Investigation of an automatic speech recognition software for numbers trigger management in remote simultaneous interpretation from English to Thai.

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An Independent Study Submitted in Partial Fulfillment of the Requirements
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ประสิทธิภาพของการใช้โปรแกรมเทคโนโลยีรู้จำเสียงพูดสำหรับการจัดการกับปัญหาด้านตัวเลข
ในการล่ามพูดพร้อมทางไกลจากภาษาอังกฤษเป็นภาษาไทย

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Investigation of an automatic speech recognition software for numbers trigger management in remote simultaneous interpretation from English to Thai.

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Abstract

This research aims to prove the benefits of automatic speech recognition (ASR) software for assisting in numbers interpreting from English to Thai in the environment setup of remote simultaneous interpretation (RSI). In this research, two source scripts have been developed and recorded as voice audios which have the same speaker, speed, frequencies and types of number as well as similar contexts. An experiment was conducted with five interpreting students via Zoom to compare the accuracy rate in number renditions between the conventional coping techniques such as ready-made number list or note-taking and the computer-assisted interpreting (CAI) tools such as ASR. The study shows higher accuracy rate in the second speeches where participants were allowed to use ASR. Answers gathered from one-on-one interview from participants as a way to explore users' experiences have revealed key benefits, some distractions as drawbacks and future improvement of the ASR itself and practices for participants to better integrate this tool into their workflow.

Keywords: automatic speech recognition, computer-assisted interpretating, number interpreting, remote simultaneous interpretation

Introduction

Simultaneous interpretation (SI) is a tremendously complex process in its nature and influenced by what is called problems triggers. The triggers are classified into four categories related to the speakers, the message, the interpreters and technical problems (Mankauskiene, 2016). One of the most challenging issues which is well known among interpreters occurring in the message category is numbers as they are highly informative and have low predictability (Braun & Clariri, 1996). Interpreters can have difficulties encountering too large or dense numbers. Every unit represents a particular meaning, as a result, interpreters cannot use techniques such as reformulation or paraphrasing. An experiment was conducted to explore the existing theory that numbers trigger is disruptive element not limited to certain languages. It remains disruptive in different language pairs when performing SI (Pinochi, 2009). From the experiment, the error rate of participants who incorrectly interpreted numbers from German to Italian and English to Italian are 40.6% and 41.2% confirming that numbers problem is language-independent.

Several coping techniques have been studied in order to assist in number management such as note-taking, ready-made list and automatic speech recognition (ASR). Nowadays, ASR has been developed to the stage where integration with interpreters' workflow is possible. A study by Fantinuoli et al. in 2017 has demonstrated ASR with simultaneous interpretation in the booth. However, the working condition in the booth and remote settings are not quite similar. In the booth, interpreters are shielded from outside disturbance as well as access to the technicians. In remote simultaneous interpretation (RSI), interpreters are forced to bear the stress from technicalities and absence of a partner at the spot. Having ASR to help in numbers interpreting in RSI could lead to a great decrease in stress and cognitive load. This study, therefore, aims to prove that ASR is beneficial in numbers interpreting in RSI and to explore the users' experiences.

Coping technique for numbers

Common practice for dealing with numbers is note-taking during the assignment. However, such action could require some effort resulting in lower concentration and higher cognitive load. Failure to interpret numbers correctly includes omission or approximation. Writing down numbers may not be effective as it involves adding two more tasks (writing and reading) to an already divided attention between listening and speaking, which could lead to interpreting errors. Another practice is having the boothmate jot down the figures, which definitely requires less effort (Mazza, 2001). Another method, proposed by Tepintrapirak (2014), involves preparing a list of numbers in advance to assist in multi-digit numbers interpreting. The list contains numbers starting from one hundred to one hundred billion, written as numerals and spelled out in words in both English and Thai, as shown in Figure 1.

Participants in the experiment reported that the list was proven to be beneficial when used together with note-taking for numbers that are more than five digits. However, it was also reported that the list could somewhat be a distraction due to lack of what is called automization or internalization.

