

TECHNOLOGY AND ARTIFICIAL INTELLIGENCE IN SIMULTANEOUS INTERPRETING: A MULTIDISCIPLINARY APPROACH

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ABSTRACT

The insertion of technology in simultaneous interpreting has recently raised much controversy among, inter alia, practitioners, researchers and end-service users. Precipitous developments especially in Artificial Intelligence can affect not only the façade but also the core of the profession. The world's feverish propaganda for the inevitability of technological change together with the epidemic panic from machine IQ to reach 10,000 (while Einstein's was 150) have given impetus for this research to investigate the past and present of using technology in simultaneous interpreting and explore the challenges and opportunities for collaboration between the human and the machine from a multidisciplinary perspective. It is a qualitative study which uses description, comparison, and interpretation as research methods to analyse how the human and the machine react to the process of simultaneous interpreting and assess their performance and role. It concludes that there is not much prospect that machines can replace the human interpreter at least in the near future, and that technological developments should be directed to serve the field and human interpreters in a constructive way.

Keywords: Simultaneous Interpreting; Machine Interpreting; Machine Translation; Artificial Intelligence

LIST OF ABBREVIATIONS

ANN Artificial Neural Networks
AI Artificial Intelligence
CAI Computer-Assisted Interpreting
CAT Computer-Assisted Translation
EM Efforts Model
GM Gravitational Model
MI Machine Interpreting
ML Machine Learning
MT Machine Translation
NLP Natural Language Processing
NN Neural Networks
RI Remote Interpreting
SI Simultaneous Interpreting
SR Speech Recognition
TM Translation Memory

التكنولوجيا والذكاء الاصطناعي في الترجمة الفورية: منهج متعدد العلوم

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مستخلص

أثار إدخال التكنولوجيا في الترجمة الشفهية في الآونة الأخيرة الكثير من الجدل بين من يمارسون الترجمة الفورية والباحثين ومستخدمي تلك الخدمة بشكلها النهائي، ضمن آخرين. ويمكن أن تؤثر التطورات المتسارعة خاصة في مجال الذكاء الاصطناعي ليس فقط على واجهات أو شكل مهنة الترجمة الفورية بل أيضاً على جوهرها. لعل الدعاية العالمية المحمومة لحنمية التغيير التكنولوجي جنباً إلى جنب مع الذعر المتفشى من إمكانية وصول معدل ذكاء الآلة إلى ١٠٠٠٠ (بينما وصل معدل ذكاء أينشتاين إلى فقط ١٥٠)، قد أعطيا زخماً لهذا البحث لدراسة وتحليل استخدام التكنولوجيا في الترجمة الفورية في الماضي والحاضر واستكشاف التحديات و فرص التعاون بين الإنسان والآلة من منظور متعدد العلوم. فهي دراسة نوعية تستخدم الوصف والمقارنة والتفسير كطرق بحث لتحليل كيفية تفاعل الإنسان والآلة مع عملية الترجمة الفورية وتقييم أدائهم ودورهم. ويخلص هذا البحث إلى أنه لا يوجد احتمال كبير بأن الآلة يمكن أن تحل محل المترجم البشري، على الأقل في المدى المنظور، وأن التطورات التكنولوجية يجب أن توجه لخدمة المجال ذاته وخدمة المترجمين الفوريين البشريين بطريقة بناءة.

الكلمات المفتاحية: الترجمة الفورية؛ الترجمة الشفهية الآلية؛ الترجمة الآلية؛ الذكاء الاصطناعي

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1. INTRODUCTION

There is urgent need for a research effort directed to anticipating future trends, enabling the future generations of interpreters to prepare for the disruptive changes caused by digital technologies. (Fantinuoli 2019:13-14)

There is much controversy about the insertion of technology in simultaneous interpreting (SI), among, inter alia, practitioners, trainees, researchers, academics, and end-service users themselves. On the one hand, the pros of using technology in SI include cutting costs, speed of finding relevant information prior to the event, and the easiness and availability of the service. Ziegler and Gigliobianco (2018) argue that technology helps reduce interpreters' travel and accommodation expenses and increases availability. Fantonuoli (2019:3-5) claims that there are three drives to turn to technology in SI: the anthropological drive (through relieving professionals from some of their work burdens); the economic drive (related to productivity, optimization and reduction of costs); and the socio-psychological factor (where a technology-obsessed society pushes interpreters to accept change).

