



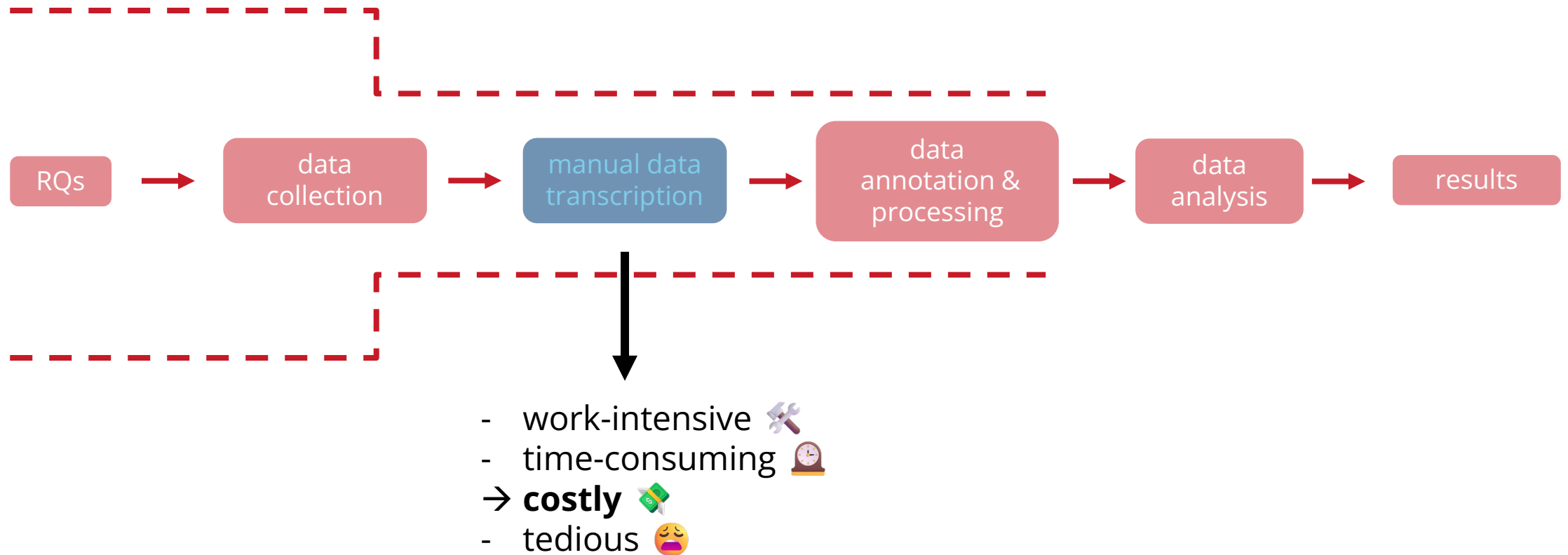
➤ Transcribing Diverse Voices: Using Whisper for ICE corpora

Interspeech 2025 - Rotterdam
JProf Dr Andreas Weilinghoff



➤ 01 Intro and previous research

'Traditional' approach in English Linguistics (and other disciplines):



01 Intro

... the higher the audio quality
... the more structured the speech
... the more 'standard' the speech
... the less speakers involved

... the better

spoken corpus
data

sociolinguistic
data

World
Englishes

(Jurafsky and Martin 2023: 331)

01 Intro – OpenAI Whisper



Radford et al. 2022

- end-to-end transformer architecture with encoder and decoder blocks
- trained on 680,000 hours of speech via unsupervised learning
- multilingual in 96 languages
- open source



Python script
whisper_to_textgrid.py
(Weilinghoff 2023)

→ “Whisper” appears 56 times in presentation titles at Interspeech 2025

01 Research aims and research questions

- identify strengths/weaknesses of Whisper for spoken corpus transcription
- integrate Whisper efficiently in spoken corpus data transcription workflows

RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

RQ2

Which variables have a **significant influence on ASR performance**?

01 Previous research – ASR in general

“Speech is easier to recognize if the speaker is speaking the same dialect or variety that the system was trained on” (Jurafsky and Martin 2023: 331)

- ASR bias towards
 - non-native speakers (e.g. Knill et al. 2018; Graham and Roll 2024)
 - regional accents (Tatman 2017; Markl 2022)
 - racial minority groups (Koenecke et al. 2020)
- influence of gender
 - better performance for female speakers
(Adda-Decker and Lamel 2005; Goldwater et al. 2010)

01 Previous research - Whisper

Whisper evaluation: (Graham and Roll 2024)

- L1 varieties: → best performance on L1 North American English
 → worse performance on British and Australian accents

 (some L2 Swedish and German accents better than some British accents; e.g. Leeds)
- worse performance on L2 varieties overall; higher English experience and pronunciation accuracy lead to better ASR performance
- worse performance on male speakers
- worse performance on spontaneous speech



➤ 02 Data and Method

RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

ICE Nigeria

(Wunder et al. 2008)

- postcolonial outer-circle variety
- compilation 2007-2013
- manually transcribed spoken component (time-aligned)

Extraction:

- 60 sound files | 12 speech categories
→ 13:05:47 hours | 94,499 words

ICE Scotland

(Schützler et al. 2017)

- inner-circle variety (not GA or SSBE)
- compilation 2014-2020
- manually transcribed spoken component (time-aligned)

Extraction:

