

Beyond the final text:
*keystrokes as a window into language development
and text production in the age of generative AI*

Ildikó Pilán

3 September, 2026, Göteborg

Outline

- Introduction
- Keystroke data for **language proficiency profiling**
 - IncluEdS project overview
 - Automatic error correction and categorization
 - KEYSORE study
- Keystroke data for **detecting AI-authored content**



[Selina](#) on [Unsplash](#). Unsplash license.

NR in a nutshell

Norwegian Computing Center – a research institute for science and innovation

- Basic research projects
- Innovation projects
- Direct assignments (public and private sector)

Our research areas



Statistical modelling and machine learning



Statistical analysis of natural resource data



Applied research in information and communication technology



Image analysis and Earth observation

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NLP “group”



Pierre Lison



Ildikó Pilán



Mark Anderson



Max Hort

Motivation

- Generative AI **transforms** how we write and **challenges** traditional notions of **authorship** and **assessment**.

UK universities warned to 'stress-test' assessments as 92% of students use AI

Survey of 1,000 students shows 'explosive increase' in use of generative AI in particular over past 12 months



Link: https://www.theguardian.com/education/2025/feb/26/uk-universities-warned-to-stress-test-assessments-as-92-of-students-use-ai?utm_source=chatgpt.com

Motivation

- Generative AI **transforms** how we write and **challenges** traditional notions of **authorship** and **assessment**.
- There is an increasing interest in methods and tools that look **beyond the final text** and learn from the **writing process** itself.
 - Detailed information about **how** the text was produced
 - Indicators of cognitive **effort** (or the lack thereof), **hesitation** etc.

Keystroke log (KL) data

```
"1761825273889": "keydown: t",
"1761825273986": "keydown: h",
"1761825273993": "keyup: t",
"1761825274033": "keydown: i",
"1761825274066": "keyup: h",
"1761825274113": "keyup: i",
"1761825274201": "keydown: s",
"1761825274257": "keydown: ",
"1761825274266": "keyup: s",
"1761825274313": "keyup: ",
"1761825274457": "keydown: t",
"1761825274498": "keydown: i",
"1761825274546": "keyup: t",
"1761825274586": "keyup: i",
"1761825274746": "keydown: l",
"1761825274796": "keyup: l",
"1761825274881": "keydown: l",
"1761825274946": "keyup: l",
"1761825275146": "keydown: Backspace",
"1761825275194": "keyup: Backspace",
"1761825275265": "keydown: Backspace",
"1761825275334": "keyup: Backspace",
"1761825275425": "keydown: Backspace",
"1761825275458": "keyup: Backspace",
```

Unix timestamp

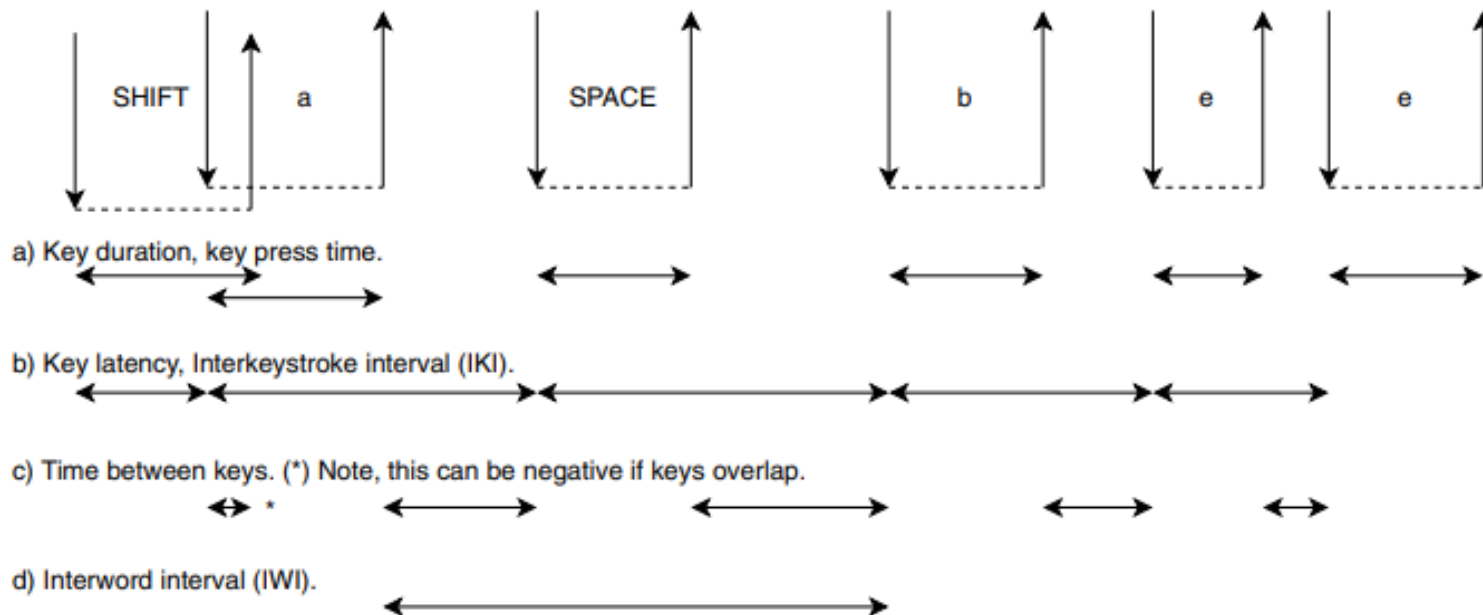
← Raw logs can be “summarized” (linearized)

