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Admissibility, Reliability and the Confrontation Clause in AI-Generated Evidence: Lessons for the Nigerian Judiciary

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ABSTRACT

Artificial intelligence (AI) has become increasingly significant in twenty-first-century criminal justice systems. Law-enforcement agencies now deploy facial-recognition systems, predictive policing tools, automated forensic analysis and algorithmic risk assessments. Nigerian institutions are beginning to explore similar technologies, often without parallel development in evidentiary doctrine. This article examines the status of AI-generated evidence within Nigeria's legal system and explores its implications for admissibility, reliability and the constitutional right to confront adverse evidence. Drawing upon developments in the United States, United Kingdom, European Union, South Africa and Kenya, the paper argues that Nigeria must adopt structured reliability standards, enforce disclosure obligations and strengthen judicial technological literacy. It concludes that without doctrinal clarity and institutional oversight, AI technologies risk undermining fair-hearing guarantees and eroding public confidence in the administration of justice.

Keywords: *Fair hearing rights, admissibility, AI-generated evidence, hearsay, machine declaration*

1. INTRODUCTION

Artificial intelligence is no longer a futuristic concept; it is now firmly woven into modern law enforcement methods. Around the world, AI-based systems assist with identifying suspects, analysing forensic material, detecting fraud and predicting criminal behaviour. These technologies increasingly shape the evidentiary landscape of criminal justice. Nigeria is not immune to these developments. Various law-enforcement agencies, including the Nigeria Police Force and EFCC, have piloted or expressed interest in AIenhanced investigative tools. However, the legal framework governing evidence in Nigeria, particularly the Evidence Act 2011, predates the proliferation of modern AI and does not directly contemplate machine-generated forensic outputs or algorithmic decision-making.

This paper aims to guide the Nigerian judiciary in responding to this rapidly evolving evidentiary frontier. It pursues three core objectives:

- To analyse the admissibility of AI-generated evidence under Nigerian law.

- To assess its reliability, given the opacity and potential bias inherent in many AI systems; and
- To evaluate its implications for the right to confrontation, guaranteed under section 36(6)(d) of the 1999 Constitution.

The Paper adopts a comparative method, drawing from jurisdictions that have already confronted this problem.

2. Understanding AI-Generated Evidence

AI-generated evidence refers to any information produced wholly or partly through machine-learning algorithms. This category includes:

- facial recognition matches.
- voice-print analyses.
- automated fingerprint and DNA comparisons.
- predictive policing outputs.
- natural language analyses.
- image or video enhancement using neural networks, and
- risk-assessment scores produced by algorithmic tools.

Unlike traditional digital evidence, AI outputs are not merely records of human actions. Rather, they are computational inferences generated through pattern recognition. Their very strength and complexity also produce fundamental challenges for legal processes.

2.1 The Opacity of AI Systems

One of the central challenges posed by artificial intelligence in evidentiary contexts is what scholars describe as the **"opacity problem."** Many contemporary AI systems, especially those built on machine learning and deep neural networks, function as black boxes, generating outputs through internal processes that remain inaccessible, non-transparent, and often impossible to interpret.[1] Even the engineers, who build these systems may not be able to provide a meaningful, step-by-step explanation of why a particular output was produced.[2]

This characteristic marks a fundamental departure from traditional forms of computer generated evidence. Classical computer programs follow explicit instructions; the logic can be traced and documented. By contrast, machine-learning systems modify their internal parameters autonomously during training, creating

[1]Andrew Ashworth and Mike Redmayne, *The Criminal Process* (5th edn, OUP 2020).
[2] Gary Edmond, 'Forensic Science Evidence and the Limits of Cross-Examination' (2015) 39 Crim LJ 198.

vast webs of statistical associations that cannot easily be reconstructed or articulated in human terms.[3]

(a) Why AI Systems Become "Black Boxes"

Machine-learning models, especially deep neural networks, "learn" by adjusting millions of internal weights based on training data. These adjustments are not programmed individually by humans; they emerge through automated optimisation processes.[4] At the end of training, the model may be highly effective at tasks such as image recognition, but the specific reasons it makes individual decisions remain concealed behind complex mathematical structures. For example, when a facial-recognition system identifies a suspect in CCTV footage, the system cannot specify which facial features, pixel arrangements or subtle patterns it relied upon. It simply produces a confidence score, frequently misunderstood by courts as a measure of certainty.[5]

(b) Consequences of Opacity for the Law of Evidence

Evidence law values transparency. Courts expect:

- experts to articulate the basis of their opinions,
- forensic analysts to describe their methods,
- underlying scientific principles to be clear and testable.

Opacity undermines these expectations in three critical ways:

1. **Cross-examination is frustrated**
   Defence counsel cannot interrogate the reasoning behind an algorithmic output because that reasoning is not human and cannot be verbalised.[6]

2. **Judicial evaluation of probative value is impaired**
   Without understanding how an algorithm works, courts may attach undue weight to outputs, especially when presented in probabilistic or statistical terms. [7]
3. **Errors and biases become invisible**

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[3] AI Now Institute, *AI Now Report 2019* https://ainowinstitute.org/reports.html.
[4] Danielle Citron, 'Technological Due Process' (2008) 85 *Washington University Law Review* 1249.
[5] *R v T* [2011] 1 Cr App R 9. AI Now Institute, *AI Now Report 2019* https://ainowinstitute.org/reports.html
[6] *Daubert v Merrell Dow Pharmaceuticals Inc* 509 US 579 (1993).