- 60 sound files | 12 speech categories
→ 11:50:31 hours | 111,418 words

02 Data and Method

corpus	file_name	file_duration	word_count
ICE Nigeria	bdis_01	00:12:47	2143
ICE Nigeria	bdis_02	00:07:46	1165
ICE Nigeria	bdis_03	00:03:23	587
ICE Nigeria	bdis_04	00:07:58	1296
ICE Nigeria	bdis_05	00:01:16	201
ICE Nigeria	bnew_01	00:05:24	555
ICE Nigeria	bnew_02	00:09:07	1143
ICE Nigeria	bnew_03	00:16:27	1473
ICE Nigeria	bnew_04	00:15:24	1231
ICE Nigeria	bnew_05	00:12:54	887
ICE Nigeria	btal_01	00:08:17	1056
ICE Nigeria	btal_02	00:02:51	503
ICE Nigeria	btal_03	00:01:46	193
ICE Nigeria	btal_04	00:08:59	1198
ICE Nigeria	btal_05	00:04:28	708
ICE Nigeria	leg_02	00:23:27	3979
ICE Nigeria	leg_04	00:15:59	2352
ICE Nigeria	leg_11	00:06:19	1212
ICE Nigeria	leg_08	00:02:44	586
ICE Nigeria	leg_09	00:03:59	790
ICE Nigeria	nbтал_01	00:16:55	1536
ICE Nigeria	nbтал_02	00:06:11	521
ICE Nigeria	nbтал_03	00:21:40	2346
ICE Nigeria	nbтал_04	00:26:56	3409
ICE Nigeria	nbтал_05	00:19:25	2391
ICE Nigeria	parl_01	00:07:53	1069
ICE Nigeria	parl_02	00:07:47	1089
ICE Nigeria	parl_03	00:11:16	1350
ICE Nigeria	parl_04	00:16:21	2012
ICE Nigeria	parl_05	00:12:06	2327
...

corpus	file_name	file_duration	word_count
ICE Scotland	bdis_01 (s1)	00:08:53	470
ICE Scotland	bdis_02	00:20:45	3030
ICE Scotland	bdis_03	00:06:00	1115
ICE Scotland	bdis_04	00:13:58	2964
ICE Scotland	bdis_05	00:11:56	2914
ICE Scotland	bnew_01	00:02:14	159
ICE Scotland	bnew_02 (s1)	00:02:48	93
ICE Scotland	bnew_03 (s1)	00:01:39	96
ICE Scotland	bnew_04 (s1)	00:03:36	179
ICE Scotland	bnew_05	00:01:47	305
ICE Scotland	btal_01	00:02:37	415
ICE Scotland	btal_02	00:02:34	453
ICE Scotland	btal_03	00:03:24	473
ICE Scotland	btal_04	00:02:52	379
ICE Scotland	btal_05	00:07:51	934
ICE Scotland	leg_01	00:19:08	2033
ICE Scotland	leg_02	00:22:32	2168
ICE Scotland	leg_03	00:02:29	324
ICE Scotland	leg_04	00:10:39	1333
ICE Scotland	leg_05	00:05:04	713
ICE Scotland	nbтал_01	00:21:55	3040
ICE Scotland	nbтал_02	00:30:00	4835
ICE Scotland	nbтал_03	00:11:17	1739
ICE Scotland	nbтал_04	00:04:45	713
ICE Scotland	nbтал_05	00:02:31	387
ICE Scotland	parl_01	00:20:54	3782
ICE Scotland	parl_02	00:20:09	3427
ICE Scotland	parl_03	00:11:31	1776
ICE Scotland	parl_04	00:25:21	4178
ICE Scotland	parl_05	00:36:08	5900
...

- different varieties
- different file sizes
- different speech forms
- monologues and dialogues
- different speaker groups
- different quality



RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

- retrieval of audio files and reference transcriptions (→ plain .txt)
- re-transcription of files with Whisper models (tiny, base, small, medium, large_v2, large_v3) via AMD EPYC 7402 processor
- normalization and comparison of manual reference transcription and Whisper transcriptions via **Word Error Rate (WER)** using werpy library (Armstrong 2024) via Python script

$$WER = \frac{S + D + I}{N}$$



<https://www.andreas-weilinghoff.com/#code>

RQ2

Which variables have a **significant influence on ASR performance**?

- annotation for metadata (corpus, text category, model, sound quality, speaker number, gender, file duration)
- following approach of Graham and Roll (2024):
→ linear mixed effects modelling of WER with lme4 (Bates et al. 2015) and lmerTest (Kuznetsova et al. 2017) packages in R (R core team 2024)

RANDOM FACTORS	TYPE	LEVELS
sound file	categorical	120 individual sound files
FIXED FACTORS	TYPE	LEVELS
corpus	categorical	ICE Nigeria, ICE Scotland
text category	categorical	bdis, bnew, btal, btran, com, cr, dem, leg, les, nbtal, parl, unsp
model	categorical	tiny, base, small, medium, large_v2, large_v3
quality_2	categorical	okay, bad
speaker number binary	categorical	mono, poly
gender	categorical	female, male, mixed
file duration (min)	numerical	1-48



