Logging Keystrokes in Writing by English Learners

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Introduction

In this work we **collect** and **analyse** data representing the essay writing process from start to finish, by recording every **keystroke** from multiple writers participating in our study.

We describe our **data collection** methodology, the **characteristics** of the resulting dataset, namely **KUPA-KEYS**, and the **assignment of proficiency levels to the texts**

Introduction: Why Keylog data?

- A great deal of information about the writing process can be captured
- We can potentially detect **when learners are struggling** with their **writing**
- We might potentially enable **supportive interventions** to **aid the learner**
- Insights into **linguistic creativity** and **language complexity** in **production**
- Detect **malpractice in education or assessment settings** - Generative AI

Introduction: KUPA-KEYS Dataset

We have compiled a dataset of **texts**, **keystroke logs** and **metadata** for public release, which can be used for any of the aforementioned purposes, including research around **automated essay assessment**.

It contains a copied text and creative essay written in English by **1,006 crowdsourced participants**, both native speakers and non-native speakers of the language.

The **K**ing's College London & **U**niversité **Pa**ris Cité Keys (**KUPA-KEYS**) dataset is publicly available for non-commercial use* and our research code for data collection is open-source

* https://huggingface.co/datasets/ALTACambridge/KUPA-KEYS

Related Work: Other Datasets

Keystroke datasets generated from participants transcribing a **fixed-text** are more common (Allen, 2010; Giot et al., 2012) with the largest being reported in Dhakal et al. (2018) consisting of 136 million keystrokes.

On the contrary, datasets that include free-text are not as extensive, with one of the earliest ones being **Clarkson I** (Vural et al., 2014), comprised of 840,000 keystrokes produced by 39 participants

One of the largest datasets available is described in Sun et al. (2016), known as the **Buffalo dataset**, comprising 2.14 million keystrokes from **148** participants (both transcription and free-text included)

Related Work: Comparisons

Murphy et al. (2017) provides the **Clarkson II** dataset, where keystroke data were collected in an uncontrolled environment from 103 subjects, yielding a total of 12.6 million keystrokes.

Our dataset is distinct from the ones above because we focus on essay writing by both learners and native speakers of English, with both text-copy and free-text composition.

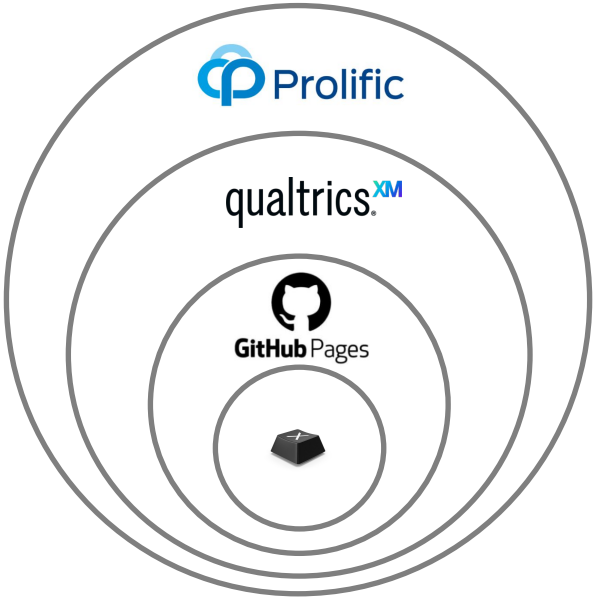
A new Kaggle shared task was launched in October 2023*. KUPA-KEYS is smaller, but includes logs from a transcription task, our essays are scored on a greater scale, and the alphanumeric characters are preserved.

* https://www.kaggle.com/competitions/linking-writing-processes-to-writing-quality

Data Collection: Protocol

- Recruited 1045 participants through Prolific crowdsourcing platform
- Participants were directed to Qualtrics for data collection
- After metadata collection they were redirected to our GitHub pages
- JavaScript keylogger in each page captured their keystroke data

Data Collection: Protocol



After the survey, participants were redirected from Qualtrics to our text authoring site

Participants were required to complete two writing tasks: a **copy-text** task & an **essay-writing** task

Data Collection: Copy-Text task

- 300 word excerpt from Steve Jobs' Speech at Stanford University
- Contains 197 distinct English Digraphs
- Extensive enough to be used for user-specific baselines
- Used by Sun et al. 2016 (Buffalo Dataset) - Data Augmentation

Data Collection: Essay-Writing task

- "Just for fun" prompts from the English learning platform Write & Improve*
- We chose "just for fun" prompts as opposed to level-specific prompts
- They are deliberately creative
- They are suitable across different proficiency levels
- We selected ones which tend not to elicit personal information
- Each participant was randomly allocated to one prompt (10 total)

* https://writeandimprove.com

Data Collection: Essay-Writing task (examples)

A Special Place.
If you could be anywhere in the world right now, where would you choose to be? Describe the place. Why do you want to be there?