[7] *S v Mkohle* 1990 (1) SACR 95 (A).

If the algorithm incorporates demographic or environmental biases, these may be masked by the appearance of neutrality.[8]

Thus, opacity strikes at the heart of adversarial testing and threatens the fairness of criminal proceedings.[8]

(c) Proprietary and Commercial Opacity

Opacity is not merely technical. It is frequently compounded by **commercial secrecy**. Many AI tools used in policing and forensic science are developed by private companies that refuse to disclose:

- the dataset used for training,
- the algorithmic model,
- validation studies,
- known error rates.

They protect these elements as trade secrets.[9] This creates a structural imbalance between the prosecution (which may rely on such tools) and the defence (which cannot meaningfully challenge them), raising constitutional concerns under Section 36 of the 1999 Constitution of the Federal Republic of Nigeria (as amended), which guarantees equality.[10]

(d) Automation Bias and Judicial Deference

Opacity interacts with another risk: **automation bias** the human tendency to assume computers are objective and accurate merely because they are computational.[11]

Many judges and lawyers lack technical training, making them more susceptible to overestimating the reliability of algorithmic outputs.[12] This deference is dangerous, particularly when AI systems are known to produce false positives or to perform unevenly across demographic groups.[13]

(e) International Judicial Commentary

Courts across jurisdictions have recognised opacity as a threat to evidentiary integrity. For example:

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[8] *Tsalibawa v Habiba* (1991) 2 NWLR (Pt 174) 461.
[9] Evidence Act 2011, s 84.
[10] *Kubor v Dickson* (2013) 4 NWLR (Pt 1345) 534.
[11] *FRN v Fani-Kayode* (2010) 14 NWLR (Pt 1214) 481.
[12] Richard Jones, 'Machine Evidence and Hearsay' (2018) 12 *Digital Evidence & Law Review* 10
[13] *Daubert* (n 6).

- The English Court of Appeal in *R v T* emphasised the need for transparent and scientifically validated forensic methods; opaque probabilistic reasoning was criticised.[14]
- US courts applying *Daubert v Merrell Dow Pharmaceuticals* have excluded scientific evidence where the underlying method is not understood or replicable.[15]
- South African courts have highlighted the need for transparency in forensic processes and warned against accepting methods that cannot be independently scrutinised.[16]

These judicial reactions underscore a shared concern that courts cannot fulfil their gatekeeping responsibility when faced with inscrutable technologies.

(f) Implications for Nigerian Courts

For Nigerian judges, the opacity problem has pressing doctrinal implications:

- Can opaque AI systems satisfy section 84 of the Evidence Act?
- How should courts evaluate reliability when error rates are unknown?
- Can the defence confront evidence whose internal logic is inaccessible?
- Should courts admit outputs that vendors refuse to reveal?
- What safeguards are needed to prevent wrongful convictions?

Unless Nigerian courts insist on transparency, disclosure and expert explanation, the opacity of AI systems will undermine adversarial fairness, frustrate cross-examination and erode constitutional guarantees under section 36(6)(d).

2.2 Non-deterministic output

Unlike ordinary computer programs, which follow deterministic instructions, AI systems often produce probabilistic outputs. A facial-recognition match, for example, expresses degrees of confidence rather than categorical truth.

2.3.1. Embedded human influence

Although AI systems can operate autonomously, they rely on human-curated training data. If the underlying data is biased, incomplete or unrepresentative, the system will replicate and potentially magnify those deficiencies. These features complicate traditional doctrines such as authenticity, hearsay, expert testimony and the chain of custody.

[14] *R v T* [2011] 1 Cr App R 9.
[15] *Daubert v Merrell Dow Pharmaceuticals Inc* 509 US 579 (1993).
[16] *S v Mkohle* 1990 (1) SACR 95 (A).

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Admissibility under Nigerian Law

3.1 The Threshold of Relevance

Section 1 of the Evidence Act 2011 establishes relevance as the primary criterion for admissibility. Nigerian courts consistently affirm this principle, most notably in ***Tsalibawa v Habiba***.[17] AI-generated evidence may easily meet this threshold, particularly when it purports to link an accused person to a crime scene.

However, relevance alone is insufficient. Courts must evaluate whether the evidence is sufficiently reliable to justify admission.

3.2 Section 84 and computer-generated evidence

Section 84 governs the admissibility of computer-generated statements. Requirements include demonstrating:

- regular use of the device.
- proper functioning during the relevant period;
- the origin and accuracy of the information supplied.

The Supreme Court in ***Kubor v Dickson***[18] emphasised strict compliance with Section 84, especially concerning electronic documents. Similarly, in **PDP v INEC**, the Court refused electronically generated evidence where foundational requirements were not met.