One HUNDRED	หนึ่งร้อย	100
TEN hundred (one thousand)	หนึ่งพัน	1,000
Twenty hundred	สองพัน	2,000
One THOUSAND	หนึ่งพัน	1,000
TEN thousand	หนึ่งหมื่น	10,000
Twenty thousand	สองหมื่น	20,000
One HUNDRED THOUSAND	หนึ่งแสน	100,000
One MILLION	หนึ่งล้าน	1,000,000
TEN million	สิบล้าน	10,000,000
One HUNDRED MILLION	หนึ่งร้อยล้าน	100,000,000
One BILLION	หนึ่งพันล้าน	1,000,000,000
TEN billion	หนึ่งหมื่นล้าน	10,000,000,000
One HUNDRED BILLION	หนึ่งแสนล้าน	100,000,000,000

Figure 1 Ready-made number list by Tepintrapirak (2014)

Automatic Speech Recognition (ASR) or Voice to Text is the process of converting human speech signals to a sequence of words by means of a computer program (Jurafsky & Martin, 2009). ASR has been developed for more than thirty years but it had not been integrated in SI until very recently. In the past, several problems arose from ASR such as long reaction time, inability to cope with human's disfluency and the fact that there was a malfunction pulling up the correct technical terms from its database (Fantinuoli, 2017). With the advancement in deep learning and neural network for Artificial Intelligence in present days, ASR has been considerably improved to be helpful for interpreters. It may face some resistance from the community as it is relatively new compared to other computer-assisted interpretation (CAI) tools such as terminology management. Speech-to-text converters can be found in basic tools such as dictate function in Microsoft Word or voice typing in GoogleDoc. There was an experiment of the prototype of ASR implemented within the framework of InterpretBank which was tested for the ability to assist interpreter in a booth. The results showed that it could correctly transcribe all of numbers and technical terms concerning renewable energy. However, it failed under certain circumstances such as non-native accent and unknown words (Fantinuoli, 2017).

Methodology

In order to investigate how helpful ASR is to interpreters when coping with numbers, an experiment was carried out with five participants who were students in the interpretation program who had received formal training in interpretation and also on note-takings for two years. They were familiar with ASR software Otter as they had the opportunity to use it in class. This provides familiarity to the users and create a higher possibility to access the benefits of ASR integration. The participants were also interviewed at the end of the experiment to gather feedbacks regarding users' experiences of the ASR in the workflow.

The Experiment

Participants were asked to perform RSI in the experiment which was conducted via Zoom. In the experiment, there were two source audios. The speeches were written by the researcher to ensure their comparability. Both speeches are 10-minute long and have the same number types which are classified into four types. The first one is dates and the second one is whole number that is less than ten thousand followed by the third one which is 10,000 to 1 billion and the last one is more than 1 billion. They also shared the same speaker, speed, number frequency (numbers/min) and total numbers for the full videos (total numbers/10mins). Each minute contains the four types of numbers (one number per one type) which amounts to 40 numbers in 10 minutes. Then, the source scripts were converted into audio by Microsoft's text-to-speech generator which offered natural-sounding voice and were recorded to be used in the experiment.

For the first speech, only note-taking and ready-made list were allowed for participants to use as shown in Figure 1. In the second one, ASR was used along with the conventional coping techniques in order to reflect the realistic practice of interpreters. The ASR software, Otter, is available on its website. The screen of the main device is for Otter transcription is shown in Figure 2.