This is a <0.576>test <1.184>text for <0.696>this till<DEL3>
ool. <3.680>I’m su< DEL2 > <0.961>just making up some
text.

These show:

Pauses
Revisions
Burst

Examples of time-based indicators from keystrokes



Challenges for wider adoption

- **Privacy:**
 - keystroke logs are more revealing (includes deleted content)
 - possibly identifying (used also for login verification)
- **Technical and methodological:**
 - distinguish between cognitive processes and noise at scale,
 - adapt to variability in writers, (educational) settings, devices
- **Trust and usability:**
 - reliable, actionable insights for a variety of (pedagogical) purposes

Keystroke data for language proficiency profiling

The IncluEdS project

- **IncluEdS:** Keystroke-Based Language Proficiency Profiling for **Inclusive Education and Society** (2026 –2029, Norwegian Research Council)
- Partners:



UNIVERSITETET
I OSLO

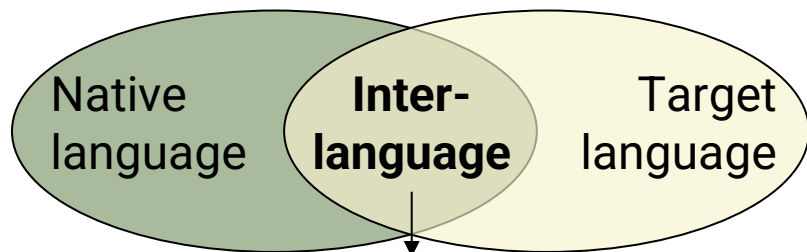


- P(ilán) I(ldikó) 😊

IncluEdS: objectives

- **Collect** a **keystroke-log dataset** written by learners of **Norwegian** as a second language (L2).
- Compare learners **pausing** and **revision** behavior at **different L2 levels**.
- Leverage this data in interpretable **machine learning models** for **L2 writing assessment**.
- **Test** the **reliability** & pedagogical **usefulness** of these methods.

Second Language Acquisition (SLA) and CEFR



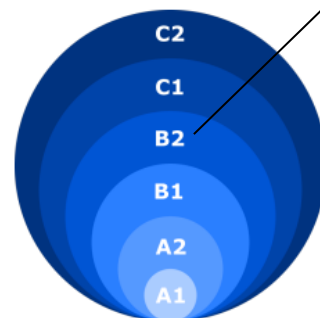
Shows systematic **developmental patterns**

- *Subject-Verb agreement*
- *Noun phrase agreement*
- *Plural*

Order of acquisition of linguistic structures. (Pienemann, 2005).