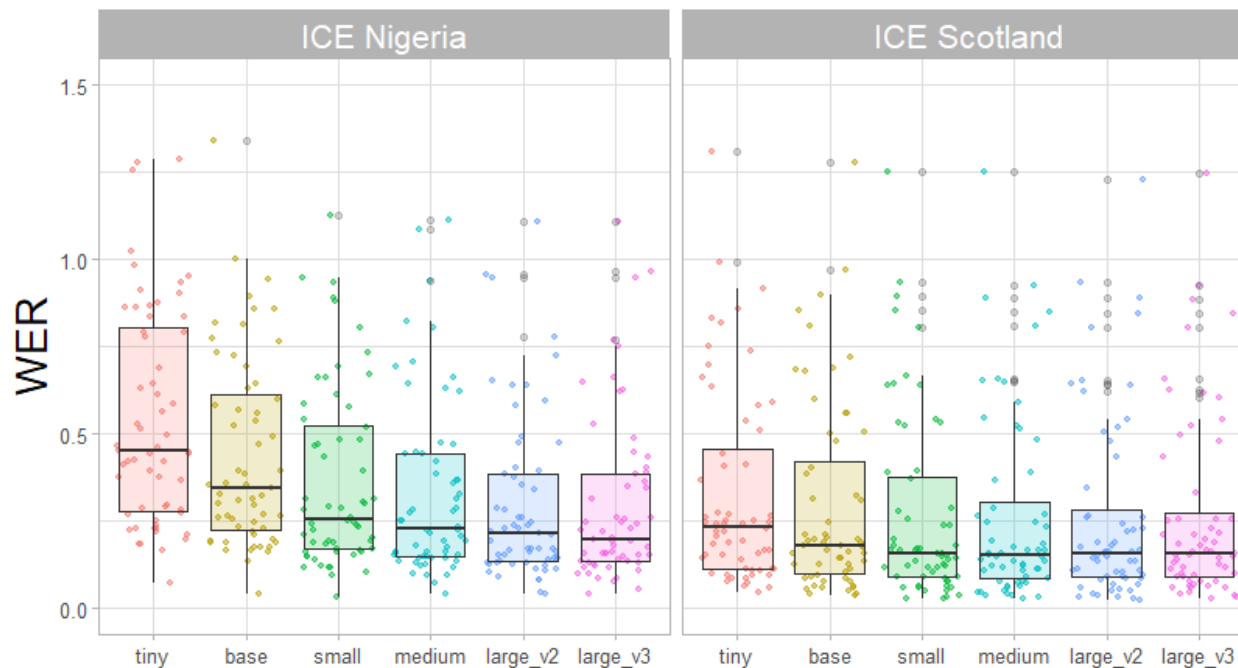
➤ **03 Findings**

03 Findings

RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

Corpora and Whisper Models



Whisper model	ICE Nigeria		ICE Scotland	
	mean WER	std dev	mean WER	std dev
tiny	0.54	0.30	0.32	0.28
base	0.45	0.30	0.29	0.27
small	0.36	0.26	0.27	0.27
medium	0.33	0.25	0.26	0.27
large_v2	0.30	0.24	0.26	0.27
large_v3	0.29	0.24	0.26	0.26

RQ2

Which variables have a **significant influence on ASR performance?**

Extremely high R^2 values for best model:

```
wer ~ (model * corpus) + (model * quality_2) + text_category + speaker_number_binary +  
gender_simplified + (1 | file_name)
```

Marginal R^2 : 0.72



Conditional R^2 : 0.95



RQ2

Which variables have a **significant influence on ASR performance?**

```
wer ~ (model * corpus) + (model * quality_2) + text_category + speaker_number_binary + gender_simplified + (1 | file_name)
```

Significant factors:

model

→ 10%, 21%, 25%, 30% decrease of WER with model size

corpus

→ 11% decrease of WER for ICE Scotland

quality

→ 24% decrease of WER for good quality audio

text_category

→ increase of WER for text categories: *com, cr, dem, leg, les, unsp*

speaker_number

→ 19% increase of WER for audio files with several speakers

gender

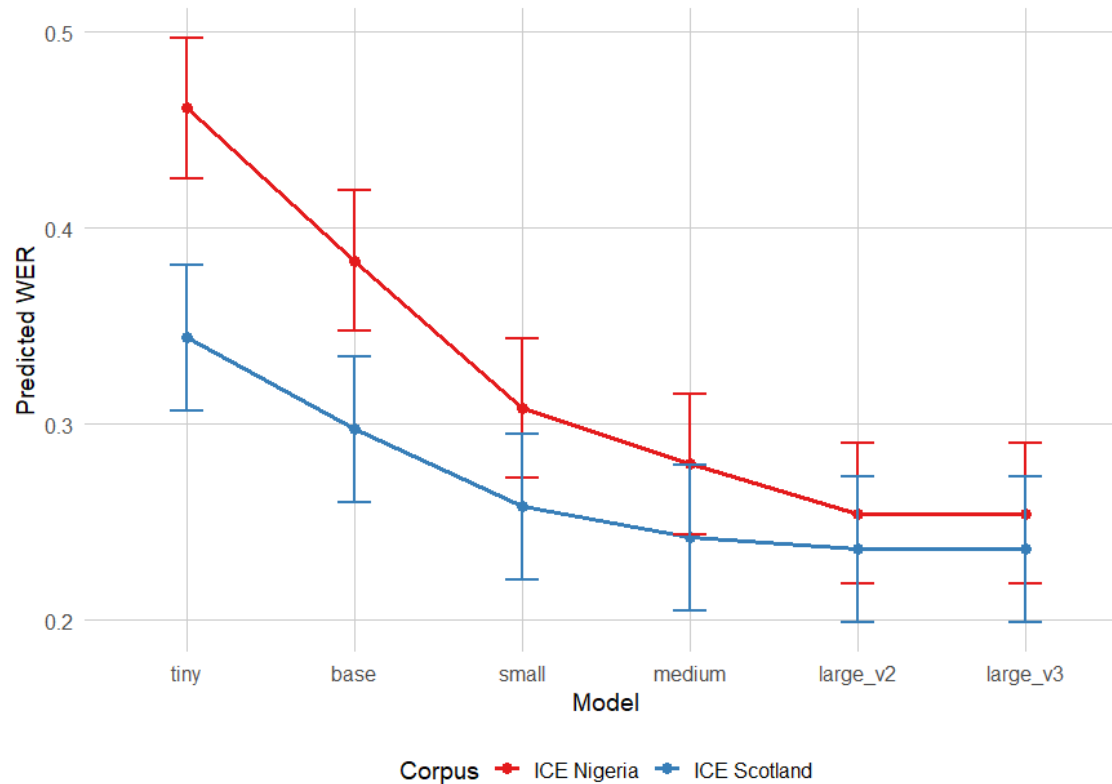
→ 8% increase of WER for audio files with male speakers