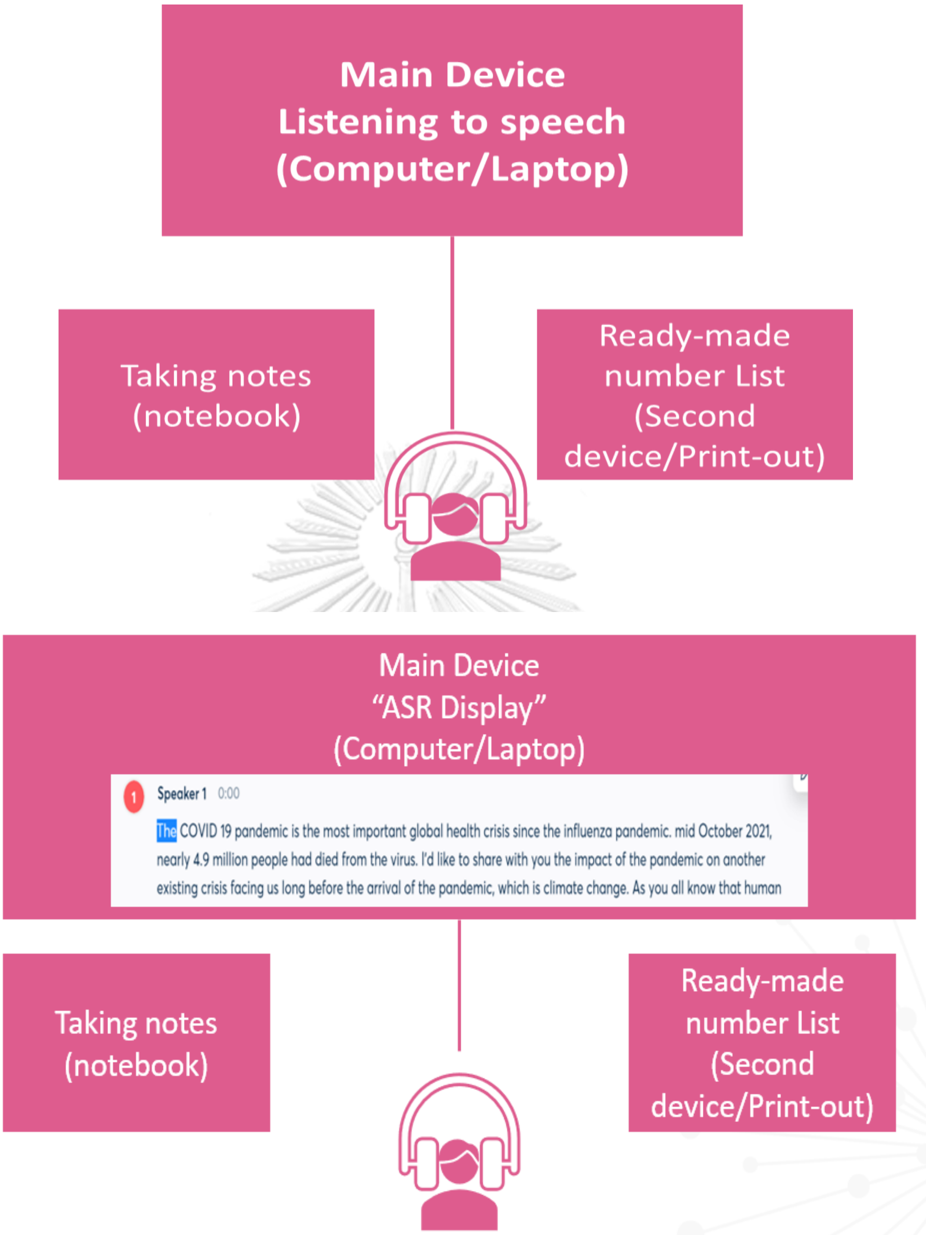


Figure 3 Second speech experimental setup

All of the ASR screen and audio files were shared by the researcher's computer. All participants were given five minute per speech to study the context and the provided relevant technical terms prior to the experiment. The participants were informed of the rules such as using only the number coping techniques designated in this research. The renditions were recorded.

The errors analysis and accuracy rate calculation

Number rendition accuracy assessment

The recordings of participants' renditions were transcribed and marked for errors according to the criteria adapted from Braun and Clarici (1996)'s. The original criteria consist of omission, transposition, approximation, syntactic, lexical and phonological mistakes. In this study, three more error types were added, namely, indefinite number, substitution and incomplete dates and each was given the multiplying factor to reflect the severity of mistakes. Then, each error made by participants was multiplied by the factor to yield weighted scores. Examples of how number renditions were marked are as follows:

- Omission: the source said 25 people and participants miss the number 25 entirely.
- Addition: Numbers are added when there's none in that segment of the source speech.
- Substitution: For example, the source said 25 people and participants interpreted as 60.
- Lexical mistake: the order of magnitude of the number is correct, but some of its components have been changed. For example, the source said 35 but interpreted as 39.
- Approximation: Numbers are estimated in the magnitude order rather than every digit. For example, the speaker said 84,150,000 and participants interpret as 84,000,000.
- Transposition: All components are interpreted correctly but their order was changed such as 321 rendered as 312.
- Syntactic mistake: The right components are present in the rendition but in the wrong order of magnitude such as 57 rendered as 570.
- Phonological mistake: The speaker said 18 but participants interpret as 80 because of the similar pronunciation.
- Indefinite numbers: numbers are replaced with phrases such as "large amount", "a lot of", etc.
- Incomplete dates: Participants interpreted only months or years but not dates such as 22 May 2022 rendered as May 2022.

The errors in number renditions made by participants are weighted by the factors displayed in Table 1.

