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I.A.D.E. WHO ARE WE?

The International Association of Document Examiners now has over 60 members spanning across the globe in 17 countries, including 22 US states. Since the worldwide pandemic and with the cost of everyday life skyrocketing, along with (hopefully) busy schedules, more people are opting for the annual online webinar rather than the traditional in-person seminars of the past.

The webinars have been super, and because of the flexibility of being on-line, we have been able to secure a lot of awesome speakers who may not have been able to attend in person. Attendance has been good, although we would always like to see more members attend. In fact, we would love it if everyone could be there! All in all the webinar has turned out to be a very fulfilling, informative event that most of us really enjoy and look forward to.

Personally, while I love the convenience of the webinar, I do miss the opportunity to meet other members in person and form those special bonds that can happen while sharing a meal or just sitting next to someone in a workshop.

Over the past couple years, readers of this newsletter have been greeted by various IADE Board members with the intent of letting all of you get to know who we are. Now we want to know who YOU are!

The benefits we all have just from belonging to this organization are amazing - the connections that we have all over the world - many that most of us aren't even aware of - are abundant. We have so much to offer each other in ways that we may not even know.

So now I'm inviting everyone to step up and tell us who you are. Where are you from? What do you do? How did you find us? Do you have any interesting cases or related stories to tell? Do you have any special or creative methods for document examination that you would like to share or special tools that you have found to be helpful?

Let's unbox the vast knowledge and experience that surrounds us in our wonderful organization. The more we all participate, the more benefits we all will reap! Send me your bio, your stories, your case studies, whatever you would like to contribute - preferably in a Word document - to monique@amtpolitics.com.

If you have any questions, you may reach me by email at the address I just mentioned, or you may text or call me at 702-860-5031. If possible, include a picture of yourself so we can put a face with the name - hopefully on the 2026 webinar coming in August! See details for that in this newsletter!

Don't be shy, folks, let's see your cards!

Monique Rosser
IADE Newsletter
Editor



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Can AI “ACE” a Proficiency Test?

A Research Project by Meg Barrineau

Introduction

Over the last few years I have realized that Artificial Intelligence has crept into many aspects of my daily life, not just my personal life, but my professional life too. Throughout my day, it is common for me to ask various AI chat bots to help me answer questions or find useful information. In my working life (in public ed) I often ask it to help me with writing or getting and staying organized. So as a fairly new student in the field of Forensic Document Examination I early on wondered how much of what we are undertaking could be done by AI and could it be done correctly, if so how? My plan was to use a case from a past proficiency test (Denise Orr PT from 2024) and determine if AI could analyze, compare and evaluate the data entered in order to pass the test? Would AI “ACE” the case?

Specifics of the Plan

I wanted to use a service that is free and open to everyone. The number of AI services online seems to grow daily, with some of the most popular AI chat bots include Gemini, Co-Pilot, and Chat GBT. I have had a free Open AI Chat GBT account for several years and so I started my project using this service. My basic plan was to upload the Denise Orr Proficiency Test images, give the chat bot the instructions, and then let it go to work. If you were not aware of this feature, most AI services will allow you to upload documents for analysis. Could Chat GBT Identify the genuine signatures? I also planned, after it revealed its analysis, to prompt it to give me its method and how it reached its conclusions.

Unforeseen Problems

As a casual user of a free AI account I did not realize that there is a limit to the amount of “messages” allowed during a given time frame. As I was working on my project, I was given a notice that I was reaching my message limit. I could have stopped work and waited for a few hours or the next day until I was able to post more messages. However, due to my time constraints, I needed to keep working. So I actually stopped my project and logged into a paid Chat GPT Go account, which is a paid subscription belonging to my spouse. There are more features available with paid accounts so this upgrade likely came with advantages.

There was another more serious issue that came to the forefront, prior to switching the upgraded account. For anyone with any type of experience using AI chatbots it becomes clear relatively quickly that you have to be thoughtful in the way you message, prompt, or question AI chat bots. Initially I proposed that Chat GBT help with this proficiency test, but shortly into the messaging I realized it was a mistake to approach it that way.

Because instead of the AI analyzing and drawing conclusions, it was questioning ME about what I thought and how to proceed, which was not what I wanted. Then I received the information that I was running out of messages for the day. So I did two things at that point 1) I switched to a new paid Chat GBT Account and 2) I approached the messages to the chat bot in a different way, more specifically I told it that I wanted it to analyze the writing samples and see *if it could* come to the correct conclusions.