On the other hand, some people oppose using technology in SI. Technology has negatively influenced the interpreter's remuneration. The quality of machine translation (MT) is also questioned. It contributes to deprofessionalisation, de-skilling of the workforce and 'commoditization of interpreting' (Fantinuoli 2019:11). The traditional prestigious settings and ergonomics of this job are changing and may become obsolete. Pessimistic views see technology as a threat, possibly replacing the interpreter himself. Autor (2019:3) thinks that an occupational change in "the structure of work in industrialized countries has polarized, with employment increasingly concentrated in high-education, high-wage occupations and low-education, low-wage occupations, at the expense of traditionally middle-skill career jobs" a matter which has made many professions, where technology can replace the human, outdated.

The insertion of technology in SI has affected interpreters, professional settings, service users, the concept of quality, etc. Therefore, research is

directly required anticipate "future trends, enabling the future generations of interpreters to prepare for the disruptive changes caused by digital technologies", Fantinuoli (2019:13-14) says. The world's feverish propaganda for the inevitability of technological change together with the epidemic panic from machine IQ to reach 10,000 (while Einstein's was 150) have given impetus for this research to look into SI as integrated into the emerging technology. Hence, this study aims to investigate the past and present of using technology in SI and explore the challenges and opportunities for human-machine collaboration from a multidisciplinary perspective. It derives its theoretical underpinnings from interpreting studies, cognitive analysis and computer science especially that branch which employs certain algorithms and techniques to simulate the human mind capabilities, AI. It is a qualitative study which uses description, comparison, and interpretation as research tools to analyse how the human and the machine react to the SI process and assess their performance and role. It enunciates challenges and makes use of opportunities to better address and anticipate possible technological developments and more importantly to proceed this industry in a constructive rather than a destructive way.

The significance of this study embarks on the topic, the large number of the industry and service users, and the theoretical and methodological frameworks. Integrating technology in SI is an infant area of research and it is becoming a "somewhat segregated subdiscipline", O'Hagan (2013:503) maintains. Gaps exist in our full understanding and evaluation of this phenomenon. The size of those involved in the field is huge, including professionals, trainers and trainees, service users, skate-holders, etc. The theoretical framework delving into multi-disciplines would hopefully answer questions from various prisms. Also the methodology, which compares between human and machine performances and seeks possible cooperation between them, would hopefully represent a new addition to the field. The literature review, too, draws the attention of scholars to an overlooked fact that coding and decoding (the core of MT) dates back to the 9th century, not the 1930s as generally assumed. Moreover, directing technological innovations towards a constructive ethical goal is not only necessary but also vital for the profession.

The paper is divided into three main sections in addition to this introduction and the conclusion: a review of the literature, the theoretical and methodological frameworks, and a description of and a comparison between human and machine SI processes and performances and

discussion of possible human-machine collaboration to enhance the profession.

2. REVIEW OF THE LITERATURE

Interpreting is as old as the need of humans to communicate with other nations. But the beginning of inserting technology in the process of translation came in the mid-20th century. Yet, coding (the core of MT) dates back to the 9th century. Developments in MT and later in MI, particularly in the last ten years, are so quick that futuristic visions may seem crazy at worst and fictionist at best. Scholars and various users of the service do not agree on the evaluation of the role of technology in SI. Some argue in favour and see it as an opportunity, others argue against with skepticism that the machine may replace human interpreters. Some feel helpless and obliged to use technology; others call for making use of the available opportunities and engage in a dialogue to minimize the consequences. The controversy is intense and a review of the literature may help us approach the issue on solid ground.