03 Findings

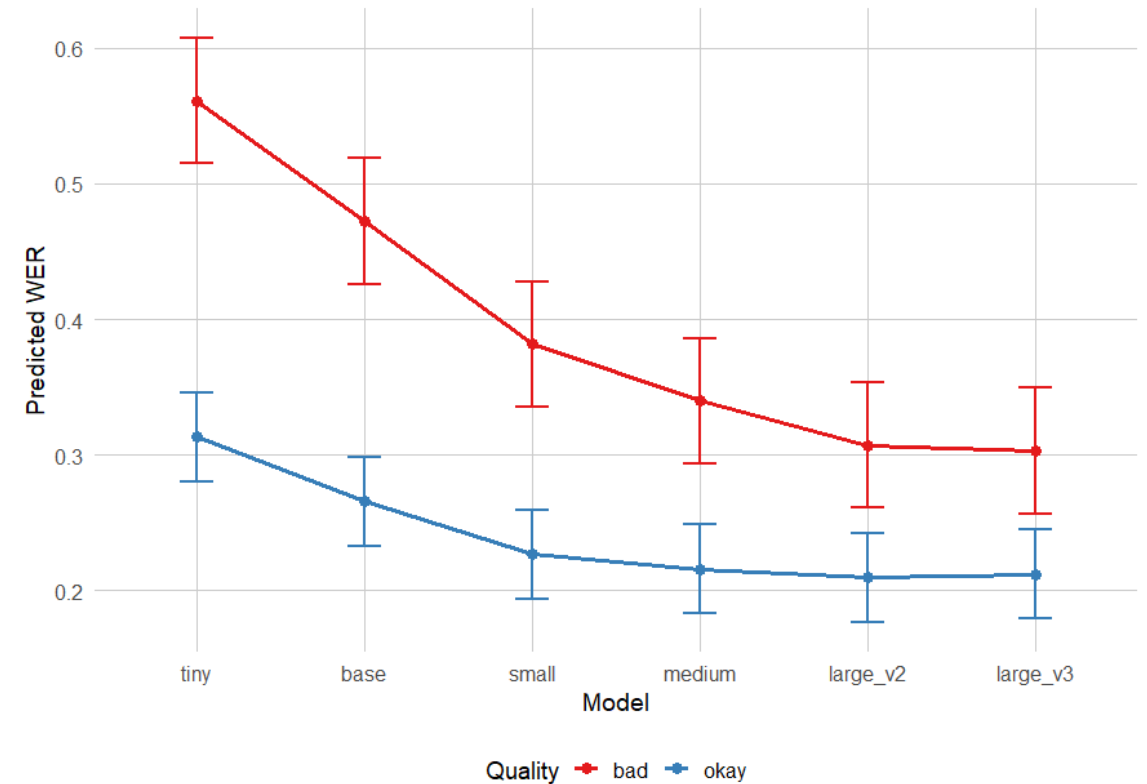
RQ2

Which variables have a **significant influence on ASR performance?**

Interaction Effect of Model and Corpus on WER



Interaction Effect of Model and Quality on WER





➤ **04 Discussion**

04 Discussion

Hallucinations for specific files across different models

- bad quality audio
- long periods of silence
- speaker overlaps / interruptions
- switch to Nigerian Pidgin English

Whisper small

At UJ, he cautioned supervisors on the need to follow the enumerators and ensure that proper enumeration is affected. It doesn't mean once we are a supervisor, you find yourself, you wait linearly, looking for help now. Look at some people walking, are they doing the right thing? That's what you think. That's what you think. That's what you think. That's what you think. That's what you think. That's what you think.

Whisper base

At UJ, he cautioned supervisors on the need to follow the enumerators and ensure that proper enumeration is affected. It doesn't move walls here, it's super special, you find yourself with Legally, you can go out now. Look at some people walking, are they doing the right thing? That's what you do. That's what you do. That's what you do. That's what you do. That's what you do. That's what you do. That's what you do.

04 Discussion

- idealized instead of verbatim transcripts

→ problematic for close transcription

→ increase in WER

→ CrisperWhisper (Wagner et al. 2024) as alternative?

