Audio-based Crowd-sourced Evaluation of Machine Translation Quality

Sami Ul Haq[1,2], **Sheila Castilho**[1,2], **Yvette Graham**[2,3]
[1]ADAPT Centre
[2]Dublin City University (DCU), Ireland
[3]Trinity College Dublin (TCD), Ireland
sami.haq2@mail.dcu.ie sheila.castilho@dcu.ie ygraham@tcd.ie

Abstract

Machine Translation (MT) has achieved remarkable performance in recent times, with growing interest in speech translation and multimodal approaches. However, despite these advancements, MT quality assessment remains largely text-centric, typically relying on human experts who read and compare texts. Since many real-world MT applications (e.g., Google Translate Voice Mode, iFLYTEK Translator) involve translation being spoken rather than printed or read, a more natural way to assess translation quality would be through speech as opposed text-only evaluations. This study compares text-only and audio-based evaluations of 10 MT systems from the WMT General MT Shared Task, using crowd-sourced judgments collected via Amazon Mechanical Turk. We additionally, performed statistical significance testing and self-replication experiments to test reliability and consistency of the proposed audio-based approach. Crowd-sourced assessments based on audio yield rankings largely consistent with text-only evaluations but, in some cases, identify significant differences between translation systems. We attribute this to the richer, more natural modality of speech and propose incorporating speech-based assessments into future MT evaluation frameworks.

1 Introduction

Reliable evaluation process is critical in the development and refinement of MT systems. MT evaluation (MTE) often relies on both automated and manual measurement techniques. Manual evaluation is always a preferred choice and provides a deeper understanding of system quality, while automatic evaluation metrics (AEMs) often serve as a proxy for human judgment (Castilho et al., 2018). AEMs support reusable assessments, system comparison and rapid MT deployment. However, AEMs face several issues including their inability to handle contextual and cultural nuance, the dependency on reference translation, and domain-specific challenges. Therefore, despite being time-consuming and expensive, human assessment is still a fundamental requirement for reliable evaluation.

The annual Conference on Machine Translation (WMT) is the primary forum for collecting human judgments to evaluate metrics and participating systems in its shared translation task each year. In early evaluation campaigns, 5-point adequacy and fluency ratings were gathered from participants as the primary evaluation metric (Koehn and Monz, 2006). Subsequent WMT campaigns adopted a ranking-based evaluation approach as the official metric (Vilar et al., 2007), with rankings still collected from participants of the evaluation campaign. Regarding fluency as a measure of MT output quality, Graham et al. (2013a) argued that using a 1-100 continuous scale yields better inter-annotator consistency compared to a five-point interval scale. Supporting this, Bojar et al. (2016) found strong correlations between adequacy and fluency-based evaluations. These findings led WMT to replace relative ranking with adequacy-based Direct Assessment (DA) on a continuous scale as the official metric (Bojar et al., 2017). For into-English translation tasks, WMT frequently relied on crowd-workers for its human evaluation campaigns. Crowd-based evaluations allow for a fast and cheap MT quality evaluations (Callison-Burch, 2009). When coupled with quality-controlled annotations, non-expert crowd assessments show better inter-annotator consistency (Graham et al., 2013a, 2017). However, Castilho et al. (2017b) found that crowd-workers, compared to professional translators, were less capable of detecting subtle MT errors. Studies by Läubli et al. (2018) and Toral et al. (2018) also favored the use of professional translators over researchers or crowd-workers due to their ability to differentiate between human and machine translations. Consequently, WMT revised its evaluation procedures to prioritize professional transla-

Proceedings of the Tenth Conference on Machine Translation (WMT), Volume 1: Research Papers, pages 52–63
November 8–9, 2025.

tors over crowd-workers (Kocmi et al., 2022, 2023). Despite its limitations, crowd-based assessment remains the most convenient choice for certain tasks, particularly monolingual DA, which does not require human raters to have bilingual knowledge (Graham et al., 2017), making it easier to conduct. More recently, WMT performed evaluations using Error Span Annotation (ESA) protocol (Kocmi et al., 2024), which requires annotators to assign an overall score to each segment, similar to DA and classify errors based on severity (e.g. major or minor).

The human evaluation process has evolved over time; however, there is still no consensus on the best approach to evaluating translation quality (Castilho et al., 2018). Current MT evaluation metrics primarily considers text, despite the fact that many real-world MT applications involve spoken rather than written translation. Most importantly, the recent emergence of pre-trained multimodal models (Barrault et al., 2023) has enabled support for direct speech-to-speech, text-to-speech and speech-to-text translation, however appropriate methods for evaluation for these systems are yet limited or borrowed from text-domain (Salesky et al., 2021; Sperber et al., 2024).

We argue that speech, as a natural and expressive modality, can provide more reliable measures of MT quality. To support this claim, we propose incorporating text-to-speech (TTS) technology into direct MT assessment, allowing for a direct comparison between text-only and speech-enabled evaluation approaches. Our study collects human judgments for German-English translations from WMT shared task using crowd-workers hired via Amazon Mechanical Turk. The evaluation consists of two conditions: (i) a text-only setup, replicating the conventional method where evaluators compare written MT output with a reference translation, and (ii) a text-audio setup, where evaluators listen to the MT output while reading the reference translation. We perform self-replication experiments and statistical significance tests to assess the consistency and reliability of the proposed method.

A comparative analysis of these evaluation conditions yields two key findings. First, rankings derived from text-audio evaluations are broadly similar to the original evaluations but also show notable differences compared to conventional setups, with the audio-based method demonstrating a substantially greater ability to detect significant differences between translation systems. We hypothesize that this difference arises because speech is a natural and rich modality, capable of conveying prosodic and expressive features that text alone cannot capture. Second, consistent with prior research, our results confirm that crowd-workers tend to assign lower rankings to human translations that diverge from the reference, while favoring literal machine translations (Castilho et al., 2017a; Fomicheva, 2017). Furthermore, self-replication experiments reveal a higher positive correlation between repeated runs of audio-based evaluations, indicating improved reliability and consistency of this new approach.

