomed to predefined patterns and styles.
3. Limited Skill Development: Depending solely on AI text generators may discourage individuals from honing their own writing or research skills, limiting their ability to create content independently.

Mitigation Strategies are as the following:

1. Education and Awareness: Promote awareness about the capabilities and limitations of AI text generators, encouraging users to use them as tools rather than replacements for their own skills.
2. Balanced Integration: Encourage a balanced approach, where AI text generators complement human skills rather than replace them entirely.
3. Diverse Learning: Encourage users to explore various sources of information and not solely rely on AI-generated content to foster a more comprehensive understanding of a topic.

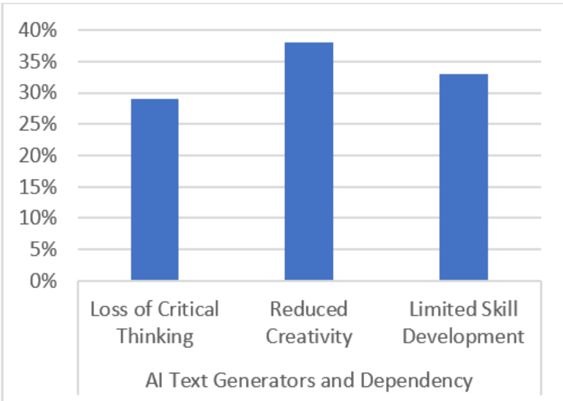
Addressing cognitive overload involves designing user-friendly interfaces and customization options, while mitigating dependency involves promoting awareness, maintaining a balanced approach, and encouraging diverse learning.
Tables 3b presents the data analysis of the Cognitive overload component and Figure 3b presents their rates.

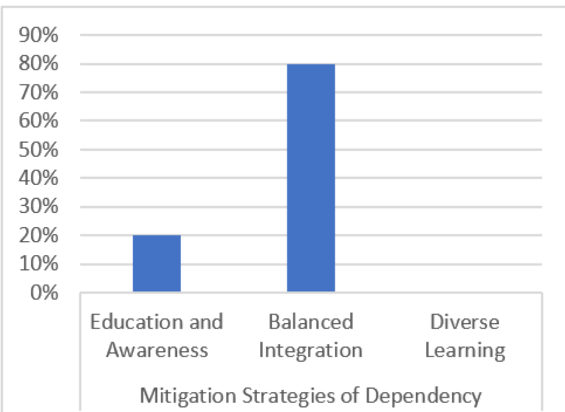
Table 3b. Rates of Dependency and Mitigation Strategies

AI Text Generators and Dependency	Loss of Critical Thinking	29%
	Reduced Creativity	38%
	Limited Skill Development	33%
Mitigation Strategies of Dependency	Education and Awareness	20%

	Balanced Integration	80%
	Diverse Learning	0%

Figure 3b. Rates of Mitigation Strategies and Dependency





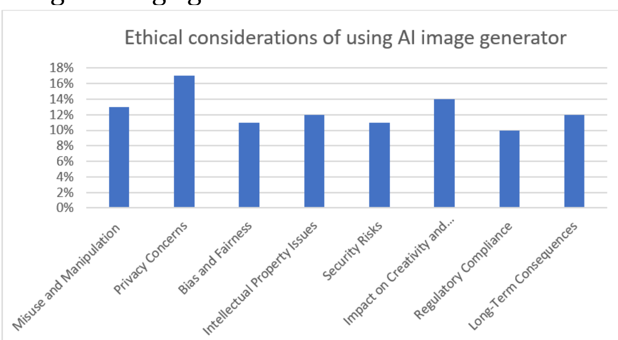
The use of AI image generators raises various ethical considerations that should be carefully examined and addressed. This research investigates some key ethical considerations associated with using AI image generators.

Misuse and Manipulation was found to be 13% of the participants results. Misuse and Manipulation are presented in deepfakes and manipulation of reality. AI image generators can be used to create highly convincing deepfake images and videos that can be misused for malicious purposes, such as spreading misinformation, creating fake news, or impersonating individuals. Manipulation of Reality is the ability to generate realistic images which might be exploited to create false evidence, deceive people, or manipulate public opinion. 17% of privacy concerns were found with the highest rates in Unauthorized Use of Personal Data. If the AI image generator is trained on a dataset that includes personal images without proper consent, it could potentially infringe on individuals' privacy rights. Privacy concerns also are impacted by Creation of Synthetic Identities. There is a risk that AI-generated images could be used to create synthetic identities for malicious activities. 11% of bias and fairness seems to have an impact on the ethical considerations of using AI generators. Dataset Bias is examined for bias and fairness. If the training data used for the AI image generator is biased, it may lead to the generation of images that perpetuate and reinforce existing societal biases. Another component is the impact on underrepresented groups. There is a risk that certain groups may be disproportionately affected if the AI model is not trained on a diverse and representative dataset. 12% of intellectual property issues affect ethical considerations. Determining the ownership of AI-generated images and ensuring proper attribution can be challenging, leading to potential intellectual property disputes. 11% of the security risks is showing some Generation of Malicious Content. AI image generators could be exploited to create harmful content, such as fake identity documents or offensive imagery. 14% is the impact of creativity and authenticity on ethical considerations of using AI generators such as devaluation of Genuine Content. The widespread use of AI-generated content may devalue the efforts of human creators and erode the authenticity of visual media. 10% of the respondents believed that regulatory compliance has an impact on laws and regulations. Ethical considerations also involve ensuring that the use of AI image generators complies with relevant laws and regulations, particularly in areas such as privacy and data protection. The last component of ethical considerations is the long-term consequences that resulted in a rate of 12% from participants responses. The widespread use of AI-generated images could have long-term societal consequences, affecting cultural norms, trust in media, and the perception of reality. Addressing these ethical considerations requires a multi-stakeholder approach involving technologists, policymakers, ethicists, and the broader public. Striking a balance between innovation and responsible use is crucial to ensure that AI image generators contribute positively to society while minimizing potential harms. Table 4 and Figure 4 present the rates found in the ethical consideration variable of the fourth hypothesis.