EU: CEFR

(Common European Framework of Reference for Languages)



B2: Has a *good command* of simple language structures and some complex grammatical forms, although they tend to use complex structures rigidly with some inaccuracy.*

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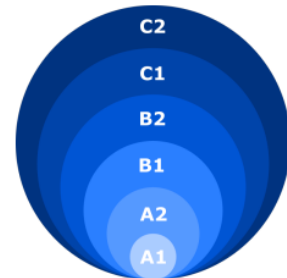
Pauses
Revisions
Burst



NLP tools



CEFR



IncluEdS: ongoing data collection

- **Participants:**
 - L2 Norwegian learners
 - 16+ years old,
 - A2-B2 levels mainly
- **Tasks** (ca. 90 min. in total):
 - Background survey
 - Copy task
 - Essay task (45 min)
- **Setting:** in classroom, no external resources are allowed

ScriptLog: copy task

OPPTAK

AVSPILLING

ANALYSE

INNSTILLINGER

KODE: 111111

OPPGAVE-ID: copy

START

STOPP

Ord: 0

Kopieringsoppgave:

Skriv den første setningen fort 7 ganger, én per linje:

- gratulerer med dagen kjære onkel

Skriv den andre setningen fort 7 ganger, én per linje:

- hyggelig å møte deg

Ikke rett små feil. Ikke bruk store bokstaver eller punktum.

Klikk START.

Skriv deretter teksten din her.

Klikk STOPP når du er ferdig.

gratulerer med dagen kjære onkel
gratulerer med dagen kjære onkle
gratulerer med dagen kjære onkel
gratulerer med daen kjære onkel
grstulerer med dsngen kjære onkel
gratulerer med dagen kjære onkel
gratulere med dagen kjære onkel
hyggelig å møte deg
hyggeleig å møte deg
hyggelig å møte deg
hyggelig å møte deg
hyggelig å møte sdeg
hyggelig å møte deg
hyggelig å møte deg

ScriptLog: essay task

KODE: **test00**

OPPGAVE-ID: **essay**

START

STOPP

Oppgave-ID: Ord: 0

Essay

Skriv din egen tekst i boksen nedenfor.

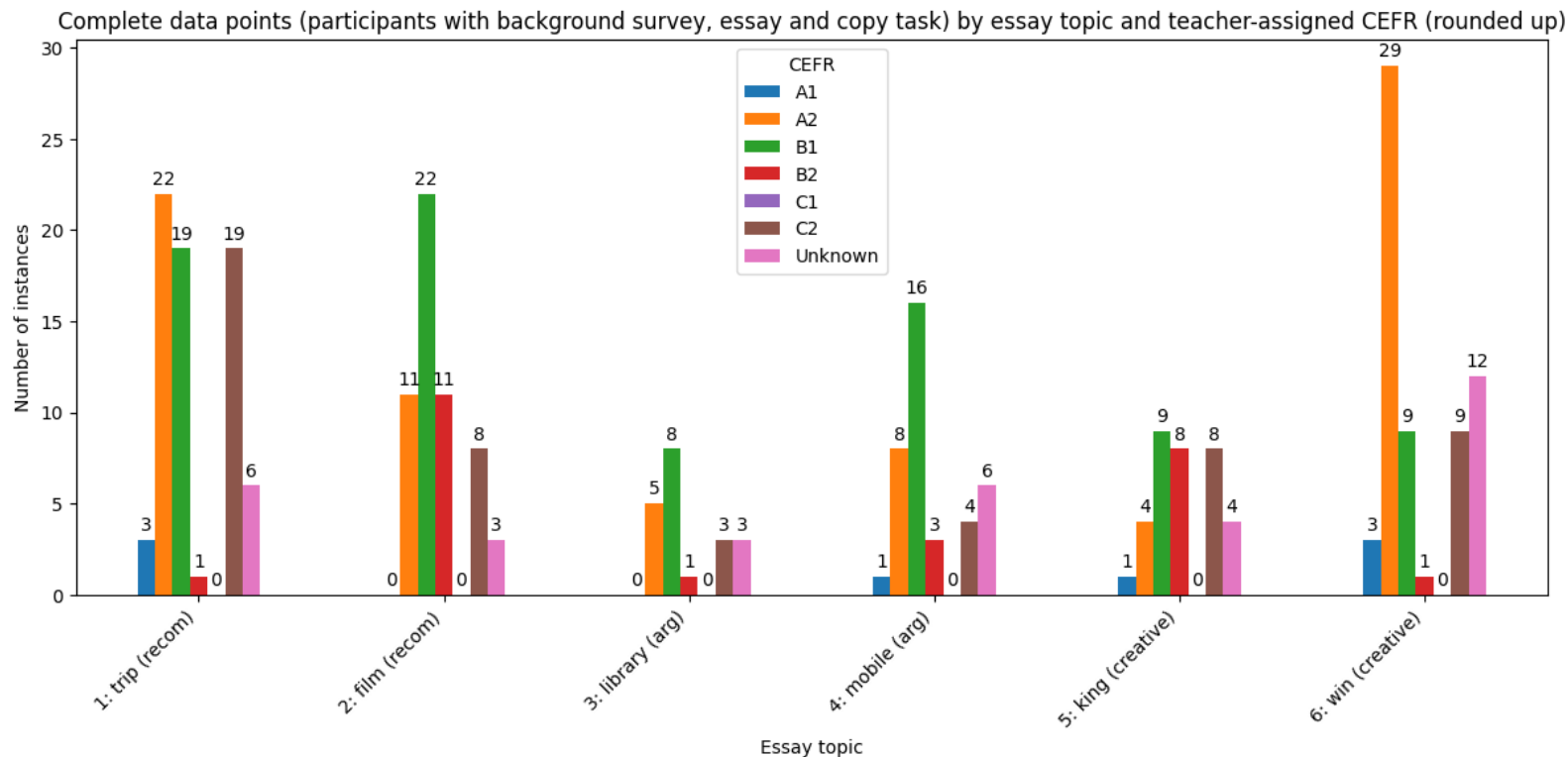
Skriv inn Oppgave-ID øverst.