Domain	#segments	Avg. doc length
conversation	462	6.8
ecommerce	501	18.5
news	506	14.5
social	515	15.6

Table 1: Number of segments and average document length (#segments per document) of German-English data used in the general translation test sets.

2 Methodology

2.1 Data set

We used MT outputs from WMT 2022 German-English translation task, comprising around 20,000 translations submitted by 10 participating systems, with each system contributing approximately 2,000 translations. This original evaluation set is a bilingual corpus drawn from different domains, as shown in Table 1, with document lengths varying considerably by domain. To ensure balanced domain representation while preserving document order, a subset of documents was randomly sampled from each domain. We use on average 450 segments per system for multimodal[1] and text-only experiments.

The WMT evaluation campaign has already published results from crowd-based human evaluations of the submitted systems. As WMT now conducts bilingual ('source-based') evaluations using professional translators, we focus on WMT 2022—the most recent workshop to perform monolingual DAs.

[1]In this study, multimodal is used to refer to text-audio based setup

2.2 Assessment Design

AMT crowd-sourcing service was used to design and collect human judgments, with each task consisting of 100 segments. A single segment along with a reference translation is presented at one time. Where possible, segments are collected and shown in document context. In adequacy based assessments, crowd-workers are asked to rate how adequately an MT output expresses the meaning of the reference translation. The scores are collected on 0–100 visual analog scale (VAS) for each segment. Additionally, rater quality control mechanism is implemented to filter out ratings from non-reliable raters, as outlined by Graham et al. (2017). At the end of the task, evaluators have the option to provide feedback on their experience.

The segment-level ratings were used to calculate system-level rankings. At the end of the evaluation, we provide two types of segment-level scores, averaged across one or more raters: raw scores and z-scores, with the latter standardized for each annotator. The final score of an MT system is the mean standardized score of its ratings after filtration. Multiple judgments are collected per segment, increasing the number of annotators per translation enhances the consistency and reliability of the mean score. Since reference-based assessment required only knowledge of the English language; the selection criteria required participants to be native English speakers.

We compare judgments collected using following two different setups:

- *Text-only*: MT output and reference translations, both are presented as text (Figure 1).
- *Multimodal*: MT output is presented in audio (TTS) and reference translation as text (Figure 2).

Overall, we gathered approximately 12,000 crowd-sourced judgments for German-English language pair using DA. Compared to ordinal ranking or relative preference judgments (Callison-Burch, 2009), direct estimation facilitates more robust statistical analysis, thus making it suitable for crowd-sourced annotations (Graham et al., 2013a). When combined with quality control mechanisms, direct assessments have shown effective and relatively consistent human judgments of MT quality in WMT evaluation campaigns (Specia et al., 2020; Akhbardeh et al., 2021; Kocmi et al., 2022).

2.2.1 Text-only setup

We randomly sampled 500 segments per system (with the addition of quality control segments, the total could be increased). The selected translations are then converted into bit-mapped images, in order to deter workers from using speech feature of Web Browsers to read-aloud the translations.

In this scenario, the workers are shown the reference and the MT output as text and asked to rate MT output by moving the slider (as shown in Figure 1). For task simplicity, we kept the structure of assessment similar to existing evaluation setups (Graham et al., 2017; Kocmi et al., 2022). The ratings are collected per segment in a sequential manner, adhering to the document order where feasible. However, longer documents may need to be divided into smaller units to comply with the limit of 100 segments per task. The setup restricts assessors from revisiting and modifying ratings of previous segments to ensure integrity of quality control measures.

2.2.2 Multimodal setup

For comparison, the same segments sampled for the text-only scenario were considered in this experiment. However, this setup utilises TTS technology to present the MT output in an audio-equivalent form. To make the task less cognitively taxing, we present only the MT system's output in audio form. For this, we used the Google Cloud Text-to-Speech (TTS) Service (GCS)[2] to generate audio representations of MT outputs. The service was employed with its default human-like voice settings, which are noted for their high quality and clarity. GCS is well-suited for long-form content[3] due to its close approximation of human speech and its ability to provide an enhanced listening experience (Cambre et al., 2020).

2.2.3 HITs

Both multimodal and text only assessments are carried out separately. Each task, referred to as "HITs" (Human Intelligence Task) contains 100 translations in total for each setup. In addition to system output, a set of quality control segments was added, keeping the total size of HIT to 100. The quality control segments consists of exact repeats (*ask_again*) and degraded translations

[2] https://cloud.google.com/text-to-speech

[3] For multimodal experiments, in total a human assessor may have to listen up-to 20 minutes of machine translation outputs, therefore along with accuracy of TTS, a pleasant listening experience is important.