Unforgettable.
Write a short story with the title 'Unforgettable'. Your story must have a beginning, a middle and an end. The end must be surprising.

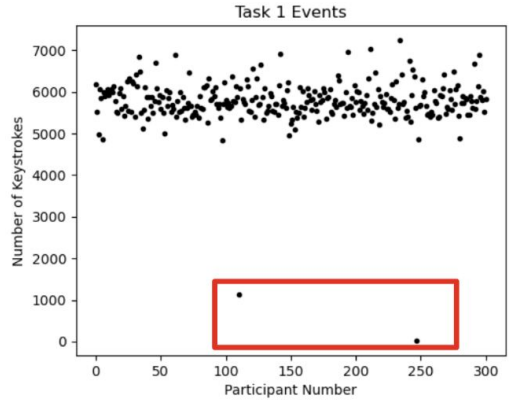
Data Collection: Participants

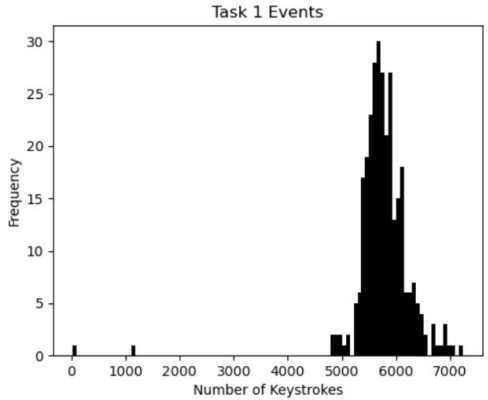
- After a pilot study we found that it took ~30 min for completion (total)
- We paid each participant £7.50 GBP/ $9.20 USD for the full survey
- Participants spent on average 33.9 min [copy: 9.6 min, essay: 13.4 min]
- Essay threshold: initially 250 words - reduced to 150 to attract beginners
- We recruited 1,045 participants in three phases of crowdsourcing

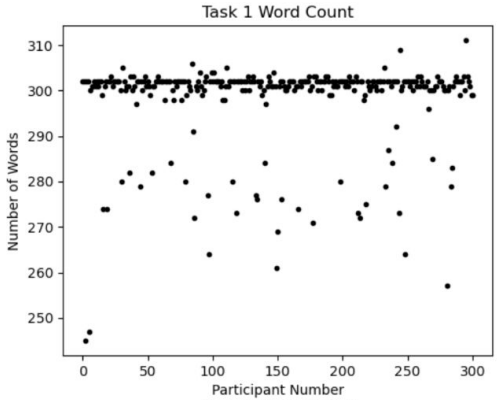
Data Collection: Common Rejection Reasons

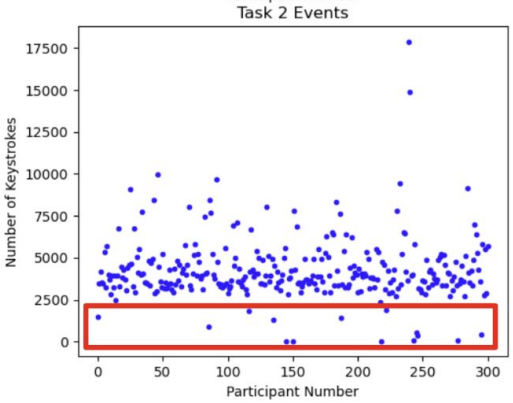
- Essays less than 80% of the minimum stated word length
- Copied and pasted text from external sources (even for copy-text task!)
- Typed in another language and translated at the end
- Most participants were asked to withdraw their submission before rejecting

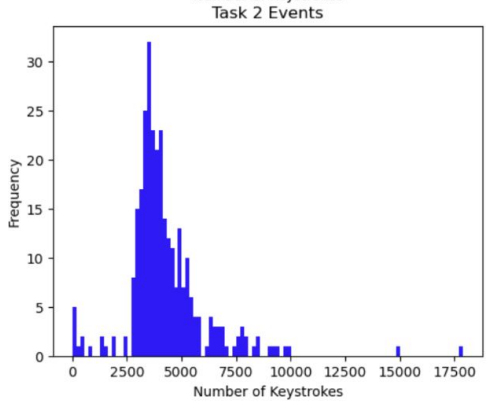
Data Collection: Common Rejection Reasons