Human transcription

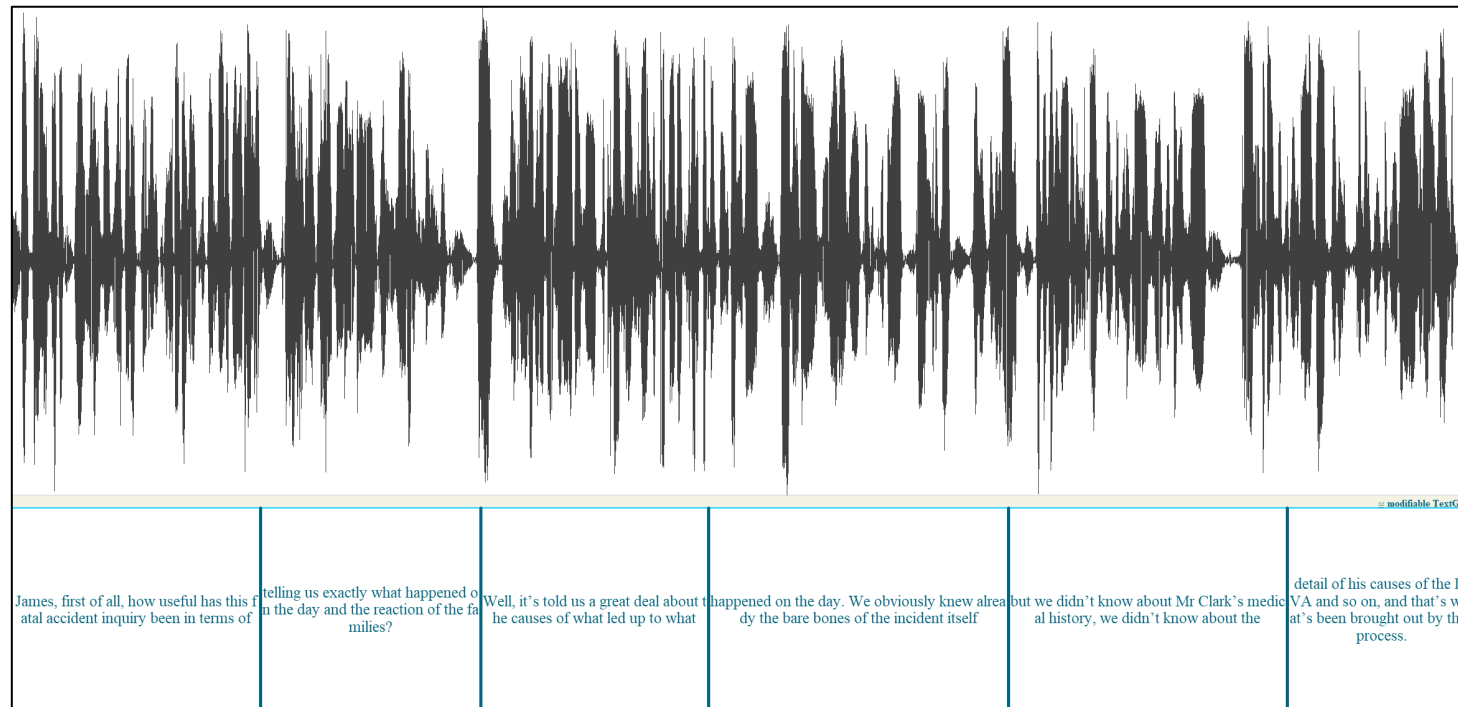
the position **that** as **as** of just now is that **I-** I've obviously spent time yesterday covering matters which substantially were not in the note of argument **now** and that took a little bit more time **erm a-** and so **erm erm** today I **I** think I can probably go quite a lot faster

Whisper transcription

The position as of just now is that I've obviously spent time yesterday covering matters which substantially were not in the note of argument, and that took a little bit more time, and so today I think I can probably go quite a lot faster

04 Discussion – speaker diarization

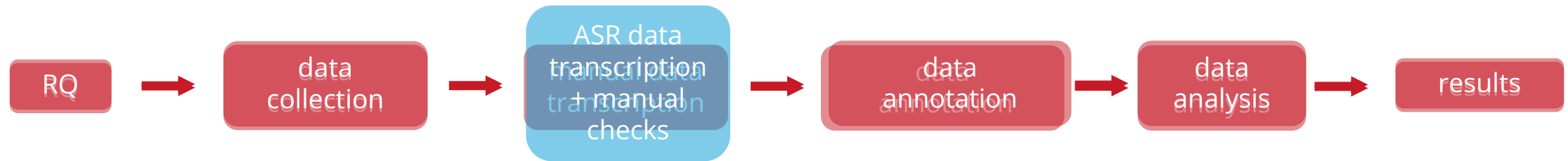
- **lack of speaker diarization (Radford et al. 2022, p. 3)**
- limited capabilities of WhisperX (Bain et al. 2023) and pyannote (Bredin, 2020) or Whisper and NVIDIA NeMo (Ashraf, 2024)



04 Discussion

- some human reference transcripts worse than Whisper transcripts
→ increase in WER