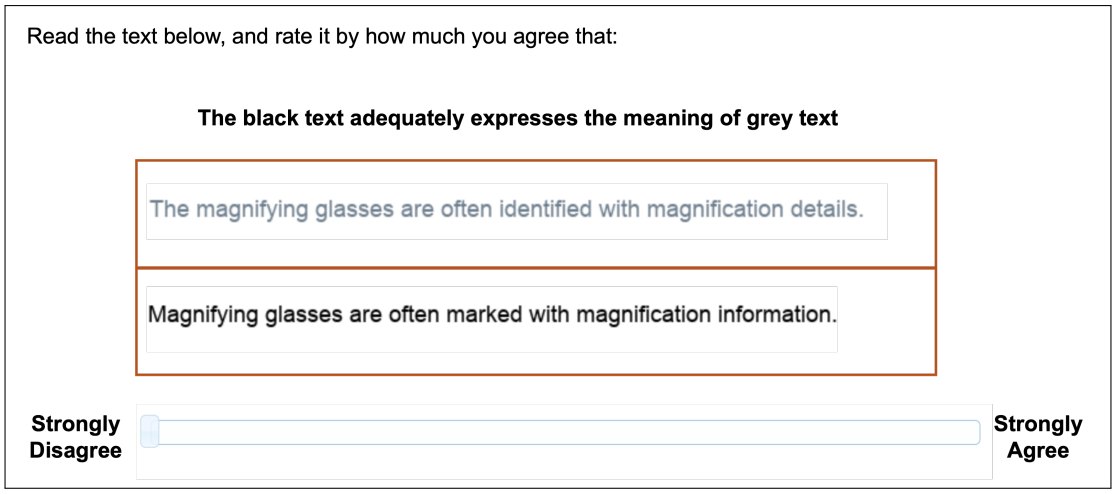


Figure 1: Screenshot of the text-only assessment interface, as presented to an AMT worker. Reference text is presented in grey while MT output is shown in black text. The slider is initially placed at left most corner; workers move it to the right in reaction to the question.

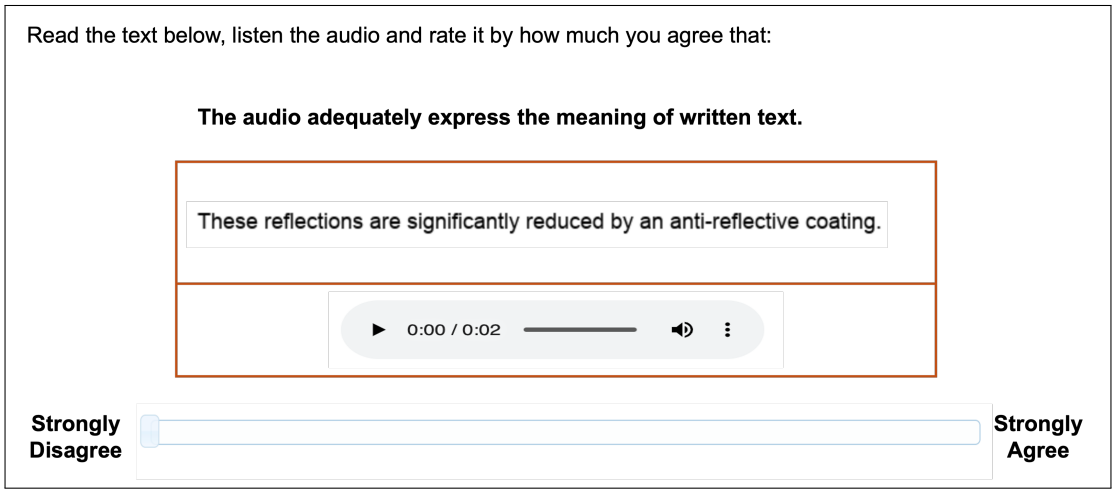


Figure 2: Screenshot of the multimodal assessment interface, as presented to an AMT worker. Worker can use audio control to listen translations, the text in presented in the image form. The slider is initially placed at left most corner; workers move it to the right in reaction to the question.

(*bad_reference*), duplicated from system outputs. Thus, each HIT consists of approximately 20% quality control segments (used to estimate workers' reliability) and 80% genuine system outputs. To create *bad_reference* pairs, we followed the strategy of randomly substituting words in a sentence, as outlined in Graham et al. (2013b). For the multimodal setup, the quality control segments were first prepared using the same strategy in text form and then converted into audio using the TTS API.

Judgments from crowd workers with limited or no knowledge of the assigned task pose a significant risk of inconsistency and discrepancies in the results. Expert-based MT quality assessment is the preferred approach; however, it incurs high economic and time costs, making crowdsourcing a viable alternative. Consequently, assessing worker reliability becomes critically important in crowd-sourced evaluations. Quality control segments within HIT allow for reliability estimates based on workers distribution of scores assigned to *bad_reference* and *ask_again* items. These estimates are based on following two assumptions:

1. The consistent assessor will assign significantly higher score to the system producing high quality translations compared to a system producing inferior outputs.

2. The consistent assessor will assign highly similar scores in repeated evaluations of the same translations.

Analysis of assumptions 1 and 2 can provide a measure of workers' ability to differentiate between a good and inferior translation. Assumptions 1 and 2, based on the sets of *bad_reference* and *ask_again* translations, posit that a consistent worker would assign significantly lower scores to degraded (*bad_reference*) translations and similar scores to repeated (*ask_again*) translations. For this, we apply the Wilcoxon rank-sum test to compare the score differences between *ask_again* and *bad_reference* translation pairs, with a resulting p value as an estimate of reliability. The expectation is that the difference in scores for degraded translation pairs will be smaller than for repeated judgments. A lower p-value ($p < 0.05$) indicates higher reliability, demonstrating that the worker can effectively distinguish between high-quality and degraded translations. As shown in Figure 3, conscientious workers assigned lower scores to degraded translations compared to the original references. Furthermore, for repeated segments, they exhibited a consistent scoring pattern by assigning similar scores to identical pairs.

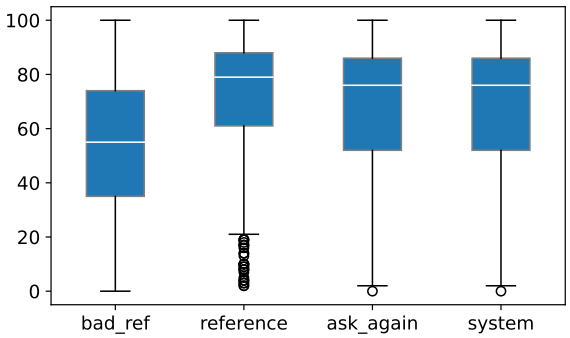


Figure 3: Score distributions of reliable workers across different quality control segments: $bad\_reference$, ask_again, and original system outputs.