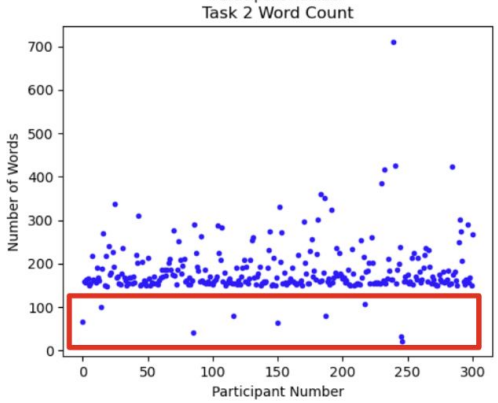












Data Processing

- Automatically graded each essay with W&I API
- Three qualified human assessors graded each essay
- 35 participants were rejected by human assessors
- Reasons: off-topic, offensive, potentially distressing
- Removed 4 more from post-processing (tablet/mobile)
- Therefore, the public release features 1006 essays

W&I score	CEFR level
0	–
1	A1.i
2	A1.ii
3	A2.i
4	A2.ii
5	B1.i
6	B1.ii
7	B2.i
8	B2.ii
9	C1.i
10	C1.ii
11	C2.i
12	C2.ii
13	C2.ii

Dataset Description: KUPA-KEYS

We conducted a thorough data cleaning process to streamline the generation of three primary tables, conveniently saved in CSV format

KUPA-KEYS-META

- Metadata
- Demographic information
- Post-processing data
- Human markers' evaluations
- Automarker evaluations
- Original prompts
- Final submitted text

KUPA-KEYS-TASK-1

- copy-text task keylog events

KUPA-KEYS-TASK-2

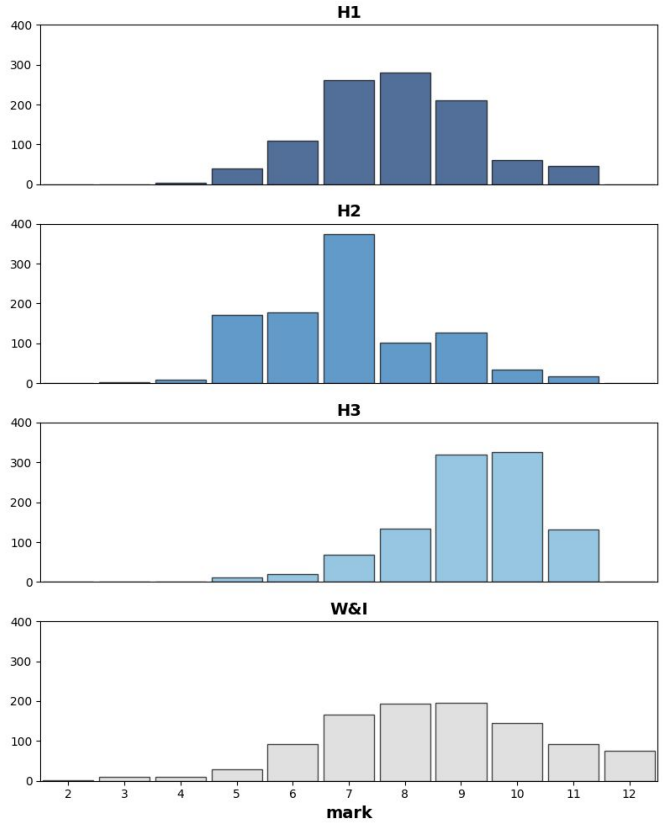
- essay-writing task keylog events

Dataset Description: KUPA-KEYS

KUPA-KEYS-TASK-<i>

id	time	type	key	key_code	alt_key	ctrl_key	meta_key	shift_key	is_repeat	range_start	range_end	text
xa2	563.4	down	'I'	KeyI	-	-	-	True	-	0	0	-
xa2	564.7	capture	-	-	-	-	-	-	-	-	-	'I'
xa2	564.7	input	-	-	-	-	-	-	-	1	1	'I'
xa2	691.6	up	'I'	KeyI	-	-	-	True	-	1	1	-
xa2	708.0	up	'Shift'	ShiftLeft	-	-	-	-	-	1	1	-
xa2	708.3	down	' '	Space	-	-	-	-	-	1	1	-
xa2	709.6	input	-	-	-	-	-	-	-	2	2	' '
xa2	835.6	up	' '	Space	-	-	-	-	-	2	2	-