Type of error	Factor
Omission	1.5
Addition	1.5
Syntactic	1.5
Substitution	1.5
Lexical	1
Phonological	1
Transposition	1
Indefinite numbers	1
Approximation	0.5
Incomplete dates	0.5

Table 1 Factors for weighted scores of errors in number renditions made by participants

Omission, addition, substitution and syntactic mistakes were given a factor of 1.5 which is the highest factor in order to reflect the severity of the misinterpretation that could be damaging to interpreters' reliability. For example, the source speech talked about providing food for 570 guests. If the rendition was 57, that would heavily affect the outcome of the event and this error was syntactic mistake.

Indefinite number, lexical, phonological and transposition mistakes were given a factor of 1 due to the lesser negative impact resulting from the rendition. For lexical mistake, if the source speech was 35 and was misinterpreted as 39, the order of magnitude remained correct and the rendition was very close to the original number. Therefore, this limited negative impact to certain level.

Incomplete dates and approximation were given a factor of 0.5 which could be considered as minor mistakes. Interpreters might miss the dates but interpreted months and years. Approximation could also be viewed rather as a coping method. However, this research was designed to differentiate the scores between participants who made mistake by approximation and those who could give correct rendition. Hence, a factor of 0.5 for approximation.

Accuracy rate calculation

After obtaining the weighted errors of participants, the weighted errors were converted to accuracy scores and then to accuracy rate as demonstrated in one example below.

Participant 1 had a weighted error score of 38.5. The highest possible error score is 60 on the basis of 40 numbers x 1.5 highest error severity factor. Therefore, Participant 1 interpreted numbers correctly for a score of 21.5. (Highest error score of 60 minus 38.5 error score is equal to an accuracy score of 21.5.) His accuracy rate was calculated by multiplying by 100 the quotient from the accuracy score (21.5) and the maximum score (60). The result was 35.83%.

The Users' Experiences

Immediately after the completion of the simultaneous interpretation, participants were asked to give an one-on-one interview in order to gather users' experiences. Each participant was given ten minutes during the interview session. Participants were asked not to share feedback among one another as it might have some influence over their own opinion. The questions can be found in the appendix section. The answers were recorded. The feedbacks were used to draw conclusion regarding cognitive load arising from ASR, ASR benefits and the difficulty of the source speeches.

Results and Discussions

The most occurring errors in number renditions

Errors by types of number

There were four types of numbers in the speeches: dates, less than 10,000, 10,000 – 1 billion and more than 1 billion. In each minute, there were four types of such numbers for both speeches. Numbers more than 1 billion caused the most problem in both speeches to all participants as anticipated due to the complexity and low predictability of the numbers. For example, no participants interpreted 3.4 trillion US dollars correctly. The second most misinterpreted number type was numbers between 10,000 – 1 billion. Dates caused the least errors because participants usually said the correct months and years but skipped the dates.

Errors by categories

Omission was the type of error that occurred the most in the number renditions for both speeches. In the second speech with the use of ASR, almost half of the total errors were omission. From the analysis of the rendition, it was found that participants chose to omit numbers when they could not keep up with the speakers and many numbers appeared in close segments. Omission usually happened with multi-digit numbers such as millions, billions and trillions. In the first speech, participants did not attempt to convey the number using approximation or indefinite number. With ASR in the second speech, participants chose the approximation technique to cope with the numbers as they could now saw the transcription. However, omission remained the top errors.

It is worth noting that substitution was second most occurring error that participants made in the first speech. All participants produced this type of error which was in contrast with the rendition in the second speech as none of the participants made any substitution.

Apart from omission and approximation, syntactic errors are in the third of the top errors. Participants heard the numbers but seemed to be confused with the multi-digit numbers and therefore rendered the wrong digits. For example, the original

200.5 billion was interpreted as 2 million. Another example is wrong units, the original 5,444,000,000 gram was interpreted as 5 billion ton or 5 billion unit.

Indefinite numbers were in the fourth. This category includes using the quantifier words such as "increasing number", "high amount", "many tons", "a lot of", etc. However, the errors in this category was quite low as participants tried using approximation more than rendering indefinite numbers which do not contain much information or they would rather omitted the numbers entirely in case they were not able to catch up with the speed.

Lexical and phonological categories almost never occurred in the renditions of both speeches. Incomplete dates in the Speech 1 was higher than Speech 2 as participants skipped the dates and rendered only months and years.