Table 2 provides statistics on the number of workers involved in each assessment type and the percentage of workers who passed the quality control threshold. A similar trend was observed across both assessment types, with nearly 20% of workers meeting the reliability criteria. To determine whether to accept or reject HITs, the mean score differences for *bad_reference* and *ask_again* pairs were carefully analyzed, rather than relying solely on automatic quality control checks.[4] This is further reflected in the difference between the number of approved workers and those who met the quality control criteria. Rejected HITs were rescheduled to obtain fresh judgments.

[4]In addition to statistical tests, other measures were in place to detect robotic or low-quality submissions, such as extremely short completion times, lack of slider movement, and assigning the same rating to every judgment.

3 Results

System rankings are calculated for each setup using filtered judgments—only those that passed the quality control criteria. Quality control segments (*bad_reference* and *ask_again*) are excluded from the final system rankings. System rankings are based on the mean raw and standardized (z) scores. To compute the standardized score for each system, individual scores are first normalized using each worker's mean and standard deviation (as per equation 1). The standardized scores for all segments corresponding to a system are then averaged to obtain the system-level score (Graham et al., 2014). Since HITs are structured so that a single worker may assess multiple systems, standardising the scores helps mitigate individual biases and harmonise outputs across workers.

Table 3 presents the raw and standardized scores of the participating systems across different experiments, with the last three columns showing the official results from WMT. Systems are ordered from best to worst based on their average standardized scores, with the raw score used as a secondary criterion when standardized scores are identical to two decimal places.

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

The text-only results show increased correlation between the raw and standardised score, with few exceptions such as system `LT22` and `JDExploreAcademy`, which would have ranked better according to raw score. This close correlation suggests an even distribution of segments from different systems across workers and may also be attributed to the homogeneous nature of the task (text-only data). It is important to note that these rankings may not fully reflect actual system performance or align with the official WMT rankings, as we used a smaller set of judgments per system compared to WMT22, with the primary objective of investigating and comparing audio-based and text-based evaluations.

In the multimodal scenario, the differences in system rankings between z scores and raw scores are more pronounced. Based on the raw scores, a

	Workers			Translations		
modality	Total	Approved	Pass QC	Total	Approved	Pass QC
text only	225	47	42 (18.50%)	23.3k	5.1k	4.6k (19.7%)
multimodal	242	52	48 (19.83%)	26.1k	6.0k	5.3k (20.3%)

Table 2: Numbers of workers and translations, before and after quality control for multimodal and text only experiments.

different ranking emerges, with Lan-Bridge performing best. This divergence may be caused by the differing nature of the evaluation setup, particularly the use of both audio and text for evaluation. The out-of-sequence numbers in order column (Table 3) highlight differences in system rankings across different experiments.

A direct comparison of the mean standardized scores across both tables reveals substantial differences in system rankings. For example, in the text-only evaluation, Online-W outperforms PROMT based on standardized scores, whereas the multimodal evaluation ranks PROMT as the top-performing system. Similarly, Online-G is ranked sixth, below Online-A, Online-W, and Online-Y in the text-only setup, but is rated higher than these systems in the multimodal evaluation. For most other systems, rankings diverge by one or two places between setups, with the exception of Human-B, which consistently ranks as the lowest-performing system in both evaluations. Ideally, Human-B (the human reference translation) should be the top-performing system. However, the results suggest that crowd-workers struggled to distinguish between human translations and MT outputs. This aligns with prior research suggesting that crowd-workers tend to favor literal, straightforward translations, resulting in lower rankings for human translations that deviate from the reference (Fomicheva, 2017; Freitag et al., 2021).

3.1 Significance Test Results

Since both approaches yield different system rankings without a clear indication of which better reflects actual performance, more robust testing is required to determine whether the observed ranking differences are genuine. To address this, we employ two techniques: statistical significance testing and self-replication. Significance testing estimates the likelihood that ranking differences between system pairs occurred by chance, while self-replication examines the reproducibility of results to verify their reliability and consistency.

The results of significance tests are visualised as heat maps in Figure 4 for the multimodal and text-only setups. Specifically, we apply one-sided Wilcoxon rank-sum test to compare the standardized human assessment score distributions for each pair of systems.

Tables with head-to-head comparisons between all systems are included in Appendix A.

The significance matrices are constructed under the hypothesis that the scores of system X are significantly better than those of system Y at a given confidence level, p. A comparison of the text-only and multimodal heat maps reveals that the multimodal approach results in a slightly higher proportion of significant differences between systems with fewer uncertainties. For example, at a confidence level of $p < 0.05$, the text-only method identifies relatively few significant differences, whereas the multimodal method demonstrates more distinct separations among systems. For example, the multimodal heat map shows that Online-G performs significantly better than JDExploreAcademy, LT22, Lan-Bridge, and Online-B, as confirmed by its higher multimodal average z-score. Similarly, for Online-A, both the text-only and multimodal evaluations lead to similar conclusions.