Table 4. Ethical considerations of using AI image generator

Ethical considerations of using AI image generator	
Misuse and Manipulation	13%
Privacy Concerns	17%
Bias and Fairness	11%
Intellectual Property Issues	12%
Security Risks	11%
Impact on Creativity and Authenticity	14%
Regulatory Compliance	10%
Long-Term Consequences	12%

Figure 4. Components of Ethical considerations in using AI image generator



The fifth hypothesis of this study examines User proficiency with AI tools which can vary widely, as it depends on factors such as individual skills, experience, and the specific AI tools in question. The following components are five tested proficiency levels that users may have with AI tools.

1- Novice/Beginner has limited or no experience with AI tools. 2% of them have basic understanding of the concepts but lacks hands-on experience in AI generator tools. It requires guidance and training to use AI tools effectively.

2- Intermediate which has some practical experience with a rate of 8% in AI tools and can perform basic tasks and understands fundamental concepts. This component may require occasional reference or support for more advanced features.

3- Advanced requires proficient in using a variety of AI tools are found to have an impact of 13% only. It can independently apply advanced techniques and algorithms and it is comfortable experimenting with parameters and configurations. Advanced level also may have developed custom solutions or projects using AI.

4- Expert are highly skilled and experienced in AI tools and techniques with a rate of 27%. They are capable of designing and implementing complex AI systems and they often contributes to the development of AI tools or research in the field. Experts can provide mentorship and guidance to others.

5- Master/Leader recognized as an authority in the AI field and they lead AI projects and teams and they have a 50% impact on the examined hypothesis. Leaders contributes significantly to advancements in AI research and may have a deep understanding of both the theoretical and practical aspects of AI. User proficiency is dynamic and can evolve over time as individuals gain more experience, undertake training, and work on diverse AI projects. It's important to note that AI is a rapidly evolving field, and staying current with the latest advancements is crucial for maintaining high proficiency levels.

Continuous learning, participation in AI communities, and engagement with real-world projects can contribute to enhancing proficiency with AI tools.

Table 5 presets the rates of User proficiency with AI generating tools and how they contribute on the relationship between evidences and judgment accuracy. Figure 4 presents the chart of results found.

Table 5. The impact of User proficiency with AI generating tools

User proficiency with AI generating tools	
Novice/Beginner	2%
Intermediate	8%
Advanced	13%
Expert	27%
Master/ Leader	50%

5. FINDINGS AND RESULTS

For the first hypothesis, the results of the study reveals that there is a negative moderation effect of risk of bias or misrepresentation in using AI image generator on the relationship between digital evidences and judgment accuracy. The second hypothesis was examined and the research findings reveal that there are varied moderation effects of using subjectivity and interpretation AI image generator on the relationship between digital evidences and judgment accuracy. It is proven by the study that the third hypothesis is accepted as there is a negative moderation effect of cognitive overload and dependency of generated images the relationship between digital evidence and judgment accuracy. It is found that cognitive overload has an impact on the complexity of the generated images. It is also proven by the study that there is a negative moderation effect of ethical considerations in using AI image generator on the relationship between digital evidence and judgment accuracy. This means accepting the fourth hypothesis. On the contrary, this research finds that there is only a positive moderation effect of user proficiency with AI tools on the relationship between digital evidence and judgment accuracy. The results show that the more experienced the users of AI generating tool are the more they can have an impact on the relationship of digital evidences and judgment accuracy. The findings and results of this research mean that the first four hypothesis were accepted and the last hypothesis has only one dimension and it is partially rejected.

6. CHALLENGES AND LIMITATIONS

Challenges may arise when different experts or investigators have different subjective views on the same evidence, leading to debates or disagreements. The limitations of digital forensic tools and techniques may introduce interpretation challenges. For example, the recovery of deleted data or the attribution of actions to specific individuals may involve some level of interpretation. To address these challenges, it is essential for investigators and digital forensic experts to document their processes, methodologies, and interpretations thoroughly. Additionally, the legal system may require the validation of forensic tools and methodologies to ensure the reliability of digital evidence in court. Continuous training and collaboration among professionals in the field are also crucial to enhancing the objectivity and accuracy of digital evidence analysis.

7. CONCLUSION

The moderating effect of AI picture generators on the relationship between evidence and sound judgment is examined in this work. This relationship can be intricate and dependent on several factors. The accuracy of the evidence could be negatively impacted by certain possible effects. To determine whether risk factors such as subjectivity and interpretation, cognitive overload or dependency, risk of bias or misrepresentation, and user proficiency with AI tools have an impact on the production of false images produced by AI image generator tools, these factors are tested. According to the study, there is a significant influence from AI Image Generator on the correlation between reliable judgments and the evidence. Artificial intelligence image generators have the potential to strengthen the evidence of bias that judges cannot foresee, which could result in biased verdicts.

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