Inter-annotator Agreement



H1: evenly distributed
H2: more strict
H3: more lenient
W&I: evenly + lenient

A2	B1	B2	C1	C2
4	111	549	323	19
0.4%	11%	54.6%	32.1%	1.9%

AC = 0.854

$$P_e = \frac{1}{g-1}\sum_{k=1}^{g}\pi_k(1-\pi_k)$$

$$\pi_k = \frac{1}{|\mathcal{A}|}\sum_{a\in\mathcal{A}} p_{a,k}$$

(Gwet 2002; Yannakoudakis and Cummins 2015)

Inter-annotator Agreement

Spearman's rank correlations

	H1	H2	H3	W&I
H1	–	0.633	0.711	0.574
H2	0.633	–	0.567	0.563
H3	0.711	0.567	–	0.514
W&I	0.574	0.563	0.514	–
Avg	0.639	0.588	0.598	0.550

Strong and significant correlations on the whole. Judgements of the human assessors correlate with each other more than they do with the automarker

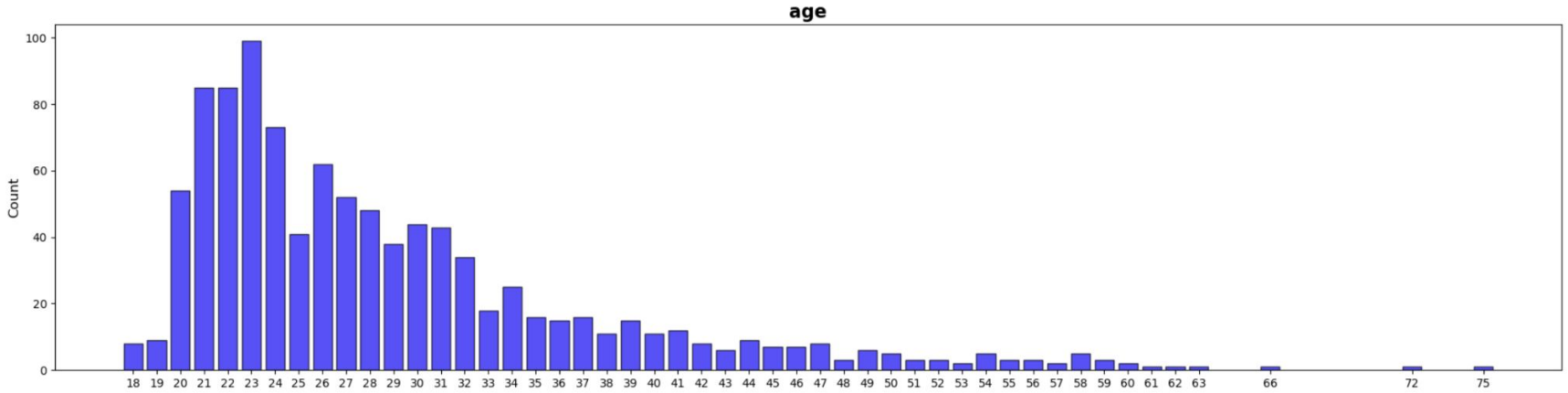
Inter-annotator Agreement

RMSD

	H_{avg}	H1	H2	H3
H1	0.622	-	-	-
H2	1.288	1.487	-	-
H3	1.371	1.695	2.586	-
W&I	1.543	1.708	2.241	1.770

