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Beyond the Instrument: A Human-Centric Forensic Framework for Questioned Document Authentication in the Digital Age

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Abstract- Powerful analytical technologies increasingly shape questioned document examination, yet the evidential meaning of a document still depends on human action, cognition, and behavior. Handwriting is a learned neuromuscular activity with identifiable regularities. Still, it is also variable across context, health status, emotional condition, and writing task, which makes source attribution an interpretive rather than purely instrumental problem (Hicklin et al., 2022; Singh et al., 2025; Nikolaychuk & Bila, 2023). At the same time, large validation work shows that forensic handwriting comparison can achieve useful accuracy, while still having nontrivial error and inconclusive rates and remaining vulnerable to cognitive bias, especially when judgments are made without structured safeguards (Hicklin et al., 2022; Cooper & Meterko, 2019; Kunkler & Roy, 2023). This paper proposes an equipment-independent, human-centric framework for questioned document authentication built on three linked pillars: the cognitive-scriptographic nexus, the material-semiotic interface, and the forensic intelligence paradigm. The first pillar treats handwriting as a behavioral biometric produced by distributed neural and motor processes rather than as a static pattern alone (Burgio et al., 2026; Qi et al., 2025; Ferrer-Ballester et al., 2017). The second pillar integrates line quality, pen lifts, spacing, pressure, and document substrate features into a single action-based interpretation model instead of separating physical and expressive evidence (Ellen et al., 2018; Cieśla, 2021; Kerniakevych-Tanasiichuk et al., 2021). The third pillar extends questioned document examination from case resolution to systematic intelligence generation through structured recording of forgery methods, alteration patterns, and cross-case linkages (Baechler & Margot, 2016; Baechler et al., 2012; Song et al., 2026). The literature supports such a framework most strongly when it is paired with explicit limits: contemporaneous standards for impaired writers, blind verification, contextual information management, and hybrid human-AI workflows rather than replacement of expert judgment (Singh et al., 2025; Bird & Yang, 2024; Can et al., 2026; El-Din, 2022). The main contribution is therefore not a rejection of instruments, but a structured interpretive model that makes human reasoning in questioned document examination more transparent, reproducible, and legally defensible.

Keywords— Questioned document, Human health, Neuromuscular, Forensic, Criminalistics, AI, QD, Handwriting

I. INTRODUCTION

Questioned document examination still addresses classic questions of authenticity, origin, alteration, and source, but the domain of those questions now spans handwritten, printed, copied, and increasingly digital documents (Bird & Yang, 2024; Adedayo & Olivier, 2025). Reviews of the field show that research since 2000 has heavily emphasized analytical techniques for inks, paper, printers, intersecting lines, and dating, reflecting a broad instrumental expansion (Calcerrada & García-Ruiz, 2014). That expansion has improved discrimination of physical materials, but it does not itself resolve the interpretive problem of linking observed traces to the acts and states of writers, forgers, or document producers (Bird & Yang, 2024; Cieśla, 2021).

The scientific basis of handwriting examination has been under sustained scrutiny. A global review notes continuing debate about validity, reliability, cognition, and quality assurance in forensic handwriting work (Bird & Yang, 2024). The strongest empirical response to that scrutiny is the large-scale PNAS study of practicing forensic document examiners, which found that handwriting comparison can be accurate and reproducible under many conditions, but not infallible, especially when evidence is limited or difficult (Hicklin et al., 2022). A human-centric framework is therefore timely because the core challenge is not whether humans should be removed from the process, but how human judgment should be structured, constrained, and explained.

II. LITERATURE REVIEW

Handwriting is a behavioral biometric grounded in neural, cognitive, and motor processes. Reviews and experimental studies describe handwriting as a distributed brain function involving planning, execution, and sensorimotor integration, with fine motor output carrying individual regularities that can support identification (Burgio et al., 2026; Qi et al., 2025; Ferrer-Ballester et al., 2017). Machine and deep learning studies in writer identification reinforce that individuality is expressed not only in visible letter forms but also in kinematic, spatial, and dynamic features (Hasan et al., 2024; Bulacu & Schomaker, 2007; Sethi et al., 2025). Text-independent methods and longer handwriting samples often preserve more writer-specific information than short practiced signatures alone (Bulacu & Schomaker, 2007; Salkanovic et al., 2025).