Klikk START.

Essay topics

1. Recommendation: excursion
2. Recommendation: film
3. Argumentative: library closing
4. Argumentative: no mobiles in school
5. Creative: king/queen for a day
6. Creative: winning money

About 300 essays collected so far



Error correction and categorization

- LLM-based automatic **error correction**
 - Based on 5 example sentences
 - Evaluated on 12 manually corrected IncluEdS texts
 - To do: experiment with more LLMs + re-evaluate

4. LEARNER ERROR CORRECTION



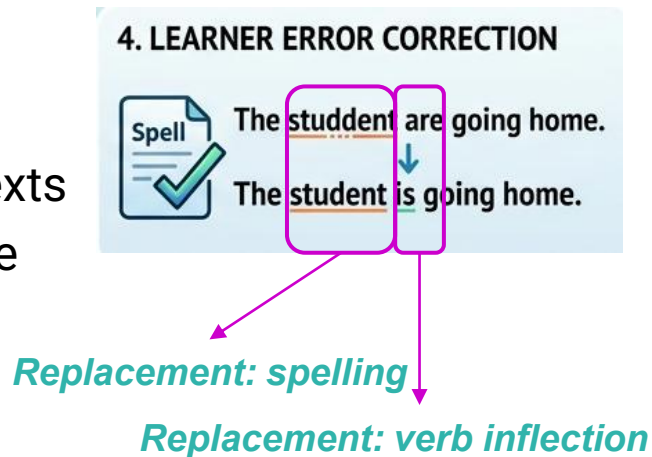
The studdent are going home.



The student is going home.

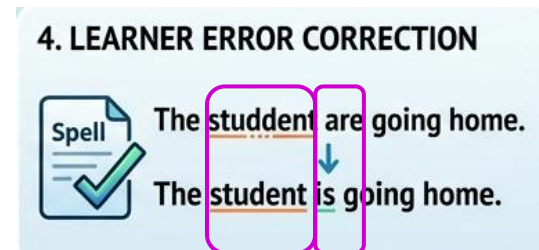
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Error correction and categorization

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 - Based on 5 example sentences
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 - To do: experiment with more LLMs + re-evaluate
- Rule-based **edit extraction** + **error categorization**
 - Adapted the [ERRANT](#) tool to Norwegian
 - Evaluation on the **ASK corpus** (L2 Norwegian)
 - Mapping of ERRANT to ASK error categories
 - To do: evaluate on IncluEdS essays



Replacement: spelling

Replacement: verb inflection

ORT (Orthography)

INFL (Wrong inflected form)

How well do these automatic approaches work?

- **Error categorization:**
 - Quite well in general
 - Differences between categories

Category	Precision	Recall	F0.5
Correct span	0.919	0.893	0.913
Correct span + tag (All tags)	0.796	0.774	0.791

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- Correction:**

- some under- and overcorrection -> we will try different prompts & LLMs

SAMPLE 5

SOURCE: De ikke snakke, de er ofte elene vi må hiepe hverandre.

PRED: De kan ikke snakke, de er ofte alene og vi må hjelpe hverandre.

REF: De snakker ikke, de er ofte alene og vi må hjelpe hverandre.