3.2 Self-replication Results

Figure 5 presents scatter plots comparing initial and self-replicated judgments from multimodal and text-only experiments. To assess the consistency of judgments collected using the multimodal (text and audio) approach, we conduct two independent runs and compute the Pearson correlation (r) between the initial and self-replicated results. In Figure 5 (a), self-replicated and original multimodal assessments are plotted on the x-axis and y-axis, respectively. Figure 5 (b) illustrates the correlation for text-only and multimodal scores, with the former on the x-axis and the latter on the y-axis. A high correlation would be indicated by points

System	text			official-text			multimodal		
	raw ave.	ave. z	order	raw ave.	ave. z	order	raw ave.	ave. z	order
PROMT	73.05	0.14	3	66.02	-0.127	10	69.63	0.19	1
Online-G	68.81	0.06	6	64.1	-0.057	4	68.76	0.19	2
Online-A	74.06	0.19	2	67.3	-0.070	5	74.61	0.18	3
Online-W	74.16	0.22	1	70.8	-0.023	2	70.74	0.14	4
Online-Y	72.16	0.13	5	66.5	-0.089	7	69.89	0.14	5
Online-B	71.49	0.14	4	66.3	-0.092	8	67.10	0.08	6
JDExploreAcademy	72.89	0.05	8	68.1	-0.038	3	67.85	0.07	7
LT22	74.36	0.05	7	64.8	-0.126	9	64.52	0.07	8
Lan-Bridge	68.29	0.05	9	68.8	0.004	1	71.24	0.04	9
Human-B	66.94	-0.12	10	68.3	-0.086	6	63.45	-0.16	10

Table 3: Comparison and system rankings based on scores from the text-only and multimodal (text + audio) setup for the German–English translation direction. Systems are ordered by their average standardized (z) scores. In cases of a tie in z scores, the average raw (raw ave.) score is used as a secondary ranking criterion.

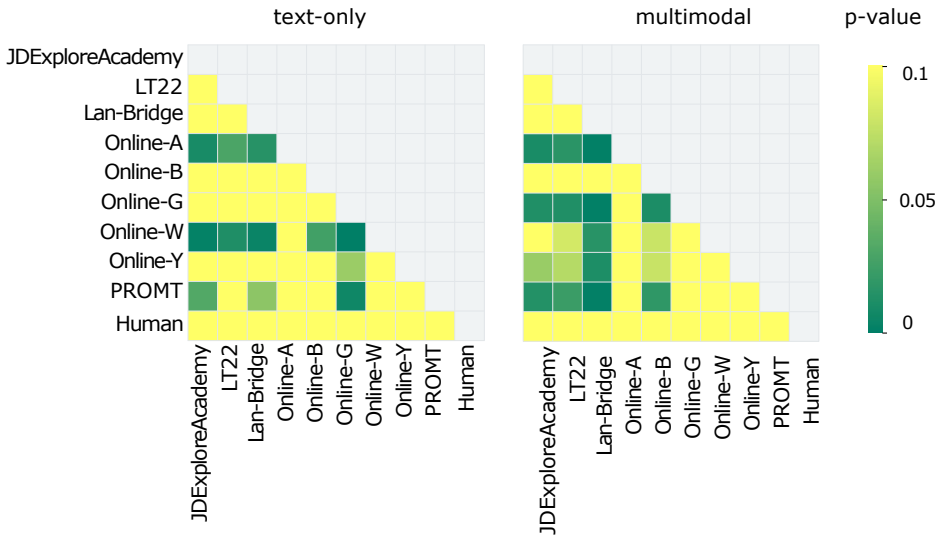
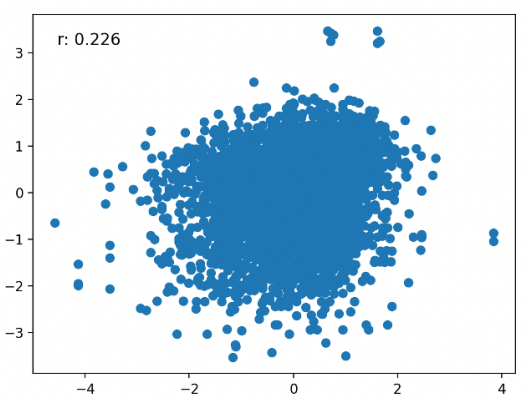


Figure 4: Significance test outcomes for text-only and multimodal method of human evaluation. Colored cells indicate that the scores of the row i system are significantly greater than those of the column j system.

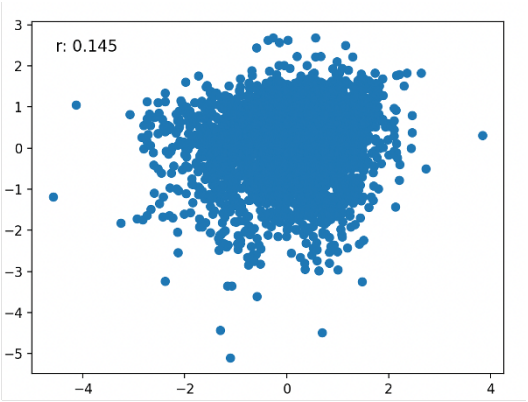
closely aligning with a straight line. While both approaches show a weak positive correlation, the multimodal setup exhibits a slightly higher correlation than the text-only setup, suggesting the potential of audio-based evaluation for providing reliable MT quality estimates.

3.3 Discussion

The results of significance and correlation tests suggest that speech can offer consistent and valuable insights into MT quality. We hypothesize that these differences arise because speech is a richer modality, capable of conveying prosodic and expressive features (Kraut et al., 1992). As a result, evaluators listening to translations were better able to detect major variations and unnatural-sounding MT outputs. Furthermore, feedback from evaluators at the end of the assessment indicated no challenges with audio-based evaluation. For instance, one worker stated that "all the audio samples were good," while another noted that "the audio is very clear". A general comment read, "the HIT is very unique, and there were no issues during the experiment". These preliminary results, obtained using non-expert crowd workers, suggest the effectiveness of speech in MT evaluation. However, further investigation may be required, and a more fine-grained approach—such as error annotation—could help better quantify the impact of audio in MT assessment.



(a) Self-replication (multimodal vs multimodal)



(b) text-only vs multimodal

Figure 5: Scatter plots illustrating the correlation (r) between different evaluation approaches. (a) shows the correlation between two runs of the multimodal approach, while (b) compares the results of the text-only and multimodal approaches.