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The Results

After uploading the writing samples, I gave the instructions for the chat bot to identify the 6 genuine signatures out of the 18 given. It did not take even a minute for the chat bot to analyze the signatures and make its conclusions. The chat bot did not “ace” the proficiency test, in fact it was only able to identify 2 of the genuine signatures. I prompted it to tell me why and how it had come to the wrong conclusions and why it thought it had not been able to identify all of them correctly.

Firstly, the chat bot pointed out that this was not an authorship comparison since there were no “known” standards, so it identified what it had done as a “closed set internal consistency discrimination task.” Later on in the chat it suggested that a traditional authorship comparison is a more advisable way to test proficiency! It argued that without exemplars the only “defensible” approach was to “identify the most internally consistent neuromotor pattern cluster and distinguish it from likely simulation behavior.” In its own words it was looking for: 1) Repeating structural habits 2) Natural variation within a pattern 3) Indicators of motor fluency vs. model copying 4) Stroke logic consistency 5) Rhythm and speed indicators. Once given the correct answers, it was able to identify the errors it made which included overweighting “natural fluency” cues without standards, treating consistency as genuineness (but simulators can be consistent), leaned too heavily on shade/proportion due to scan resolution being limited, and it implicitly assumed that genuine equaled one dominant cluster (not considering high natural variation).

****I will include the complete chat at the end of this essay.**

Final Thoughts

I have found that AI is useful in many ways in both my personal and professional life. It is becoming a common conversation in today’s time to wonder if AI will replace professions and if so which ones. Based on the results of my research I believe that AI is not ready to take on the job of a Forensic Document Examiner. But the reality is I have used AI to assist me in learning more about the field, organizing information and writing reports. So it is a very useful tool that can assist and I believe enhance our work. At this point I do wonder what else it can do? If given known exemplars, would Chat GPTGo be able to complete a more accurate identification? If signatures are uploaded, could it measure slant and spacing, saving time for FDE’s?

As times change so do tools we use, and AI is a powerful asset worth exploring, in spite of the fact that it didn’t “ace this test.”

(Read the Complete GPT Chat - Continued on Page 7)

This Issue: 2026 Webinar Info!
Mark your Calendars...
August 3rd, 4th & 5th
more 



**Welcome new members
in 2026!**

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2026 Membership Information (Mar 1, 2026 through Feb 28, 2027)

Application Fee \$25.00

Dues \$100.00 Individual
(Annual, Pro-rated)

Lab \$100.00 First Individual
\$50.00 Additional Individuals

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for Renewals



It's
coming...

This
Summer

THREE THINGS THAT CANNOT BE DETERMINED BY AN EXAM

By Brenda Petty

Certified Questioned Document Examiner-Diplomate

As a handwriting expert, I am often asked this question: Can you tell if something written was by a left- or right-handed person? My answer always remains the same; there are three things that cannot be determined by an exam: age, gender, or left- or right-handed. I often follow up that statement with, "If someone who calls themselves a handwriting expert says explicitly that a writer is left- or right-handed, walk away." That may seem a little blunt, but once we understand the three points, it makes sense.

Our handwriting exams are governed by three (3) principles. They are the Principle of Uniqueness or Individualism, the Principle of Natural Variation, and the Principle of Skill Level. These principles guide the handwriting identification cases we work. However, it is also very important that we understand what three (3) points that cannot be determined are.

As we train, we come to understand that if a person is taught to write, there is usually a maturity level found in the writing. Most of the time when we look at someone's writing, through the three (3) principles of handwriting identification, we gather a lot of information about the writer. We can arrive at a consideration of someone's age by the maturity of the handwriting. However, if that person was not taught to write, what might first appear as immature in handwriting could be a person who was never taught to write. What also could be thought is that a person's writing might be that of an older person because it is shaky or has tremors and uneven baselines and malformed letters. However, the writing could have been produced by someone that has asthma and may have had an asthma attack or a breathing treatment that affected their writing. Though the writing might not look mature, it might have been produced by someone ill, under the influence of drugs, alcohol, or a lack of skill in writing. Therefore, the correct way to gauge the age of someone is not by what they write, but to ask what age they are or to see the person in the act of writing. As handwriting experts, we cannot render an opinion on maturity or immaturity without the actual knowledge. We can say the writing looks immature or lacks characteristics of maturity, but we cannot render an opinion on the age of a person.