SAMPLE 6

SOURCE: Jeg tror på turen den jeg likte best å spice og å gå.

PRED: Jeg tror på turen var det jeg likte best å spise og å gå.

REF: Jeg tror det jeg likte best på turen var å spise og å gå.

Examples of automatic (PRED) and manual (REF) corrections

Upcoming plans

- Manual annotation: **CEFR-levels**
 - Planned both based on the **final** texts and based on **process-enriched** version (with pause and revision information)
 - Inclusion of short **explanations**
- Manual annotation: **revision** type or intention
- Computational modeling: **explainable CEFR-level prediction**
- Quantitative SLA study: e.g. order of acquisition

KEYSCORE - Keystroke-enhanced Automated Essay Scoring (Schaller et al., 2026)

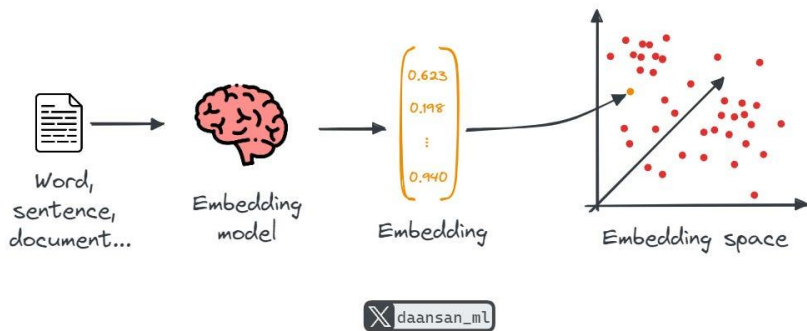


- RQ: **How early** in the writing process can we give meaningful feedback (=score) to learners?
- Task: **Essay scoring** (L2 English) with a **transformer** model (DeBERTa)
- Tested on **intermediate snapshots** at 5, 10, 15, 20 and 25 minutes of writing
- 2 conditions: essays written **with** and **without** the use of **AI chatbots**
- Tested **text features** and **process features** separately and together
 - Text f: vector representation of the text
 - Process f: mean pause duration, deletion / total keys etc.

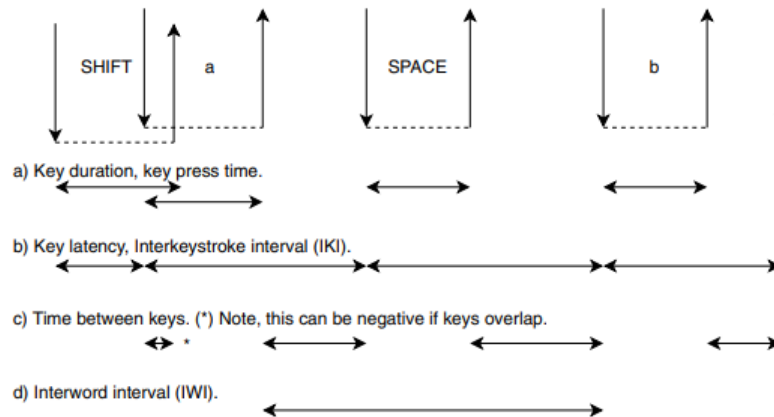
Combined feature set: text embeddings + keystrokes