At the same time, handwriting is not static. Mature writers usually show distinct patterns, but those patterns vary with environment, instrument, physical and mental state, medication, content, and conscious style change (Hicklin et al., 2022). Neurological and psychiatric conditions complicate attribution because they can produce differences that resemble disguise, tremor, hesitancy, or authorship change (Bansal et al., 2024; Ciochină, 2026; Nikolaychuk & Bila, 2023). The stroke case study is especially relevant to disputed wills or impaired signatories: without medical history and contemporaneous standards, a false exclusion could result (Singh et al., 2025).

Forgery research also supports a cognitive framing. Freehand, simulated, and traced forgeries differ in fluency, pressure, pen lifts, and line quality, and traced forms can sometimes resemble genuine signatures closely enough to challenge manual examination (Bonham, 2023; A, 2025). Dynamic-feature studies show that relevant movement information outperforms static features for signature evidence assessment and can better separate genuine from imitation signatures (Chen et al., 2017). Behavioral synthesis work further suggests that signatures can be modeled as a combination of cognitive and motor levels, which is useful conceptually because it aligns forgery detection with underlying action rather than mere shape similarity (Ferrer-Ballester et al., 2017).

A second literature stream concerns decision quality. Cognitive-bias reviews across forensic domains show robust evidence that contextual information, exemplar procedures, and prior opinions can influence conclusions, and that blinding, information management, lineups, and independent verification can reduce that risk (Cooper & Meterko, 2019; Kunkler & Roy, 2023). Survey research also shows that many examiners underestimate their own susceptibility to bias, making procedural rather than purely motivational safeguards essential (Kukucka et al., 2017).

III. METHODOLOGY

This literature supports three source domains for framework construction: validation studies of handwriting comparison, cognitive and neuroscientific studies of writing, and operational studies on bias mitigation, forgery typology, and intelligence workflows (Hicklin et al., 2022; Burgio et al., 2026; De Alcaraz-Fossoul & Roberts, 2017).

A practical development pathway is to use ACE as the underlying examination grammar and then specify what a human-centric examiner must document at each stage. The stroke case study gives a clear operational statement of analysis, comparison, and evaluation, including feature isolation, like-with-like comparison, and weighting of features by significance and cause (Singh et al., 2025). The proposed framework should therefore formalize not only what features are seen, but why each feature is behaviorally meaningful, what alternative explanations exist, and what information was withheld or controlled during judgment (Singh et al., 2025; Bird & Yang, 2024; Kunkler & Roy, 2023). Framework validation should be described modestly. Structured expert elicitation can assess usability and face validity, but it cannot substitute for blind, multi-examiner empirical testing on realistic case sets (Hicklin et al., 2022; Can et al., 2026). If retained, the manuscript should present expert review as a refinement step and identify future controlled validation as necessary before strong performance claims are made (Singh et al., 2025; Can et al., 2026).

Evidence Base

The table below summarizes the strongest evidence streams supporting a human-centric framework.

Evidence Strength	Claim
Evidence strength: Strong (9/10)	Forensic handwriting comparison is useful but imperfect, with the largest study reporting measurable false positives, false negatives, and effects of training on decision patterns (Hicklin et al., 2022)
Evidence strength: Strong (8/10)	Handwriting reflects cognitive and motor control, making it more than a visual pattern and supporting interpretation in relation to brain, behavior, and impairment (Burgio et al., 2026; Qi et al., 2025)
Evidence strength: Strong (8/10)	Bias control and structured reporting are necessary because handwriting examination is a human decision process vulnerable to contextual influence (Bird & Yang, 2024; Cooper & Meterko, 2019; Kunkler & Roy, 2023)

Figure 1: Core evidence streams supporting a human-centric framework

The literature is strongest on validation, bias, and the behavioral basis of handwriting. It is thinner on fully validated operational frameworks that integrate cognition, physical document features, and intelligence functions in one protocol (Bird & Yang, 2024; Devlin et al., 2024; Priya et al., 2025).

Results Framework

A concise framework can be organized as five operational stages.