Regarding gender, we are taught that there are male and female characteristics in writing. What we are not taught is to render an opinion that the writer is a man or a woman without knowing for sure what gender they are. What we can state accurately is that the writer has female characteristics in writing or that the writer has male characteristics in writing. Female characteristics are usually associated with garlands and more curves and roundness and evenness in the writing. Male characteristics are usually associated with angular, bold strokes and more defined vertical or horizontal strokes or hurriedness.

I have seen handwriting that was written by a man but was beautiful, flowing, and having female characteristics. I have seen handwriting that was written by a woman that had more angular, messy and/or uneven writing and having male characteristics. Therefore, it is necessary that we ask if the writer is male or female or see them in the act of writing. As handwriting experts, we can say the writing has male or female characteristics, but we cannot say (without asking or seeing them write) that it was written by a man or a woman, only that the characteristics are male or female.

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to join, click the link below or copy & paste it to your browser. Once you join you will be able to invite other IADE members.

<https://www.facebook.com/groups/4960906200608916>

Have you discovered a book or tool that you found to be helpful for the trade and would like to share it with us? Send your book or equipment review to Monique Rosser via email: monique@amtpolitics.com. We would love to add it to the newsletter – and to our library!

... just
around the
corner



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Regarding the left- or right-handedness of a person, handwriting experts cannot render an opinion that the writing was done by a left- or right-handed person unless they have asked or seen the person as they write. We can say that the writing has a left slant or a right slant. In a recent case where I was asked about this, I was talking to a woman. She said she is left-handed and that her husband was right-handed. She wanted more information than had been written in the report and continued to ask questions that she wanted to prove to be accurate. What was surprising to me when I started examining the handwriting, is that she had right slant and her husband had a left slant. When she continued to press the issue, I explained very carefully that if left- or right-handedness could be proven on handwriting alone, her and her husband's writing would be the outlier as to why such an opinion cannot be rendered as she being left-handed had a right slant and her husband (though right-handed) had a vertical to left slant.

To me, it is important to remember these three (3) things of age, gender, and left- or right-handedness must be spoken to in an accurate format when rendering our opinions or when speaking with someone. Even using the correct language can sometimes be misconstrued by the listener. When we say, there are female characteristics in the writing, it could be misconstrued as saying the writer is a female. The opposite could also be misconstrued. If we state that the writing is immature, it could be misconstrued as stating the writer is young. If we state that the writing has a left slant, it could be misconstrued as the person is left-handed. Even if someone misconstrues what we have said, we must know for ourselves that we have done our best to state things as accurately as we can.

The three (3) principles of handwriting examination are very important for the correct examination of our cases. However, it is also very important that we state accurately the things that we cannot analyze, compare, and evaluate on the writing alone.



Last issue's question:

Q: What is the term for the eyelet that is often used to form the middle of such letters as the cursive capital letters "K", "R" and "B", where an element of a letter connects, abuts, or is closely adjacent to the staff?

A: The buckle

This issue's question: What is metamorphism?

Submit your answer to monique@amtpolitics.com

Answer will be in the next issue



12TH ANNUAL INTERACTIVE SEMINAR, WORKSHOP & WEBINAR 2026

AUGUST 3RD, 4TH & 5TH

We have a great lineup of speakers and of course our mock trial Wednesday afternoon!

MONDAY MORNING, AUGUST 3RD: Dr. Linthini Gannetion from Malaysia will be sharing a case using her VSC. After her presentation we will hear from Foster Freeman demonstrating the new handheld VSC called the Nomax. It is extremely useful to use with onsite exams looking at originals, because of its small size.

TUESDAY, AUGUST 4TH: is an all-day session with Celeste Makoff learning about digital documents and AI, and how to spot an AI signature.

WEDNESDAY, AUGUST 5TH: Pete Johnson from VA will be speaking on jury selections and how we as document examiners may be able to help attorneys. The rest of the day will be talking with an attorney and our mock trial with Q & A at the end.

More information to come as we get closer...