4 Conclusion

We have presented our findings on integrating speech into human evaluation of MT quality. Our experiments with crowd workers compared MT system rankings from text-only and speech-enabled evaluation setups.

Despite using basic TTS tools and crowd workers, our study extends MT evaluation beyond traditional text-based assessments, highlighting the potential of audio-based evaluation to provide distinct insights into MT evaluation. As MT research increasingly embraces multimodal translation, our findings provide empirical evidence that text-only evaluation may be insufficient. Beyond MT, this approach could benefit fields such as automatic dubbing, AI-assisted interpreting, and multilingual speech interfaces. Overall, our study emphasizes the need for more holistic evaluation benchmarks that better reflect the complexity of real-world language use.

Our code[5] and collected human annotation data are freely available.

5 Limitations

We performed a general adequacy-based MT evaluation using crowd-workers on a limited dataset. Since the primary goal was to test whether audio-based judgments make a difference, we employed a simplified assessment approach and focused only on the German-English language pair. We acknowledge that even expert-based human judgments can be noisy, potentially leading to low inter-annotator agreement (IAA) if not carefully conducted. Nevertheless, we collected a large sample of annotations from crowd-workers to compare the two approaches. With intrinsic quality control measures, crowd-sourced annotations have been shown to achieve higher IAA (Graham et al., 2017). However, due to limited time and platform constraints, manual filtering of noisy annotations was not feasible, making it difficult to eliminate all low-quality responses. Furthermore, we did not calculate inter-annotator or intra-annotator agreement, as these aspects have already been extensively studied in the context of crowd-sourced direct assessment (Graham et al., 2013a, 2017).

Regarding the TTS model, we relied on a single vendor and did not conduct comparisons across different voices, speech rates, or providers. This restricts the generalizability of our findings, as results may vary with alternative TTS configurations. Nonetheless, we selected the model judged to have the most human-like voice based on a review of the vendor's technical documentation.

As MT quality evaluation has increasingly moved toward ESA-style (Kocmi et al., 2024) annotations (at least in WMT), audio-based evaluation could be integrated into such platforms to identify error spans by listening to translations and assigning final scores. However, accurately segmenting the audio for this purpose would pose a significant challenge.

6 Ethical Considerations

The human annotations collected via Amazon Mechanical Turk were fully anonymous. Anonymous users with MTurk accounts (meeting the defined criteria) submitted the tasks using numeric worker IDs. Although no personal identity information

[5] https://github.com/sami-haq99/Multimodal_Direct_Assessment

was revealed, we removed the worker IDs after payments were processed. Since the crowd-workers only needed to be native speakers and were not required to be expert translators, they were compensated according to the platform's minimum task rate.

In cases where crowd-workers did not meet the quality control criteria—such as submitting robotic responses or completing tasks in an unrealistically short time—we rejected their submissions and did not provide payment.

Acknowledgements

This work was conducted with the financial support of the Research Ireland Centre for Research Training in Digitally-Enhanced Reality (d-real) under Grant No. 18/CRT/6224, and Research Ireland Centre for Research Training in Artificial Intelligence under Grant No. 18/CRT/6223. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

The Authors also benefit from being members of the ADAPT SFI Research Centre at Dublin City University, funded by the Science Foundation Ireland under Grant Agreement No. 13/RC/2106_P2.

References

Farhad Akhbardeh, Arkady Arkhangorodsky, Magdalena Biesialska, Ondřej Bojar, Rajen Chatterjee, Vishrav Chaudhary, Marta R. Costa-jussa, Cristina España-Bonet, Angela Fan, Christian Federmann, Markus Freitag, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Leonie Harter, Kenneth Heafield, Christopher Homan, Matthias Huck, Kwabena Amponsah-Kaakyire, Jungo Kasai, Daniel Khashabi, Kevin Knight, Tom Kocmi, Philipp Koehn, Nicholas Lourie, Christof Monz, Makoto Morishita, Masaaki Nagata, Ajay Nagesh, Toshiaki Nakazawa, Matteo Negri, Santanu Pal, Allahsera Auguste Tapo, Marco Turchi, Valentin Vydrin, and Marcos Zampieri. 2021. Findings of the 2021 Conference on Machine Translation (WMT21). In *Proceedings of the Sixth Conference on Machine Translation*, pages 1–88, Online. Association for Computational Linguistics.

Loïc Barrault, Yu-An Chung, Mariano Cora Meglioli, David Dale, Ning Dong, Paul-Ambroise Duquenne, Hady Elsahar, Hongyu Gong, Kevin Heffernan, John Hoffman, et al. 2023. Seamlessm4t-massively multilingual & multimodal machine translation. *arXiv preprint arXiv:2308.11596*.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Shujian Huang, Matthias Huck, Philipp Koehn, Qun Liu, Varvara Logacheva, et al. 2017. Findings of the 2017 conference on machine translation (wmt17). Association for Computational Linguistics.

Ondrej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Varvara Logacheva, Christof Monz, et al. 2016. Findings of the 2016 conference on machine translation (wmt16). In *First conference on machine translation*, pages 131–198. Association for Computational Linguistics.

Chris Callison-Burch. 2009. Fast, cheap, and creative: Evaluating translation quality using amazon's mechanical turk. In *Proceedings of the 2009 conference on empirical methods in natural language processing*, pages 286–295.

Julia Cambre, Jessica Colnago, Jim Maddock, Janice Tsai, and Jofish Kaye. 2020. Choice of Voices: A Large-Scale Evaluation of Text-to-Speech Voice Quality for Long-Form Content. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13, Honolulu HI USA. ACM.