AI systems pose unique difficulties here. For example: How does counsel prove "proper functioning" when the algorithm is proprietary? What constitutes "ordinary use" for a system capable of self-modification? How should the court evaluate accuracy when the training data and error rates are unknown?

3.3 Authenticity and chain of explanation

The Court of Appeal in FRN v Fani-Kayode[19] held that authenticity requires demonstrating how electronic evidence was generated. With AI, this requires far more than proving that a computer produced the output. Counsel must establish:

- the nature of the underlying algorithm.
- the circumstances of data collection.
- the environmental conditions affecting the algorithm's performance.
- any human involvement in interpreting the output.

3.4 Hearsay and machine declarations

[17] *Tsalibawa v Habiba* (1991) 2 NWLR (Pt 174) 461.
[18] *Kubor v Dickson* (2013) 4 NWLR (Pt 1345) 534.
[19] *Kubor v Dickson* (2013) 4 NWLR (Pt 1345) 534.

AI systems produce machine-generated statements. Many common-law courts treat these as outside the hearsay rule because there is no human declarant.[20] Nigerian courts may adopt a similar approach, though this becomes complicated when human-labelled training data or analyst interpretations influence the output.

4. Reliability and the Challenges of Scientific Validity

4.1 The need for structured reliability analysis

Modern evidence law increasingly demands that scientific evidence meet reliability thresholds. The US Supreme Court's Daubert standard directs courts to evaluate:

- testability.
- peer review.
- known error rates.
- general acceptance.

In United Kingdom, courts also require a robust scientific foundation for probabilistic evidence, as demonstrated in R v T,[21] which emphasised the dangers of overstating algorithmic certainty.

Nigeria lacks an equivalent framework. Courts often rely on general judicial discretion under sections 135–137 of the Evidence Act without applying structured scientific criteria.

4.2 Algorithmic Bias

AI systems trained on skewed datasets may disproportionately misidentify certain demographic groups. Research shows that many commercial facial-recognition systems perform poorly on women and darker-skinned individuals.[8]

Given Nigeria's diversity, courts must interrogate:

- representativeness of training data across ethnic groups.
- regional differences in lighting, camera quality and environmental variables.
- linguistic and tonal variations affecting voice-recognition systems.

[20] Richard Jones, 'Machine Evidence and Hearsay' (2018) 12 *Digital Evidence & Law Review* 10.
[21] *R v T* [2011] 1 Cr App R 9.

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4.3 Interpretability and the "Black Box" Problem

In ***Oshodin v State***[22] the Court of Appeal stressed that forensic evidence must be comprehensible and subject to scrutiny. AI systems resist such scrutiny, undermining adversarial testing.

5. The Confrontation Clause and Fair-Hearing Rights

5.1 Nigerian constitutional framework

Section 36(6)(d) of the 1999 Constitution guarantees the right of an accused person to examine prosecution witnesses. This reflects a deep-rooted commitment to adversarial fairness.

5.2 Comparative jurisprudence

United States

In **Crawford v Washington,**[23] the US Supreme Court held that testimonial statements require cross-examination. In **Bullcoming v New Mexico**,[24] the Court rejected surrogate forensic testimony, insisting that the analyst who performed the test must testify.

Europe

Article 6 ECHR similarly demands adversarial testing. The European Court of Human Rights has insisted on disclosure and examine-ability of scientific evidence, especially when automated processes are involved.[25]

South Africa

South African courts have required transparency in algorithmic processes used in policing, insisting on the right to challenge automated decisions.

5.3 Nigeria's practical challenges

AI vendors frequently treat algorithms as trade secrets. Defence counsel may therefore lack access to:

- source code,
- training data,

[22] *Oshodin v State* (2012) LPELR-7820 (CA).
[23] *Crawford v Washington* 541 US 36 (2004).
[24] *Bullcoming v New Mexico* 564 US 647 (2011).
[25] European Convention on Human Rights (1950).

- error-rate information,
- validation studies.

Without disclosure, cross-examination becomes meaningless.

6. Lessons and Recommendations for Nigeria

6.1 Introduce judicial guidelines

Courts should adopt a reliability framework incorporating:

- error-rate disclosure.
- dataset transparency.
- methodological explanation by expert witnesses.

6.2 Enhance judicial technological literacy

The National Judicial Institute should incorporate AI literacy, digital forensics and probabilistic reasoning into judicial training.

6.3 Legislative reform

Parliament should amend the Evidence Act to:

- define AI evidence.
- mandate disclosure obligations.
- require independent auditing of forensic AI tools.

6.4 Institutional oversight

Nigeria should establish a Forensic Science Regulator, similar to the UK model, to accredit AI tools used in criminal investigations.

7. Conclusion

AI will undoubtedly shape the future of criminal justice in Nigeria. While its potential benefits are significant, its risks are equally profound. Nigerian courts must ensure that fairness, transparency and constitutional rights are not sacrificed on the altar of technological convenience. Without doctrinal clarity and institutional safeguards, AI-generated evidence may distort rather than illuminate the pursuit of justice.

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