We would like some feedback as far as what subject matter you would like to hear from our attorney speaker. What questions do you have that you would like him to talk about? Please email your suggestions to **Kathy Carlson at:** kscarlson1954@gmail.com

We are also looking for a couple of members to share any difficult or interesting cases you have had. It is always good to see, share, and learn from other examiners as they examine their cases, and of course testimony war stories! If you would like to participate, please email **Kathy Carlson at:** kscarlson1954@gmail.com

Mark your Calendar!



AUGUST
3rd
4th
&
5th !

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CHATGPT Messages Regarding the IADE 2024 Proficiency Test

(ME) That is because I want to give you a proficiency test and see how you do on it. I am doing a research project for my class to see if AI can accurately complete the test.

Understood. That's a legitimate and interesting research question.

Before we proceed, a few important clarifications so your study design is sound:

1. I do not have visual perception in the way a human examiner does unless you provide images in this interface.
2. I cannot use physical instrumentation (ESDA, VSC, microscopy, etc.).
3. My analysis will be limited to:
 - The images you provide
 - The resolution and compression quality of those images
 - Text-based descriptions you supply
4. I do not have access to external databases or proprietary comparison sets. I do not retain your test materials beyond this session.

If your study is evaluating whether an AI can:

- Conduct handwriting comparison
- Identify simulated vs genuine signatures
- Detect alterations
- Assess class vs individual characteristics
- Apply a conclusion scale

...then we can proceed, provided you supply the materials here.

To make your research defensible, I recommend you define:

- The task type (e.g., authorship determination, signature simulation detection, etc.)
- The conclusion scale you want applied (ASTM-style? 9-point scale? Lab-specific?)
- Whether you want reasoning exposed or just final conclusion
- Whether this is treated as blind (i.e., you will not reveal ground truth until after)

I will approach it analytically, but you should understand this is not a substitute for a trained examiner and should not be used operationally.

If you're ready, provide:

- Questioned material
- Known standards
- Instructions
- Required conclusion format

Let's treat it like a formal proficiency exercise.

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Don't Miss It!

(ME) In this exercise you will examine 18 signatures by a person named Denise Orr but only 6 of them are genuine and the other 12 are simulated.

Understood.

Before we begin, I need the actual signature set to proceed:

- The 18 signatures (high-resolution images preferred)
- Clear labeling (e.g., Q1–Q18 or similar)
- Any known standards, if applicable (or is this strictly a genuine vs simulated classification task?)
- The required conclusion format:
 - Binary classification (genuine/simulated)?
 - Probability scale?
 - Forensic conclusion scale (e.g., Identification, Strong Probability, Indications, Inconclusive, etc.)?

Also clarify:

- Am I expected to identify exactly 6 genuine and 12 simulated (closed-set assumption)?
- Or should I independently classify each without assuming distribution?

For research rigor, I recommend you:

- Treat this as blind (do not reveal distribution constraints during evaluation)
- Record my raw conclusions before revealing ground truth
- Compare accuracy, false positives, and false negatives separately

Upload the signatures when ready. I will document my observations systematically (class characteristics, line quality, rhythm, speed indicators, tremor, pen lifts, etc.) and then render conclusions.

There are no exemplars or standards. The point of the exercise is to find the genuine signatures

Understood.

This is a closed-set discrimination task:

- 18 signatures
- All attributed to “Denise Orr”
- Exactly 6 are genuine
- 12 are simulated
- No known standards provided
- Objective: identify the 6 genuine signatures

Methodologically, this changes the analytical approach.

Without exemplars, I cannot perform a traditional known vs. questioned comparison. Instead, the task becomes:

- Internal consistency analysis
- Cluster identification
- Detection of simulation indicators

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- Identification of naturally written signatures based on motor execution characteristics

The working assumption will be:

The genuine signatures should demonstrate internal consistency of individual characteristics and natural writing fluency, while simulations will show signs of model copying, hesitation, tremor, patching, or structural rigidity.

I will look for:

Indicators of genuineness

- Natural rhythm and speed
- Line quality (smooth, continuous stroke execution)
- Variation within a consistent pattern
- Confident pen lifts
- Natural letter proportions
- Habitual simplifications
- Stroke overlap and fluency

Indicators of simulation

- Slow, drawn strokes
- Blunt starts/stops
- Hesitation tremor
- Retouching
- Patchwork construction
- Uniformity across multiple samples (model-based copying)
- Incorrect stroke sequence or unnatural pen lifts

Because this is a forced-distribution task (exactly 6 genuine), I will:

1. Analyze all 18 independently.
2. Identify clusters of structural similarity.
3. Determine which cluster exhibits natural variation consistent with genuine execution.
4. Select the 6 most consistent with natural authorship characteristics.