Neural text representation

Embeddings



Keystroke features

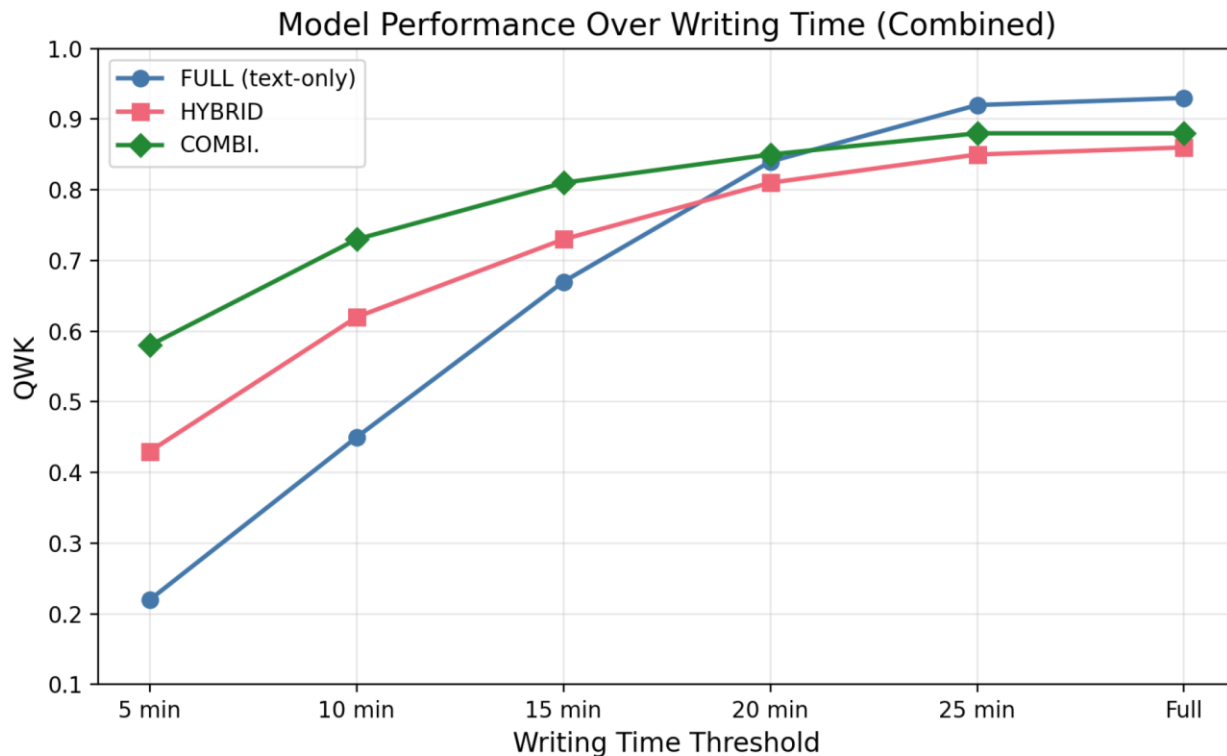


$[0.42, 0.17, 0.83, 0.31, 0.65, \dots]$



$[0.73, 0.21, 0.56, 0.89, \dots]$

KEYSCORE: results



- Process-features useful for scoring **early** (especially when chatbot used)

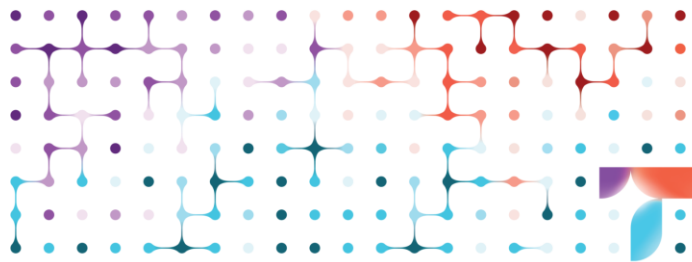
Automatic detection of AI-authored content

Connected to two research projects

TRUST AI Center

The Norwegian Centre for Trustworthy AI

Building the foundations for AI that is accurate, interpretable, inclusive, fair, safe, sustainable, and well-governed.

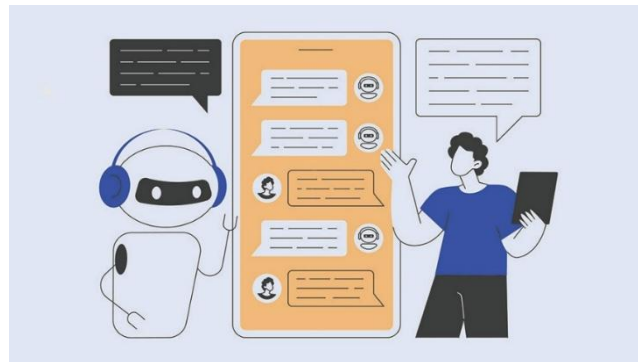


DetectAI (TRUST sub-project)

PI: Pierre Lison

2026-2030

Artificial Intelligence: Human-LLM Communication (**AICOM**) project (UiO)