(Semi-)automatic approach:
'Traditional' approach in English Linguistics (and other disciplines):



manual checks:
→ hallucinations
→ idealized transcriptions
→ speaker diarization



➤ 05 Conclusion

RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

- best accuracy for models large_v2 & large_v3 (also most robust models)
 - worse results for ICE Nigeria than for ICE Scotland overall
 - accent bias (outer circle variety)
 - Whisper more robust than other systems
- (recording quality of ICE Nigeria worse)

RQ2

Which variables have a **significant influence on ASR performance?**

- model** → the larger the model, the better the performance
- corpus** → better performance for ICE Scotland
- quality** → the better the audio, the better the results
- text_category** → better results for scripted speech
- speaker_number** → better results for monologue data
- gender** → better performance for (only) female speaker data

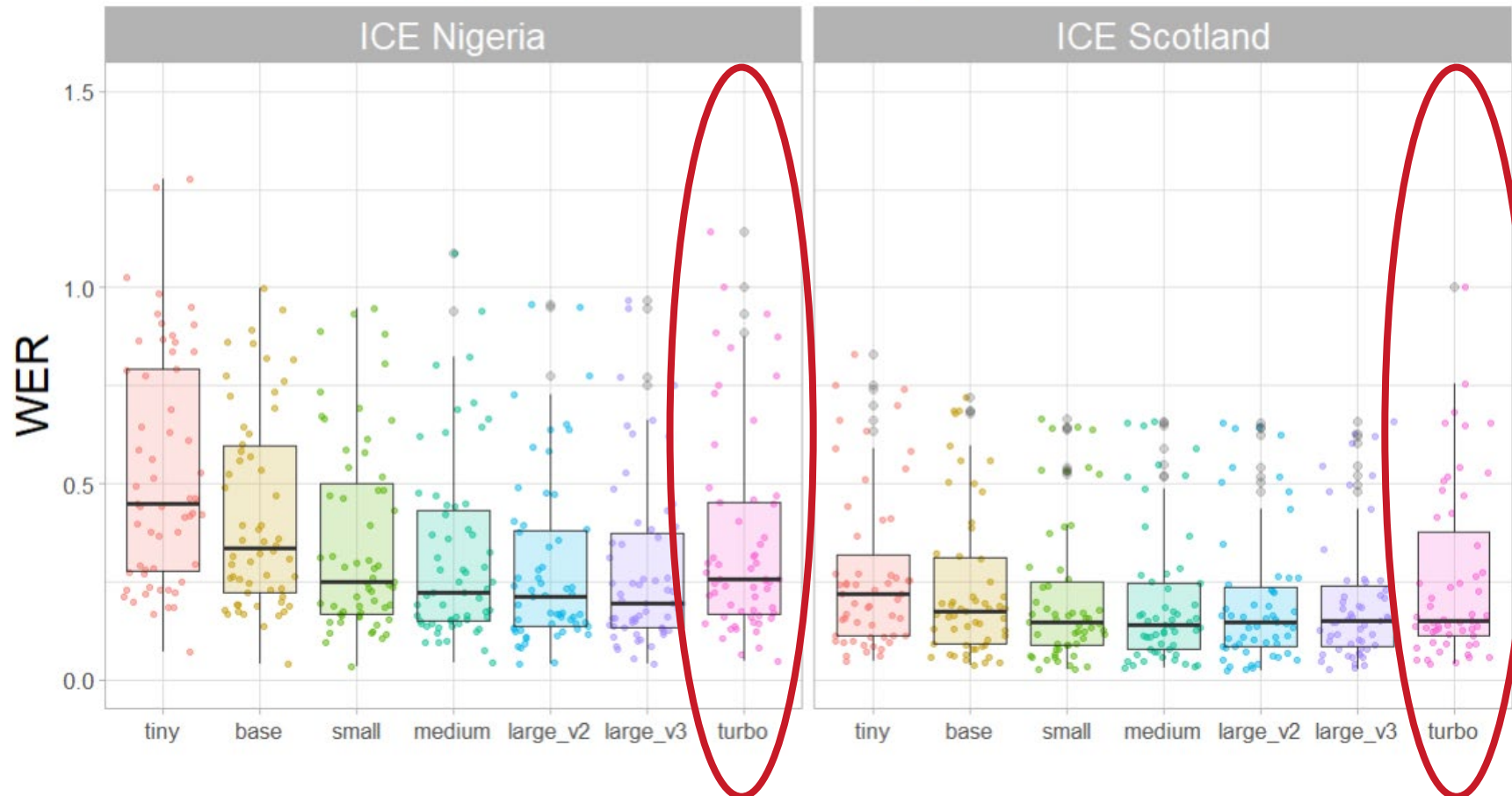


➤ 06 Outlook

NEXT STEPS

- extend dataset (more data, other varieties, model turbo)
- integrate more precise acoustic parameters into analysis and modelling
- use other evaluation metrics than WER
- compare human transcribers and Whisper more closely
- ...