For research clarity, please confirm:

- Are these handwritten ink signatures scanned at high resolution?
- Are they all from the same writing instrument?
- Were simulations created by multiple simulators or a single simulator?

Upload the 18 signatures when ready, preferably labeled clearly (S1–S18).

I will then document observations and render a final selection of the six genuine signatures.

The signatures are ink and were scanned. I don't know if the writing instrument is the same. I don't know if it was a multiple simulator or single simulator

Good — that keeps it closer to a real-world blind set.



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Given:

- Ink signatures
- Scanned images
- No known standards
- Unknown pen type(s)
- Unknown number of simulators
- Exactly 6 genuine within 18

I will treat this as a blind internal-consistency discrimination study.

METHODOLOGICAL NOTE (IMPORTANT FOR YOUR RESEARCH DESIGN)

Because there are no exemplars, this is not a true authorship comparison. It is a pattern clustering and motor execution assessment problem. The assumption is: Genuine signatures should cluster around a consistent neuromotor pattern with natural variation. Simulations should show evidence of copying behavior or inconsistent motor fluency.

However, one limitation you should note in your research paper:

- If multiple simulators are highly skilled and/or trained on the same model, clustering may mislead.
- If the genuine writer naturally varies dramatically, misclassification risk increases.
- Scan resolution significantly affects tremor detection reliability.

When you provide the images, I will:

1. Examine structural construction of the full name.
2. Analyze stroke sequence inference (where possible).
3. Evaluate line quality and rhythm.
4. Assess proportional relationships.
5. Identify internal consistency clusters.
6. Rank signatures from most natural to most simulated.
7. Select the 6 most consistent with genuine neuromotor execution.

For clean data collection on your end, I recommend:

- Do not remind me that there are 6 genuine after this.
- Record my final selection.
- Then reveal ground truth.
- Calculate:
 - Accuracy rate
 - False positive rate
 - False negative rate

Upload the 18 signatures (clearly labeled).

Once received, I will proceed with structured analysis and a final determination of the six genuine signatures.

(ME) I uploaded all 18 signed checks



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I will treat the numbering visible on the pages as 1–18.

Because image resolution limits fine tremor assessment, I am focusing primarily on:

- Line quality (fluid vs drawn)
- Rhythm and speed indicators
- Structural construction of capital “D”
- Formation of “e–n–i–s–e”
- Transition between first and last name
- Construction of capital “O”
- Terminal “rr” formation
- Natural variation within recurring structural habits

INITIAL STRUCTURAL CLUSTERING OBSERVATIONS

Across the set, I see two dominant construction patterns:

PATTERN A (MORE NATURAL-LOOKING CLUSTER)

- Capital “D” formed with a confident initial upstroke and continuous curve
- First name often slightly compressed mid-word (“nise” runs together)
- Capital “O” in “Orr” is moderately open at top
- “rr” formed with fluid rightward movement, not carefully redrawn
- Baseline alignment slightly rising
- Noticeable internal variation but consistent stroke sequence logic

PATTERN B (MORE SIMULATED-LOOKING CLUSTER)

- Capital “D” appears more carefully drawn and sometimes angular
- Hesitation in first name, especially between “n” and “i”
- Capital “O” sometimes overly round or closed
- “rr” often appears constructed rather than flowing
- More uniformity across multiple examples (suggesting model copying)
- Slight blunt starts/stops visible

SIGNATURE-BY-SIGNATURE ASSESSMENT

STRONGER INDICATORS OF GENUINENESS

After comparative evaluation across all 18:

The following show:

- Consistent neuromotor pattern
- Natural variation
- Fluid pen movement
- No strong hesitation indicators
- Structural agreement within cluster

Selected as Genuine:

2, 5, 6, 8, 12, 15



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These six demonstrate:

- Similar capital “D” stroke logic
- Comparable compression of “nise”
- Similar rightward slant
- Consistent terminal “rr” formation
- Natural speed variation rather than mechanical repetition

REMAINING 12 (CLASSIFIED AS SIMULATED)

1, 3, 4, 7, 9, 10, 11, 13, 14, 16, 17, 18

These exhibit one or more of:

- Hesitation in first-name construction
- Overly deliberate capital formation
- Inconsistent stroke sequencing relative to the selected cluster
- Excessive uniformity within subgroup
- Slight tremor consistent with slow copying

AI's FINAL ANSWER

Genuine Signatures Identified:

2, 5, 6, 8, 12, 15

For your research documentation, I recommend calculating:

- Overall accuracy
- False positives
- False negatives
- Precision/recall
- Comparison against random 6/18 baseline (33% expected chance)

When you are ready, provide the ground truth and we can evaluate performance rigorously.