Stage	Human-Centric Task	Key Evidence
Intake	Define the authenticity question and exclude irrelevant context	(Adedayo & Olivier, 2025; Cooper & Meterko, 2019)
Writer-State Profiling	Assess illness, coercion, stress, or style variability before attribution	(Singh et al., 2025; Bansal et al., 2024; Moszczyński, 2018)
Integrated Trace Analysis	Read handwriting, pressure, spacing, pen lifts, and material features as one action system	(Kerniakevych-Tanasiichuk et al., 2021; Ellen et al., 2018; Cieśla, 2021)
Conclusion Control	Use structured evaluation, blind verification, and graded reporting	(Singh et al., 2025; Kunkler & Roy, 2023; Bird & Yang, 2024)
Intelligence Capture	Record forgery technique and cross-case patterns for linkage analysis	(Baechler & Margot, 2016; Baechler et al., 2012; Song et al., 2026)

Figure 2: Operational stages in a human-centric document framework

The framework's first pillar, the cognitive-scriptographic nexus, anchors individualization in learned but variable motor behavior. That is consistent with classic writer-identification work showing text-independent individuality and with newer digital studies extracting kinematic and spatial features from handwriting dynamics (Bulacu & Schomaker, 2007; Hasan et al., 2024). The second pillar, the material-semiotic interface, treats surface form and deeper material evidence as jointly informative rather than separate silos (Cieśla, 2021; Adedayo & Olivier, 2025).

The third pillar, forensic intelligence, is a genuine addition to many conventional QDE models. Reviews show that this area remains underdeveloped relative to authentication research, despite demonstrated value for detecting patterns, links, modus operandi, and organized document fraud networks (Devlin et al., 2024; Baechler & Margot, 2016).

IV. DISCUSSION

The main strength of the proposed manuscript is that it aligns with where the field is moving: toward better scientific grounding of examiner judgments rather than simple reliance on tradition or on increasingly sensitive instruments alone (Bird & Yang, 2024; Cieśla, 2021). It also fits current evidence that AI and automation are best treated as adjuncts. Automated systems can capture weak or complex patterns, improve consistency, and assist with quantitative tasks, but human interpretation remains necessary for case meaning, legal explanation, and off-distribution problems (Bansal et al., 2024; Can et al., 2026; El-Din, 2022).

Digital and AI-generated documents create both opportunity and risk. The literature on questioned digital documents argues that physical QDE questions should be translated, where possible, into precise digital counterparts rather than treated as an unrelated domain (Adedayo & Olivier, 2025). Deepfake and synthetic-text detection studies show high performance in controlled datasets, but also emphasize generalization problems, adversarial vulnerability, false positives, explainability, and trust erosion from "impostor bias" (Ghiurau & Popescu, 2024; Boutadjine et al., 2024; Amerini et al., 2025; Khan et al., 2025).

A human-centric document framework should therefore not oppose instrumentation or AI. It should place them inside a disciplined reasoning model that specifies what is being inferred, from which traces, under which competing explanations, and with which uncertainty controls (Amerini et al., 2025; Khan et al., 2025; El-Din, 2022). The strongest single shift in the evidence is from unstructured expert impression toward validated, bias-aware, hybrid human-machine interpretation. The biggest open question is how to empirically validate integrated frameworks across physical handwriting, impairment-affected writing, and questioned digital documents under realistic case conditions.

Conflict of Interest Statement
The authors declare no conflicts of interest.

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V. CONCLUSION

The authentication of questioned documents in the digital age requires a shift from an instrument-centered approach to a human-centric forensic framework that recognizes the critical role of examiner expertise, cognitive judgment, ethical responsibility, and contextual interpretation. While advanced technologies such as artificial intelligence, machine learning, hyperspectral imaging, and digital forensic tools have significantly enhanced the capability to detect alterations, forgeries, and manipulations, they cannot replace the nuanced reasoning and professional judgment of trained forensic document examiners. Instead, these technologies should be viewed as decision-support systems that complement, rather than substitute, human expertise.

A human-centric framework promotes transparency, accountability, and interdisciplinary collaboration by integrating scientific methodologies with legal, psychological, and ethical considerations. It emphasizes standardized protocols, continuous professional training, cognitive bias mitigation, and explainable use of emerging technologies to ensure that forensic conclusions remain reliable, reproducible, and legally defensible. Such an approach is particularly important as digitally generated and AI-assisted documents become increasingly sophisticated and difficult to distinguish from authentic materials.

Looking ahead, the future of questioned document authentication lies in balancing technological innovation with human expertise. Establishing internationally harmonized standards, validating AI-assisted forensic methods, and fostering collaboration among forensic scientists, computer scientists, legal professionals, and policymakers will be essential to maintaining public trust in forensic evidence. Ultimately, moving beyond the instrument toward a human-centric forensic paradigm ensures that questioned document examination remains scientifically rigorous, ethically grounded, and responsive to the evolving challenges of the digital era.

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