2.1 Cryptology and Rule-based MT

Four critical dates can be said to be vital in paving the way for MT as we know it today: the 9th century, 1629, the 1930s-1940s, and 1967-1980s.

The Arabs' progress in cryptanalysis (coding and decoding) particularly in the 9th century was the initial block in MT as known in the 20th century. Their advanced skills in linguistics, statistics and mathematics helped them find and develop cryptology. David Kahn assures that "cryptology was born among the Arabs...they were the first to discover and write down the methods of cryptanalysis" (1977:80). Dupont (2018) in an important study describes Khan's assessment as 'prescient' and 'accurate' over the years. She mentions that Al-Kindi (born in 805 and died in 873, an Arab Muslim scholar in math, philosophy, physics, polymath, and music) wrote *Resalah fi Estekhrag Al-Mu'amma'* [A Message in Cryptanalysis] which provided detailed knowledge about systematic language, patterns and features across various languages; it was "deeply influential for the Arabic cryptologists that followed, often drawing their inspiration or substance from it" (p.3). Other famous Arab Muslim scholars include Ibn Wahshiyya (famous for his studies in alchemy, agriculture, farm toxicology, history and Egyptology, and who lived in the 9th century and died in 930), Al Farahidi (well-known philologist, grammarian and lexicographer, who lived from 718-791), Ibn Adlan (great figure in cryptology, linguistics, and literature, who lived between 1187-1268) (Al-Gazaeri 2008:163; Trans.).

In 1629, the French philosopher René Decartes proposed a universal language with universal rules based on the idea of cryptology. Then, not much had happened until the 1930s when George Artsrouni put forward the first automatic bilingual dictionary; multilingual dictionaries emerged later. In 1949 Warren Weaver made use of cryptology again through a set of proposals for MT (see also Weaver 1955). The proposals include code-breaking, information theory and the universal rules of languages. Few publications appeared between 1949 and 1966. Yet, an escalated interest in cryptanalysis grew in 1967 with David Khan's *The Code-breakers*; it offers no new ideas but it reviews the history of cryptography since Al-Kindi (Al-Gazaeri 2018:159). All those contributions helped develop translating some technical and commercial texts by low-cost machine-based systems in the 1970s. In the 1980s, MT systems (like Systran, Ariane-G5, Logos, etc.) were installed in main frame computers. Until then, technology was used on a limited level. Generally, 'tangible successes' in MT were noticed in the 1980s and early 1990s through applying rule-based linguistic approaches which linguists and translators wrote manually for each source and target language pair (Doherty 2016:952).

2.2 The Data-driven Technological Turn

MT and machine interpreting (MI) progressed with the invention of micro-computers, related internet sites like Altavista's Babel Fish and Google's various tools, speech recognition (SR) and speech synthesis, Web 2, machine learning (ML) and deep machine learning, natural language processing (NLP), neuro-translation, etc.

During the 1990s, technology was used significantly through some computer-assisted tools (CAT) where MT started to flourish. The first major technological turn was ignited by a large size of actual human translations saved in translation memories (TMs). Here, "MT research experienced a further paradigm shift from prescriptive, top-down, rule-based approaches to descriptive, bottom-up, data-driven approaches chiefly in the form of statistical MT—a paradigm shift that has led to the second major technological shift in contemporary translation", Doherty (2016:952) explains. Free online translation programmes, like Google Translate, Bing Translator, Linguee, Babylon and Reverso, to name just a few, have made access not only free but also easy to anyone around the globe.