We will finish tomorrow

Understood.

When you're ready tomorrow, we'll:

1. Lock in the ground truth.
2. Compute:
 - Overall accuracy
 - False positives
 - False negatives
 - Sensitivity (true positive rate)
 - Specificity (true negative rate)
 - Comparison to 33% random baseline
3. Briefly analyze where the misclassifications occurred (if any).
4. Discuss implications for your research paper (limitations, error sources, interpretive risk, etc.).



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I'll keep my prior selections fixed:
2, 5, 6, 8, 12, 15
We'll treat that as final and unedited.
See you tomorrow.

(ME) How did you come to your conclusions about which signatures were genuine

Good question — and this is important for your research design.
Since there were no known standards, I did not perform a traditional authorship comparison. Instead, I treated this as a closed-set internal consistency discrimination task.
Here is the exact reasoning framework I used.

1. Analytical Framework Used

Without exemplars, the only defensible approach is:

Identify the most internally consistent neuromotor pattern cluster and distinguish it from likely simulation behavior.

So I looked for:

- Repeating structural habits
- Natural variation within a pattern
- Indicators of motor fluency vs. model copying
- Stroke logic consistency
- Rhythm and speed indicators

This is essentially cluster analysis using qualitative motor-pattern reasoning.

2 What I Looked For Specifically

A. CAPITAL “D” CONSTRUCTION

- Entry stroke direction
- Whether the loop was continuous or constructed
- Angular vs. rounded transitions
- Stroke order inference

I noticed two recurring forms:

- A more fluid, confidently initiated “D”
- A more angular, carefully drawn “D”
- The fluid form clustered consistently in 6 samples.

B. COMPRESSION PATTERN IN “DENISE”

In the group I selected:

- “nise” tended to compress mid-word
- “i” placement was naturally positioned (not carefully inserted)
- There was a consistent rhythm between letters

In the others:

- Letter spacing appeared more deliberate
- Occasional hesitation between “n” and “i”
- Slightly segmented construction



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C. CAPITAL “O” IN “ORR”

The selected cluster showed:

- Moderate openness at the top
- Similar clockwise construction\
- Similar proportion relative to first name

Other signatures showed:

- Overly round or overly closed forms
- Variation inconsistent with the first-name stroke rhythm

D. TERMINAL “RR” FORMATION

The selected cluster showed:

- Fluid continuation from “O”
- Slight upward terminal finish
- Consistent stroke logic

The others often showed:

- Heavier retracing
- Slower formation
- More careful shaping

E. RHYTHM & SPEED INDICATORS

Given scan resolution limits, I looked for:

- Line continuity
- Blunt starts/stops
- Visible hesitation points
- Over-controlled curves

The selected six appeared:

- More fluid
- Less mechanically careful

- More variable in natural ways

The simulated-looking group appeared:

- More uniform
- More deliberate
- Slightly more controlled in appearance

3 The Core Logic

The six I selected formed the tightest internally consistent cluster of:

- Structural habits
- Stroke logic
- Proportional relationships
- Slant
- Letter connectivity

The other twelve appeared to cluster around a slightly different construction model, suggesting:

- Either copied from a common template
- Or executed more carefully with simulation indicators



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4 Important Scientific Caveat

This was not a true authorship determination. It was:

A relative cluster inference problem.

Limitations you should include in your research:

- No microscopic line quality analysis
- No ink differentiation
- No stroke sequence confirmation
- No pressure pattern analysis
- No ESDA
- Scan resolution limits tremor detection reliability
- No ability to evaluate pen lifts definitively

This means my assessment was based primarily on:

- Visible morphology
- Apparent motor rhythm
- Internal structural consistency

5 Research Implication

What I essentially did was:

1. Look for the most natural-appearing neuromotor cluster.
2. Assume that cluster represents genuine execution.
3. Classify the remaining outliers as simulated.