Furthermore, participants misinterpreted the ideas of the source video when they were faced with multiple digit numbers or segments that were dense in numbers. This might have resulted from the use of cognitive capacity to focus on numbers and it might have compromised the capacity to process the ideas.

The accuracy rate of number renditions

The errors in number rendition made by participants in both speeches are calculated into accuracy rate using weighted error scores which were the result of the sum of each error type multiplied by its corresponding factor.

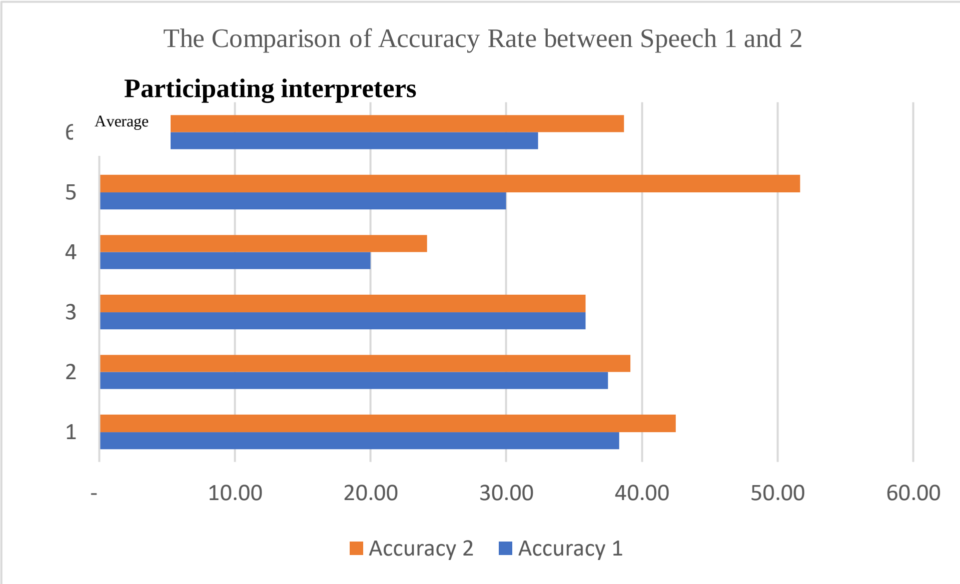
Analysis from the experiment shows that ASR technology of the software Otter has a potential to increase the accuracy of numbers interpreting in RSI for most of the participants (4 out of 5) which was in line with the feedback received from the interview. The evidence is displayed in Table 2.

Accuracy/Interpreters	1	2	3	4	5	Average
Weighted Error Scores 1	37	37.5	38.5	48	42	40.6
Weighted Error Scores 2	34.5	36.5	38.5	45.5	29	36.8
Accuracy Rate 1	38.3	37.5	35.8	20	30	32.3
Accuracy Rate 2	42.5	39.2	35.8	24.2	51.7	38.7

Table 2 Comparison of scores and accuracy rate of participants between RSI without ASR and with ASR

The total sets of numbers appearing in each speech is 40. However, the scores are weighted in order to reflect the severity of misinterpretation of numbers when coping techniques are used. Participants 1,2,4 and 5 have higher accuracy rate in Speech 2 with ASR than Speech 1 by the average of six percentage point. Participant 5 benefits the most from the ASR by an improved percentage point of 21 while others benefit by only 3-5 percentage point. Orange bar in Figure 3 indicates the accuracy in Speech 2 with ASR while blue one indicates the Speech 1. The differences can be seen better with Figure 4.

Figure 4 The Comparison of Accuracy rate between Speech 1 and 2



The numbers in the types of more than 1 billion and 10,000 – 1 billion were managed better due to the fact that those numbers were transcribed and could be read instantly by participants which led to a higher accuracy in Speech 2. Participants used approximation or even produced complete rendition.

All participants were Thai native speakers except for Participant 3 who was an English native speaker with Thai as his second language. ASR could benefit him the least from all five participants possibly because he was the only one interpreting into his second language and was struggling interpreting into a language he lacked the native proficiency.