In the 2010s, three remarkable developments affected MT: the use of statistics and probability in translation, World Wide Web 2, and humongous data repositories (O'Brien 2012:1-6). The problem with early

MT models, Doherty demonstrates, is that "these systems are limited by their relative ignorance of linguistic information and their dependence on their own training data. Thus, any new terms and formulations will be difficult to translate correctly, if they are absent from the systems' data" (2016:953). Yet, the turn from rule-based linguistic approaches to indescribable amounts of structured and unstructured data has changed the rules of the game totally. With the progress in MT, using technology in SI and MI has become the latest trend in the field. Reactions to new ideas, such as Computer-Assisted Interpreting (CAI) tools, remote interpreting (RI), telephone interpreting, and video conference interpreting, vary from scaffolding and resistance to acceptance.

2.3 Recent Studies Evaluating the Developments

Technological developments in MT and MI have accelerated since the last decade with the introduction of neural networks (NN). Concepts like AI, ML, deep machine learning, NLP and automated SR, have impacted the field. As afore-mentioned, studies evaluating those advances vary from hailing (reasons include their impact on prices, efforts and the ergonomics of the profession) to refusing (for the quality of the product and the threat of machines replacing humans, etc.). Some scholars underestimate the potential of MT and MI to produce a high quality product. Cheng (2017:241), for example, elaborates that CAT and CAI are 'far from satisfactory' in providing language solutions despite their wide applications and the use of AI, algorithms and ML. Pym disagrees, claiming that this resistance demonstrates "an attitude of defense of power rather than of quality" and that the "resistance to technological change is usually a defense of old accrued power, dressed in the guise of quality" (2011:4). Pym goes even further to assume that technology has made translators think creatively by forcing the paradigmatic on the syntagmatic (2009). Meanwhile, Cheng totally refutes the latter suggestion, indicating that over-dependence on technologisation can undermine the translators' and interpreters' critical thinking, analytical and aesthetic skills reducing them to 'machine operators' or 'post-editors'. Cheng explains how technology performs basic and repetitive translation tasks, so that only professional translators can transfer in-depth communication between different cultures.

It is said that the insertion of technology in MT and MI can assist the translator. Gile (2018:541), for instance, describes the progress in MT as 'spectacular', arguing that cost and quality are problems in human SI market and people prefer to communicate in a lingua franca instead of paying a high cost in traditional SI. O'Brien regards the human-computer interaction in translation as one "in which varying levels of repetition are

characteristic, making the task suitable for translation memory tools" and stresses the idea that MT is "a potentially suitable translation aid" (2012:102,122) for translation memories (TMs) technology "has become relatively standard in many professional domains"(p.106). O'Brien insists that "the increasing technologisation of the profession is not a threat, but an opportunity to expand skill sets and take on new roles" (p.122). This means technology can help, instead of replacing, the translator. Joscelyne says that researchers generally feel that translators "will continue to play a central role in the production of the high quality translation by fine-tuning and repairing MT output as post-editors through the feedback loops that are vital to optimising MT systems" (2010; cited in O'Brien2012:121). Moreover, technology may decrease the cognitive load and help in solving problems related to names and numbers, an opinion Bowker (2005) refutes in her pilot study "Productivity vs. Quality" attributing the use of technology to an economic motive rather than quality or a genuine desire to help interpreters.

Some studies take a balanced stand towards MT and MI technology. Doherty argues that although technology has increased productivity and quality and enhanced international communication, it poses "significant challenges and uncertainties" including SI practice and perception of interpreters' value and status (2016:947-950). Fantinuoli (2018) is optimistic about the use of technology in translation because the machine cannot replace the human for reasons related to the nature of language; translators, therefore, should seize the opportunities present in technologisation.

The review of the literature as such shows that there is still a gap in understanding the role and value of technology and AI in MT, MI and SI and that more research is needed. There is also a lack in the information available on how to lead the change instead of total submission to it.

3. THEORETICAL AND METHODOLOGICAL FRAMEWORKS

To compare between the process and performance of human SI vs. the machine's, this section is divided into two sub-sections: firstly the theoretical framework, tackling Gile's updated Efforts Model (EM) and Gravitational Model (GM) (2009; 2017), and some basic concepts borrowed from computer science, and secondly the methodological framework.