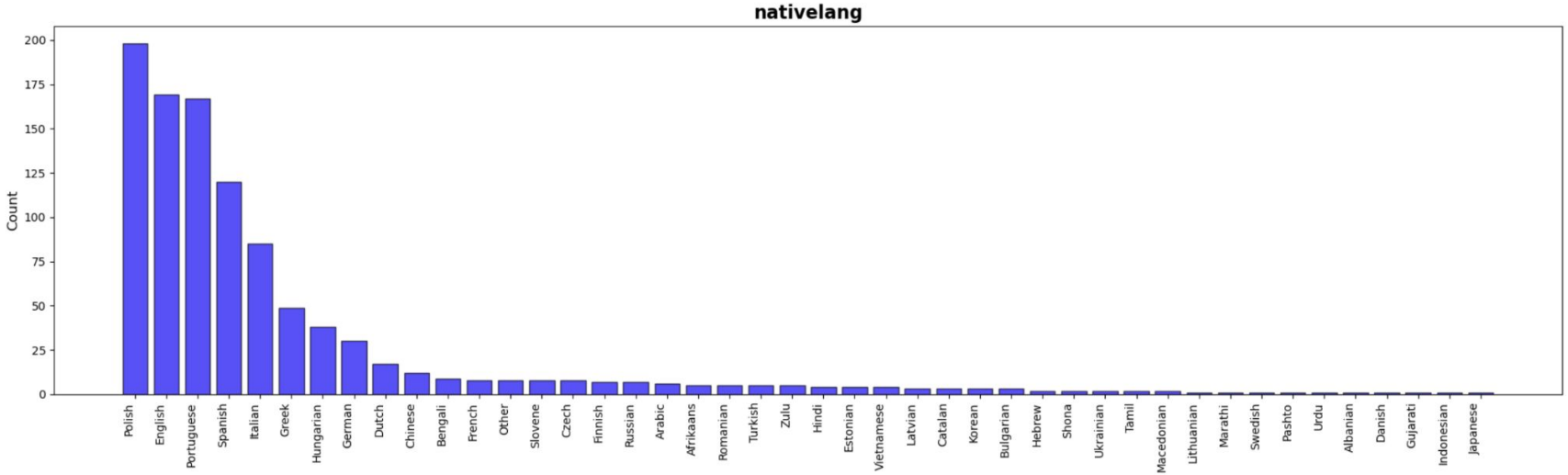
H1 is closest to the mean of human marks and has the lowest deviation from other markers including the automarker. H2 is involved in the highest RMSD values.

Data Analysis: Demographics - Age



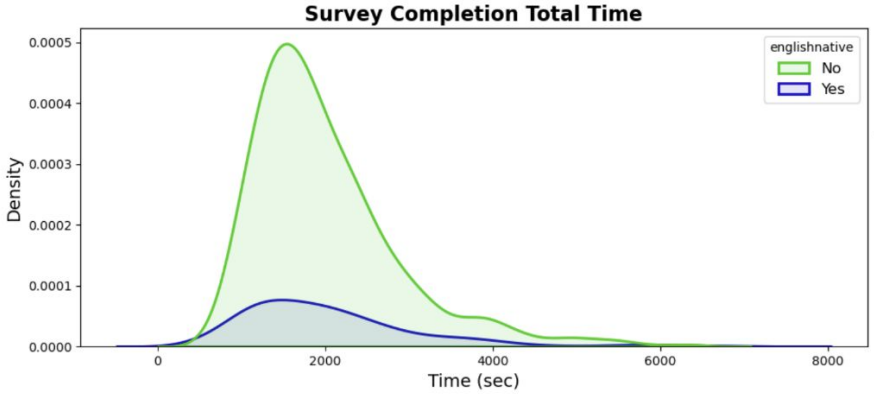
Age distribution: 25% of the participants between 18 and 23 years old, median age 26 years, 25% of the participants above 32 years old.

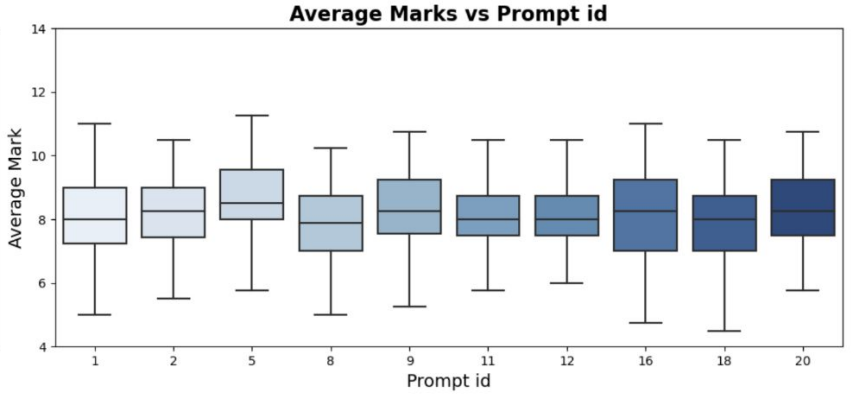
Data Analysis: Demographics - Native Language