The users' feedbacks obtained from the interviews

<u>The difficulty of the source videos excluding the number contents.</u>

Immediately after the experiment, each of the participant was asked to give a one-on-one interview to gather the most feedback without the influence of others' opinions. All participant agreed that ASR can help cope with numbers especially the ones that are more than one million due to the fact that those numbers were written out accurately and promptly enough to read. Three questions were asked to explore the experiences. The first one was to see the difficulty of the content of the source speeches excluding the numbers. All participants agreed that they were familiar with the terms and the ideas which were not difficult and resembled the actual interpretation work. There were no technical terms that they had never heard of. The speaker talked fast and appeared to be reading off some scripts which explains the density of the information. Participant 1 said “Over 80% of the ideas and terms were something that I have some experiences with.”

The experiences of using ASR in numbers interpreting in RSI

Participant 2 said “ASR was beneficial when I missed some numbers and I could just read off the transcription especially with dates and multi-digit numbers. However, I’m a slow reader and it delayed me when maeny numbers showed up in the transcription and I could not follow the speed. For billions and trillions, I stopped looking at the transcription as I could not keep up with the numbers.”

Participant 5 said “ASR absolutely helps when there are multi-digit nmumbers as I do not have to take notes and I can see them directly from the transcription. I find it very helpful in the workflow of interpreter” Participant 5 had the highest accuracy rate in the second speech which could result from his own ability to properly balance between reading and listening and the fact that he could read quite fast compared to other participants.

The cognitive load when using ASR in numbers interpreting in RSI

All agreed that ASR enhanced the process of numbers interpreting by writing out the multi-digit numbers with fast and accurate transcription. Cognitive burden was reduced by reading the numbers off from the screen instead of taking notes or memorizing. However, it was also increased when there was high density of numbers in the same segment, which required higher reading concentration and caused more distraction. This influence was shown in Participant 3 because his accuracy rate was the same in both speeches. The signs of cognitive overload, such as pauses, stuttering, etc., were found during the second speech in all participants when facing with dense number content or multi-digit numbers. Participants felt that the effort to read the transcription became so overwhelming from time to time that they could not manage their effort to deal with listening and processing.

There were some interesting feedbacks for ASR improvement from participants. Participant 1 said “For multi-digit numbers such as 780.7 million, the ASR transcription is 780 point 7 million. I feel it would be better if the transcription was 780,700,000 so that I know right away what the value is.”

Even though the participants’ feedbacks from interviews reveal the distraction caused by ASR which they thought would greatly reduce accuracy rate in the second speech, the analysis of accuracy rate from their rendition suggested otherwise. The accuracy rate of almost all participants increased in the second speech. Only Participant 3 had the same accuracy rate despite the fact that he found ASR to be helpful and it reduced cognitive overload. This is one example of the contrast between the perception of participants and the actual results. This could result from lack of familiarity with number-dense content. If participants had been exposed to frequent numbers-dense content using ASR, they might have balanced the attention of when to read the transcription and when to stop or focus more on listening.

Conclusion

Previous research suggested that despite using conventional coping technique such as note-taking, numbers remain one of the problem triggers in interpretation especially multi-digit numbers. This study attempted to prove the benefits of ASR technology to simultaneous interpreting in a remote setting.

The results were clear that the accuracy rate of numbers rendition with ASR was higher than that without ASR. Participants produced accurate renditions or used approximation technique more than the rendition without ASR. Ready-made number list and taking notes were rarely used by participants in both speeches as they were deemed not very helpful and became too much of a distraction. On the other hand, ASR was also a distraction according to the interview. Suggestions for improvement were made. For example, the transcription should be changed from 780 point 7 billion to 780,800,000 for easier reading. For interpreters, more practices are encouraged in order to better balance between when to read the transcription and when to stop if it becomes too much of a distraction. In other words, more practices are required to create the balance of using ASR as a support instead of a replacement of listening or overreliance. The positive impact of using ASR in simultaneous interpretation of this research aligns with the other related work in a different language pair (Pisani & Fantinuoli, 2021).

Even though this result cannot represent the majority of professional interpreters on a bigger scale, it certainly sheds some light on the ASR integration in interpreters' workflow for remote settings with evidence and the potential to be developed to fully assist interpreters. Greater improvement on number rendition could be expected when conducting larger participant sample sizes.

References

Braun, S. & Clarici, A. (1996). Inaccuracy for numerals in simultaneous interpretation: neurolinguistic and neuropsychological perspectives, *The Interpreters' Newsletter,* 7, 85-102.

Fantinuoli, C. (2017). *Speech recognition in the interpreter workstation*. In Proceedings of the Translating and the Computer 39 Conference, 349–352. London: Editions Tradulex.