Corpora and Whisper Models

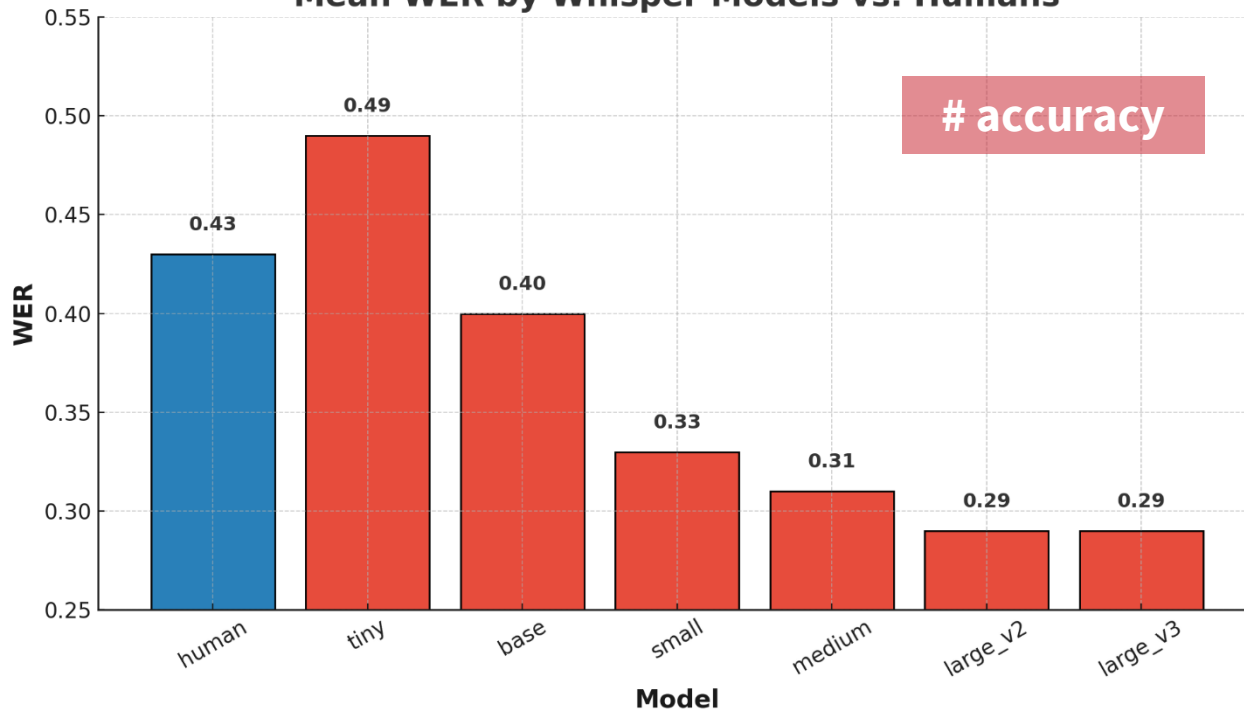


06 Outlook

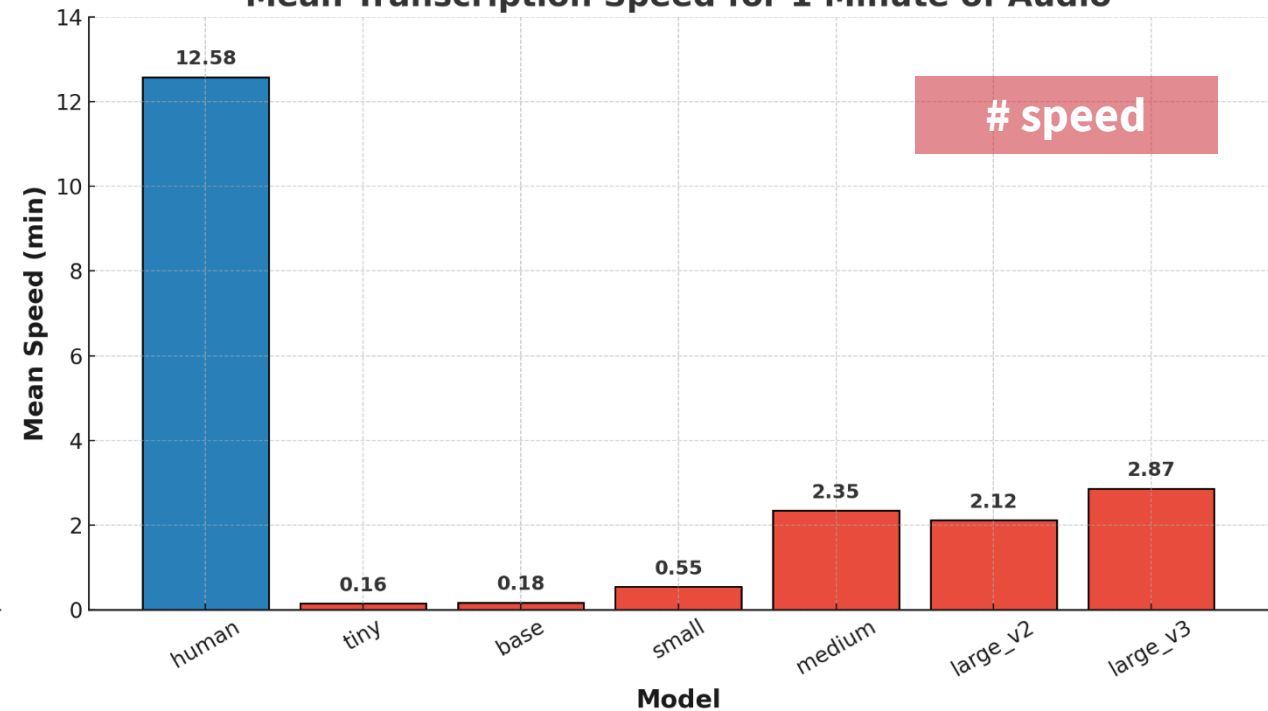
RQ3

How does **Whisper** compare with trained human transcribers in terms of accuracy and speed?