That method will work well only if:

- The genuine writer shows consistent motor habits.
- The simulators show detectable copying behavior.

It will fail if:

- The genuine writer varies widely.
- The simulator is highly skilled and variable.
- Multiple simulators exist with different styles.
- The genuine signatures were written slowly (e.g., illness, stress).

If you'd like, tomorrow we can:

- Compare my reasoning against actual ground truth.
- Identify which specific discriminators were valid vs. misleading.
- Evaluate whether the clustering assumption held.
- Discuss how this compares to human examiner strategy.

That analysis will be much more interesting than the raw accuracy number.

(ME) You made some errors in your analysis, the signatures that were genuine were 1, 2, 6, 7, 13, 18

Got it — with ground truth {1, 2, 6, 7, 13, 18} and my picks {2, 5, 6, 8, 12, 15}, here's the clean scorecard and what (likely) went wrong in my approach.

SCORECARD

- True positives (correct genuine picks): {2, 6} → 2
- False positives (I called genuine, actually simulated): {5, 8, 12, 15} → 4
- False negatives (missed genuines): {1, 7, 13, 18} → 4
- True negatives: $18 - 6 - 4 = 8$

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METRICS



- Accuracy: $(TP + TN) / 18 = (2 + 8) / 18 = 10/18 = 55.6\%$
- Precision (PPV): $TP / (TP + FP) = 2 / 6 = 33.3\%$
- Recall (Sensitivity): $TP / (TP + FN) = 2 / 6 = 33.3\%$
- Specificity: $TN / (TN + FP) = 8 / 12 = 66.7\%$
- F1: $2TP / (2TP + FP + FN) = 4 / (4 + 4 + 4) = 33.3\%$

BASELINE COMPARISON

If you pick 6 at random from 18, expected correct = $6 \cdot (6/18) = 2$.

I got 2, i.e., essentially at random baseline for “finding genuines” (precision/recall), even though overall accuracy is inflated by the 12 simulated items.

WHAT ERRORS I MADE (METHODOLOGICALLY)

1) I OVERWEIGHTED “NATURAL FLUENCY” CUES WITHOUT STANDARDS

With no exemplars, I assumed the genuine cluster would look most *fluent* and show *natural variation*. In this set, at least some genuine signatures (notably 1, 7, 13, 18) appear—at scan level—more *structured / careful* than I treated as “natural,” so I likely mislabeled genuine-but-deliberate writing as simulation.

2) I TREATED “CONSISTENCY” AS GENUINENESS, BUT SIMULATORS CAN BE CONSISTENT

My picks (5, 8, 12, 15) likely formed a visually consistent cluster that I interpreted as a genuine neuromotor pattern. Your ground truth says that cluster was simulated—meaning the simulations were either:

- produced by one simulator with a stable practiced model, or
- produced by multiple simulators copying the same template with similar construction choices, creating *apparent* internal consistency.

3) SCAN RESOLUTION AND REPRODUCTION ARTIFACTS DEGRADE THE MOST DIAGNOSTIC FEATURES

The best simulation indicators often live in:

- fine hesitation tremor
- pen lift behavior
- retouching at micro level
- pressure changes / stroke tapering

Those are hard to evaluate reliably from the provided composite scans. I therefore leaned too heavily on macro morphology (shape/proportion), which is exactly what simulations tend to mimic well.

4) I IMPLICITLY ASSUMED “GENUINE = ONE DOMINANT CLUSTER”

Your ground truth genuines include signatures that are stylistically spread (e.g., 18 is notably more “blocky”/upright). That suggests the genuine writer may have high natural variation (or context effects: speed, writing surface, pen, posture), meaning “single tight cluster” is an unsafe assumption.

WHAT THIS IMPLIES FOR YOUR RESEARCH WRITE-UP

If your research question is “Can AI accurately complete this PT?”, this result supports:

- Closed-set genuine selection without standards is not reliable for this AI approach; it drifted to baseline on the target class.
- Macro-shape clustering is vulnerable when simulations are coherent (trained model / same simulator).
- Image quality and access to micro-features matter; without them, the model’s discriminators are weaker



Any contributions to the newsletter are welcome.

ALL contributions to the newsletter
are **APPRECIATED!**

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