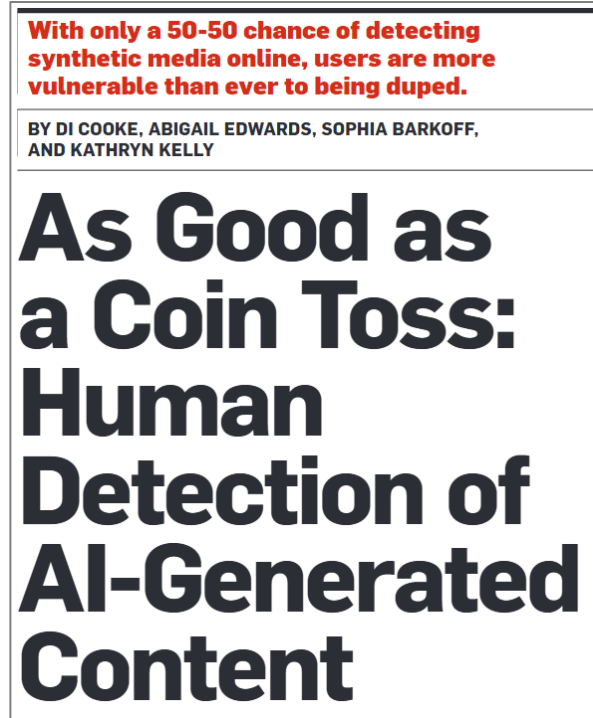
Ingrid Lossius Falkum
University of Oslo
Principal investigator



Nicholas Allott
University of Oslo
Co-Principal investigator

Detecting AI-use is hard

- **Human performance** remains **close to chance level**, particularly if AI-content is **paraphrased**. (Mehta et al., 2026)
- **Automatic methods** have several **shortcomings**. (Fraser et al., 2025)
- **Behavioral** data helps (Mehta et al., 2026)
 - But **threat models** can mimic natural keystroke dynamics...
 - Model resilience can be improved by **adversarial training** (training also on such deceptive data).



<https://dl.acm.org/doi/epdf/10.1145/3729417>

Current work: scoring suspicion of AI Use

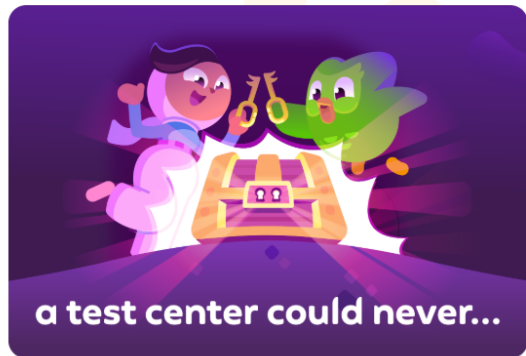
- Experimented with heuristics for flagging **suspicious text segments** in keystroke logs based on e.g.:
 - Paste-like indicators
 - large **text jump** in a very **short time**
 - very **few keydown** events for a large insertion
 - Copy-typing (or automated typing) indicators
 - **many characters** typed **quickly**
 - «**monotonous**» **writing**
 - low variance in inter-key intervals
 - almost **no corrections**
- Suspiciousness is estimated using rule-based thresholds.
- Assigns a **suspicion score** so candidate segments can be **reviewed** manually.

APRIL 10, 2025

Why can't test centers catch cheating effectively?



Sophie Wodzak



How the DET catches what test centers miss

Unlike traditional exams, the DET is fully recorded and analyzed using advanced technology to flag even the most discreet forms of misconduct. Here's how:

AI-powered **keystroke** monitoring detects unnatural typing

One of the biggest security challenges in language testing is detecting when a test taker isn't using their own words. The DET's AI tracks how responses are typed to flag suspicious behavior, such as:

- Copy-typing from an external source—If someone is transcribing text rather than thinking and writing naturally, AI can detect unusual typing rhythms and speed changes.
- Abrupt shifts in writing style—If part of an essay is written fluently but another part has unusual errors, it could indicate partial AI assistance or memorized content.
- Pausing in unnatural places—Frequent pauses at odd moments could suggest that a test taker is referring to external notes.

Unlike human proctors, who only see the final written response, the DET tracks how that response was written—making it much harder to cheat undetected.



<https://blog.englishtest.duolingo.com/why-cant-test-centers-catch-cheating-effectively/>

Rethinking writing assessment for the AI era

- Was AI used? ➡ **How** was AI used?
- Develop assessment methods that capture **collaborative human-AI writing processes**.
- Support and identify **constructive** practices in AI-assisted writing and its computational analysis via keystroke logs.

Thank you!

(Some) References

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- Fraser, K. C., Dawkins, H., & Kiritchenko, S. (2025). Detecting ai-generated text: Factors influencing detectability with current methods. *Journal of Artificial Intelligence Research*, 82, 2233-2278.
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