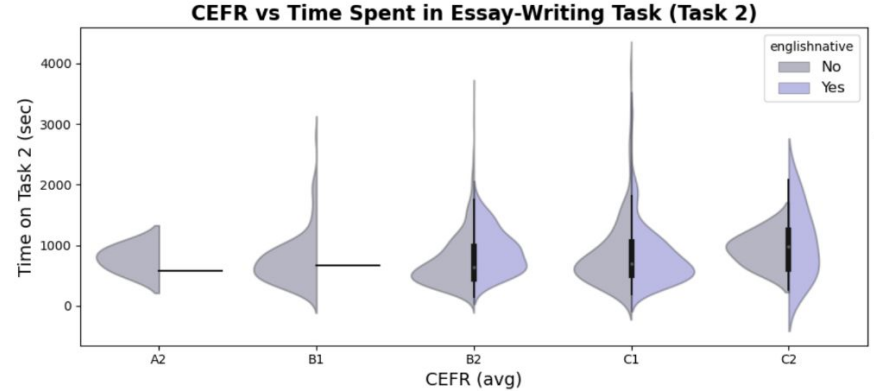


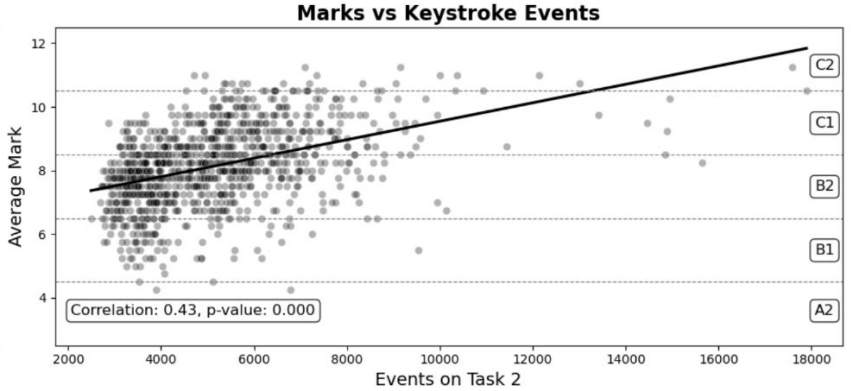
Polish was the most commonly reported native language among our participants, constituting 20% of the responses. It was closely followed by English and Portuguese, each comprising 17% of the total.

Data Analysis: Survey Completion Duration









Data Analysis: Survey Completion Duration

$$\text{K-S} = \sup_x |F_a(x) - F_b(x)|$$

We compared the **survey completion duration between native English speakers (NS) and non-native English speakers (NNS)** using the Kolmogorov-Smirnov (K-S) test.

The calculated K-S statistic was found to be 0.10, with a p-value of 0.10, suggesting **no significant difference** between NS and NNS in terms of the time required to complete the survey.

Data Analysis: Marks

Weak correlation between the **time spent on the essay task** and the **average mark received**, both from human markers and the automarker (**r=0.09**, $\rho = 0.003$)

Negative correlation between the **time they spent on the copy-text task** and the **average mark received on the essay-writing task**, suggesting that fast typists could generally achieve higher marks (**r=−0.26**, $\rho < 0.001$)

A strong correlation was evident between the **number of words** and the **average CEFR score** (**r=0.51**, $\rho < 0.001$), aligning with expectations based on previous studies

Conclusion & Future Work

- We introduce the new KUPA-KEYS dataset which includes keystroke data from 1,006 participants
- Participants completed two tasks: a copy-text task of 300 words, and an essay-writing task responding to one of 10 prompts
- The dataset also includes metadata about the individual participants, such as age, location, level of English and other languages known
- We annotated the essays with proficiency assessments from both human assessors and a pre-trained automarker
- We found a decent level of agreement amongst these assessors and initial analyses revealed some interesting results

Conclusion & Future Work

The dataset carries the potential for **further analyses of typing patterns**, indications of complex word and character sequences, and identification of **hierarchical structures in the writing process** per Ballier et al. (2019) and Leijten et al. (2019)

Conclusion & Future Work

We note that keystroke data can empower writing support for authors if we can successfully identify **when writers are struggling with linguistic constructions** (Conijn et al., 2021). This support could be in the form of writing suggestions, a chatbot or dictionary look up tools.

Conclusion & Future Work

Other future work includes the use of **features** derived from keystroke data to **enhance Transformer-based assessment models** (Mizumoto and Eguchi, 2023)

Conclusion & Future Work

Finally, the continuing challenge of **generative AI text detection** is acknowledged in recent literature (Krishna et al., 2023; Sadasivan et al., 2023), signifying a necessity for increased endeavour in this domain.

Our exploration may potentially facilitate the advent of novel research towards **generative-AI text detection** based on **event-based information including keystrokes**.

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Thank you!

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