Mean WER by Whisper Models vs. Humans



Mean Transcription Speed for 1 Minute of Audio



05 Outlook – user-friendliness

- **Whisper requires command line / programming knowledge (Python)**
- projects to increase user-friendliness



Whisper Transkriptionsservice

Achtung: Evaluationsbetrieb! Keine Garantie für Korrektheit, Verfügbarkeit oder dauerhaften Einsatz!

Dies ist der Whisper-Transkriptionsservice der Universität Koblenz. Sie können hier Sprachaufnahmen aller Art (bspw. Interviewdaten, Videos) automatisch transkribieren. Whisper ist eines der stärksten Spracherkennungssysteme der Welt und transkribiert bis zu 96 verschiedene Sprachen. Mehr Informationen finden Sie in der entsprechenden Veröffentlichung von Radford et al. (2022) (English only): Ein besonderer Vorteil dieses Webservices ist, dass sie hierüber Whisper endnutzerfreundlich nutzen können. Sie benötigen also keine Programmierkenntnisse und es entstehen keine Kosten. Die Daten werden über einen Server der Universität Koblenz verarbeitet und das Ausgangsmaterial wird anschließend zusammen mit der Transkription wieder gelöscht, was auch im Sinne des Datenschutzes von großem Vorteil ist. Sie können unten ein beliebiges Soundfile zur Transkription hochladen (bspw. .wav, .mp3, .mp4, .mov etc.), das Whisper-Modell sowie die Sprache auswählen, und dann die Transkription starten. Sie bekommen eine kurze formlose Bestätigungsmail und der Webservice schickt Ihnen dann nach der Datenverarbeitung automatisch die entsprechende Transkription in verschiedenen Formaten in einer separaten E-Mail zu.

Ihre E-Mail

Datei für die Transkription (max. 4096M) Keine ausgewählt

Whisper-Modell

Sprache

Sprecherseparierung (experimentell!) ☐

Uploadbestätigung per E-Mail ☒

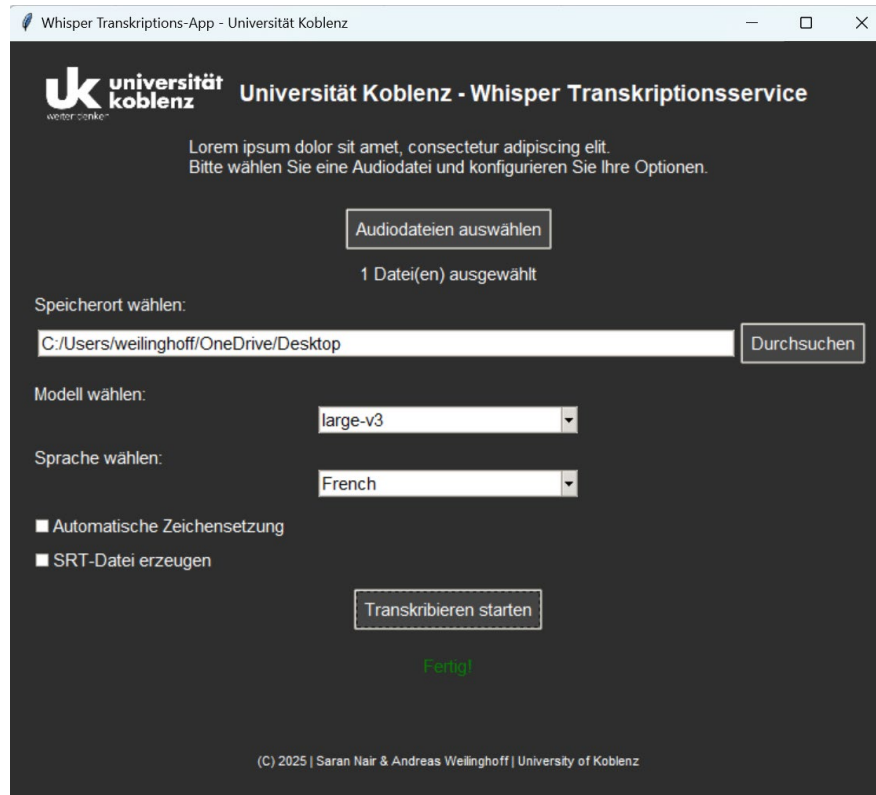
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Warteschlange

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Whisper Uni Server

05 Outlook – user-friendliness



Whisper Desktop App



https://github.com/Andreas-Weilinghoff/whisper_desktop_app

05 Outlook – user-friendliness

→ Whisper finetuning for specific varieties



RheinlandPfalz
MINISTERIUM DER JUSTIZ

Finetuning and adapting for legalese

Fine Tuning 'Whisper' for enhanced
speech recognition across diverse
English accents: Feature analysis,
Evaluation, and strategies to reduce
hallucinations

Master's Thesis

in partial fulfillment of the requirements for
the degree of Master of Science (M.Sc.)
in Web and Data Science

Finetuning for Indian & Scottish English



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**Thank you very much
for your attention!**



Uni web: <https://uni-ko.de/oUfpi>

Private web: andreas-weilinghoff.com



Dates: 26-30 May 2026 | CfP Deadline: 31 October 2025 | Web: wp.uni-koblenz.de/icame47/