Jurafsky, D. & Martin, J. (2009). *Speech and language processing: an introduction to natural language processing, computational linguistics, and speech recognition* (2nd ed.). *Prentice Hall series in artificial intelligence*. New Jersey, Pearson Prentice Hall.

Kalina, S. (2005). Quality Assurance for Interpreting Processes. *Meta: Journal des traducteurs*, *50*(2):768.

Mankauskienė, D. (2016). Problem trigger classification and its applications for empirical research. *Procedia - Social and Behavioral Sciences*, *231*, 143–148. https://doi.org/10.1016/j.sbspro.2016.09.083

Mazza, C. (2001). Numbers in Simultaneous Interpretation, *The Interpreters' Newsletter*, *11*, 87-104.

Pastor, G. (2017). *VIP: Voice-Text Integrated System for Interpreters*. Esteves-Ferreira, J et al. (Editors). In Proceedings of the Translating and the Computer 39 Conference, 367–377. London: Editions Tradulex.

Pinochi, D. (2009). *Simultaneous Interpretation of Numbers: Comparing German and English to*

Italian. An Speechal Study. *The Interpreters' Newsletter 14*, EUT Edizioni Università di Trieste.

Pisani, E., & Fantinuoli, C. (2021). *Measuring the Impact of Automatic Speech Recognition on Number Rendition in Simultaneous Interpreting*. *Empirical Studies of Translation and Interpreting* (pp.181-197). New York, Routledge.

Tepintrapirak, P. (2014). *Coping with Numbers in English-to-Thai Simultaneous Interpretation* [Master Degree's Independent Study]. Chulalongkorn University.

Yu, D. & Li, D. (2015). *Automatic speech recognition: a deep learning approach*. London, Springer.

Appendix

Interview Questions

Questions	Answers
How was the difficulty of the	

content excluding numbers content of the source videos?	
How was your experience in using the ASR for numbers interpreting in RSI?	
How was your cognitive load when using ASR in numbers interpreting in RSI?	

Ready-made number list adapted from Tepintrapirak, 2014.

10,000	10 thousand	หนึ่งหมื่น
100,000	100 thousand	หนึ่งแสน
1,000,000	1 million	หนึ่งล้าน
10,000,000	10 million	สิบล้าน
100,000,000	100 million	หนึ่งร้อยล้าน
1,000,000,000	1 billion	หนึ่งพันล้าน
10,000,000,000	10 billion	หนึ่งหมื่นล้าน
100,000,000,000	100 billion	หนึ่งแสนล้าน
1,000,000,000,000	1 trillion	หนึ่งล้านล้าน

List of numbers appearing in Speech 1 and 2

No.	Speech 1	Speech 2
1	192	mid-October 2021
2	1.6 billion	nearly 4.9 million people
3	870 million	75%
4	27January 2020	11.653 billion kilograms
5	March 4th 2022	16^{th} September 2021
6	4,454,000	200.5 billion ton
7	10 years	at least 25.2 million
8	52 billion	1.5° Celsius
9	28 April 2021	36.64 billion tons
10	24,500,00	September the 19^{th} 2019
11	4927	780.7 million ton
12	3.4 trillion US dollars	18.85%
13	6,755,000,500 schools	second month of 2020

14	June 22nd 2022	5,215.6 million metric tons
15	55,675 schools	526.1 million tons
16	5,765	10.26%
17	4,600,500,500 students	22nd in 2022
18	80,000 students	182,820,000 million ton
19	1800 dollars	55,858,000 ton
20	59.20%	15.80%
21	2019	17,670,000 million tons
22	21 million	75.70%
23	454 billion	177.83 billon ton
24	September 2020	2065
25	37.6 million	88.7 billion ton
26	35%	18.45%
27	157.54 million	18,180,800 million ton
28	5.6 billion	1987
29	July 24th 2021	1586 years
30	52,443,000 ton	12 July 2022
31	5,453	127.52 million
32	21 August 2021	198.55 billion dollars
33	5.2 billion	1958
34	525,545,000 ton	19.32 billion ton
35	259,400 ton	54.29%
36	PM2.5	192,393,255 million ton
37	435,143	794.76 billion ton
38	January 20th 2020	77.12%
39	26%	182,382,300 ton
40	5,444,000,000 grams	2050

REFERENCES

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DATE OF BIRTH	27 March 1997
PLACE OF BIRTH	Loei, Thailand
INSTITUTIONS ATTENDED	Mahidol University
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