Sheila Castilho, Stephen Doherty, Federico Gaspari, and Joss Moorkens. 2018. Approaches to human and machine Translation Quality Assessment. In *Translation Quality Assessment: From Principles to Practice*, volume 1 of *Machine Translation: Technologies and Applications*, pages 9–38. Springer International Publishing.

Sheila Castilho, Joss Moorkens, Federico Gaspari, Rico Sennrich, Vilelmini Sosoni, Panayota Georgakopoulou, Pintu Lohar, Andy Way, Antonio Valerio Miceli-Barone, and Maria Gialama. 2017a. A comparative quality evaluation of PBSMT and NMT using professional translators. In *Proceedings of Machine Translation Summit XVI: Research Track*, pages 116–131, Nagoya Japan.

Sheila Castilho, Joss Moorkens, Federico Gaspari, Andy Way, Panayota Georgakopoulou, Maria Gialama, Vilelmini Sosoni, and Rico Sennrich. 2017b. Crowdsourcing for nmt evaluation: Professional translators versus the crowd. *Translating and the Computer*, 39.

Marina Fomicheva. 2017. *The Role of human reference translation in machine translation evaluation*. Ph.D. Thesis, Universitat Pompeu Fabra. Accepted: 2017-08-01T10:07:21Z Publication Title: TDX (Tesis Doctorals en Xarxa).

Markus Freitag, George Foster, David Grangier, Viresh Ratnakar, Qijun Tan, and Wolfgang Macherey. 2021. Experts, Errors, and Context: A Large-Scale Study of Human Evaluation for Machine Translation. *Transactions of the Association for Computational Linguistics*, 9:1460–1474. Place: Cambridge, MA Publisher: MIT Press.

Yvette Graham, Timothy Baldwin, Alistair Moffat, and Justin Zobel. 2013a. Continuous Measurement Scales in Human Evaluation of Machine Translation. In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse*, pages 33–41, Sofia, Bulgaria. Association for Computational Linguistics.

Yvette Graham, Timothy Baldwin, Alistair Moffat, and Justin Zobel. 2013b. Crowd-Sourcing of Human Judgments of Machine Translation Fluency. In *Proceedings of the Australasian Language Technology Association Workshop 2013 (ALTA 2013)*, pages 16–24, Brisbane, Australia.

Yvette Graham, Timothy Baldwin, Alistair Moffat, and Justin Zobel. 2017. Can machine translation systems be evaluated by the crowd alone. *Natural Language Engineering*, 23(1):3–30.

Yvette Graham, Nitika Mathur, and Timothy Baldwin. 2014. Randomized significance tests in machine translation. In *Proceedings of the Ninth Workshop on Statistical Machine Translation*, pages 266–274.

Tom Kocmi, Eleftherios Avramidis, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Markus Freitag, Thamme Gowda, Roman Grundkiewicz, Barry Haddow, Philipp Koehn, Benjamin Marie, Christof Monz, Makoto Morishita, Kenton Murray, Makoto Nagata, Toshiaki Nakazawa, Martin Popel, Maja Popović, and Mariya Shmatova. 2023. Findings of the 2023 Conference on Machine Translation (WMT23): LLMs Are Here but Not Quite There Yet. In *Proceedings of the Eighth Conference on Machine Translation*, pages 1–42, Singapore. Association for Computational Linguistics.

Tom Kocmi, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Thamme Gowda, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Rebecca Knowles, Philipp Koehn, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Michal Novák, Martin Popel, and Maja Popović. 2022. Findings of the 2022 Conference on Machine Translation (WMT22). In *Proceedings of the Seventh Conference on Machine Translation (WMT)*, pages 1–45, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

Tom Kocmi, Vilém Zouhar, Eleftherios Avramidis, Roman Grundkiewicz, Marzena Karpinska, Maja Popović, Mrinmaya Sachan, and Mariya Shmatova. 2024. Error span annotation: A balanced approach for human evaluation of machine translation. *arXiv preprint arXiv:2406.11580*.

Philipp Koehn and Christof Monz. 2006. Manual and automatic evaluation of machine translation between european languages. In *Proceedings of the workshop on statistical machine translation*, pages 102–121. Association for Computational Linguistics.

Robert Kraut, Jolene Galegher, Robert Fish, and Barbara Chalfonte. 1992. Task requirements and media choice in collaborative writing. *Human–Computer Interaction*, 7(4):375–407.

Samuel Läubli, Rico Sennrich, and Martin Volk. 2018. Has machine translation achieved human parity? a case for document-level evaluation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4791–4796, Brussels, Belgium. Association for Computational Linguistics.

Elizabeth Salesky, Julian Mäder, and Severin Klinger. 2021. Assessing evaluation metrics for speech-to-speech translation. In *2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 733–740. IEEE.

Lucia Specia, Zhenhao Li, Juan Pino, Vishrav Chaudhary, Francisco Guzmán, Graham Neubig, Nadir Durrani, Yonatan Belinkov, Philipp Koehn, Hassan Sajjad, Paul Michel, and Xian Li. 2020. Findings of the WMT 2020 shared task on machine translation robustness. In *Proceedings of the Fifth Conference on Machine Translation*, pages 76–91, Online. Association for Computational Linguistics.

Matthias Sperber, Ondřej Bojar, Barry Haddow, Dávid Javorský, Xutai Ma, Matteo Negri, Jan Niehues, Peter Polák, Elizabeth Salesky, Katsuhito Sudoh, and Marco Turchi. 2024. Evaluating the IWSLT2023 Speech Translation Tasks: Human Annotations, Automatic Metrics, and Segmentation. ArXiv:2406.03881.

Antonio Toral, Sheila Castilho, Ke Hu, and Andy Way. 2018. Attaining the Unattainable? Reassessing Claims of Human Parity in Neural Machine Translation. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 113–123, Brussels, Belgium. Association for Computational Linguistics.

David Vilar, Gregor Leusch, Hermann Ney, and Rafael E Banchs. 2007. Human evaluation of machine translation through binary system comparisons. In *Proceedings of the Second Workshop on Statistical Machine Translation*, pages 96–103.

A Head to Head Significance test Results

The following tables (4–6) show differences in average standardized human scores for a system in that column and the system in that row for the German–English language pair. We applied the Wilcoxon rank-sum test to measure the likelihood that such differences could occur simply by chance for text-only, text-audio and WTM22 official[6] experiments. In the following tables, * indicates statistical significance at $p < 0.05$, ** indicates statistical significance at $p < 0.01$, and *** indicates statistical significance at $p < 0.001$, according to the Wilcoxon rank-sum test.

Each table contains a final column showing the total number of judgments used to calculate the results. The number for the official results is much greater than in our experiments; therefore, a direct comparison should only be made between the text-only and multimodal scores.

	HUMAN	JDExploreAcademy	LT22	Lan-Bridge	Online-A	Online-B	Online-G	Online-W	Online-Y	PROMT	No. of Judgments
HUMAN	–	-0.19	-0.20	-0.20	-0.31	-0.28	-0.19	-0.38	-0.27	-0.31	371
JDExploreAcademy	0.19**	–	-0.01	-0.01	-0.13	-0.09	0	-0.19	-0.08	-0.12	385
LT22	0.20***	0.01	–	0	-0.12	-0.08	0.01	-0.18	-0.07	-0.11	475
Lan-Bridge	0.20**	0.01	0	–	-0.12	-0.09	0.01	-0.18	-0.07	-0.11	399
Online-A	0.31***	0.13**	0.12*	0.12*	–	0.03	0.13**	-0.07	0.04	0.01	451
Online-B	0.28***	0.09	0.08	0.09	-0.03	–	0.09	-0.10	0.01	-0.02	427
Online-G	0.19**	0	-0.01	-0.01	-0.13	-0.09	–	-0.19	-0.08	-0.12	385
Online-W	0.38***	0.19**	0.18*	0.18**	0.07	0.10*	0.19***	–	0.11*	0.08	433
Online-Y	0.27***	0.08	0.07	0.07	-0.04	-0.01	0.08	-0.11	–	-0.03	417
PROMT	0.31***	0.12*	0.11	0.11	-0.01	0.02	0.12**	-0.08	0.03	–	349

Table 4: Head to Head comparison matrix of text-only judgments with significance levels and number of judgments.

[6]For official results, we used the human evaluation data provided by WMT22 organisers at: https://github.com/wmt-conference/wmt22-news-systems/tree/main/humaneval/DA.

	HUMAN	JDExploreAcademy	LT22	Lan-Bridge	Online-A	Online-B	Online-G	Online-W	Online-Y	PROMT	No. of Judgments
HUMAN	–	-0.24	-0.26	-0.21	-0.36	-0.24	-0.39	-0.33	-0.32	-0.35	445
JDExploreAcademy	0.24***	–	-0.02	0.04	-0.12	0	-0.15	-0.09	-0.07	-0.11	426
LT22	0.26***	0.02	–	0.06	-0.10	0.02	-0.13	-0.07	-0.05	-0.09	470
Lan-Bridge	0.21**	-0.04	-0.06	–	-0.15	-0.04	-0.18	-0.13	-0.11	-0.15	514
Online-A	0.36***	0.12*	0.10*	0.15**	–	0.12*	-0.03	0.02	0.04	0	435
Online-B	0.24***	0	-0.02	0.04	-0.12	–	-0.14	-0.09	-0.07	-0.11	499
Online-G	0.39***	0.15*	0.13*	0.18***	0.03	0.14*	–	0.05	0.07	0.03	487
Online-W	0.33***	0.09	0.07	0.13*	-0.02	0.09	-0.05	–	0.02	-0.02	464
Online-Y	0.32***	0.07	0.05	0.11*	-0.04	0.07	-0.07	-0.02	–	-0.04	394
PROMT	0.35***	0.11*	0.09*	0.15**	0	0.11*	-0.03	0.02	0.04	–	549

Table 5: Head-to-head comparison matrix of multimodal annotations with significance levels and number of judgments.

	HUMAN-B	JDExploreAcademy	LT22	Lan-Bridge	Online-A	Online-B	Online-G	Online-W	Online-Y	PROMT	No. of Judgments
HUMAN-B	–	-0.04	0.05***	-0.07	-0.01	0.01	-0.02	-0.05	0.03*	0.07**	2100
JDExploreAcademy	0.04	–	0.09***	-0.03	0.03	0.05*	0.02	-0.01	0.07**	0.11***	2100
LT22	-0.05	-0.09	–	-0.12	-0.06	-0.04	-0.07	-0.10	-0.03	0.02	2100
Lan-Bridge	0.07**	0.03*	0.12***	–	0.06***	0.08***	0.05**	0.02*	0.09***	0.14***	2100
Online-A	0.01	-0.03	0.06**	-0.06	–	0.02	-0.01	-0.04	0.04	0.08**	2100
Online-B	-0.01	-0.05	0.04*	-0.08	-0.02	–	-0.03	-0.06	0.02	0.06*	2100
Online-G	0.02	-0.02	0.07***	-0.05	0.01	0.03	–	-0.03	0.04*	0.09**	2100
Online-W	0.05	0.01	0.10***	-0.02	0.04	0.06*	0.03	–	0.07***	0.12***	2100
Online-Y	-0.03	-0.07	0.03	-0.09	-0.04	-0.02	-0.04	-0.07	–	0.05	2100
PROMT	-0.07	-0.11	-0.02	-0.14	-0.08	-0.06	-0.09	-0.12	-0.05	–	2100

Table 6: Head-to-head comparison matrix of WMT22 official rankings with significance levels and number of judgments.