3.1 Theoretical Framework

3.1.1 Gile's EM and GM. The first SI models appeared in the 1970s and aimed to account for the interpreting process (see for example

Gerver1975). Later models have benefited from developments in cognitive science and socio- and neuro-linguistics since the 1980s (e.g. Setton 1997; Paradis 1994), but as Gile asserts there is insufficient testing for the complexity and huge resources required (2017:2) and many studies look for errors in interpreters' actual performances. Gile (1995) developed an Efforts Model (EM) and has updated it repeatedly. He distinguishes between three types of efforts the interpreter exerts during SI operation:

- (1) *The Listening and Analysis Effort (L)*: listening to the source speech, or reception;
- (2) *The short-term Memory Effort (M)*: the memory operations during the two previous efforts;
- (3) *The Production Effort (P)*: producing target speech which includes self-monitoring and self-repair;

Then he added a fourth effort:

- (4) *The Coordination Effort (C)*: coordinating "the allocation of attention" between the previous efforts (Gile 2017:4-9).

So he puts the formula: $Sim=L+M+P+C$. The incompleteness of any of these efforts results in errors, omissions and infelicities (p.8). Gile suggests that the interpreter tends to work close to cognitive saturation level because "attentional resources required to perform adequately were not available for a particular comprehension, memory storage or retrieval or production task at a time when they were needed" (p.9). This is what he calls the *Tightrope Hypothesis*. Finally, he proposes a Gravitational Model (GM) which handles the availability of language. This variable indicates how high or low is the availability of a word or a linguistic structure to the interpreter at the time of SI. For a visual representation of the Model, he drew a circle where the centre represents the optimum availability of language units, whose drifting outward constitutes a less availability (p.14). However, Gile himself admits that his EM is not a theory, instead a model which tries to simplify information processing during SI (p.22). This model is amended to suit the purposes of this research as explained in the methodological section.

3.1.2 Artificial Intelligence. In 1956, John McCarthy coined the term 'Artificial Intelligence' and defined it as "the science and engineering of making intelligent machine, especially intelligent computer programs". There are various definitions for AI but they generally evolve around the idea that machines attempt to simulate the way humans think, take decisions and act. In so doing, this branch studies and develops the necessary theories, methods, and software and hardware systems with the hope to simulate and even extend human intelligence and capabilities.

The term is simply applied "when a machine mimics 'cognitive' functions that humans associate with other human minds, such as 'learning' and 'problem solving' " (Naderpour 2018).

The main assumption here is that machines 'learn', a concept raised in the 1980s. Tom Mitchell (1997) says that "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E" (cited in Zhou 2018:20). Therefore, ML is a type of predictive models, based on data, algorithms and statistics, which can make simple decisions. ML algorithm is "a technique through which the system extracts useful patterns from historical data" and apply them to new data (Aboulmagd et.al. 2020:1-11). Machines take decisions based on classification, regression or clustering functions.

While biological neurology was developing, artificial neural networks (ANN) were progressing from the 1940s. Simulating in a simple way the human brain which consists of 10-100 billion neurons, artificial neurons connect huge amounts of structured and unstructured data. Therefore the ability of machines to learn has increased with deep ML. NN refer to the number of layers used to process data inputs into outputs. The more the layers, the more complex the ML model becomes. MT (which appeared as early as the 1930s in the form of dictionaries) and MI have benefited a lot from ANN and deep ML especially in the last two decades. With SR technology, translation services have multiplied and the accuracy of the presented models has improved but there is still a long way to go.

3.2 Methodological Framework

This study started off the problem statement that there is much controversy about the insertion of technology in SI and how technology and AI can affect both the façade and the core of the profession. From this statement, the researcher was able to formulate the aim and research questions. It aimed to investigate the past and present of using technology in SI and explore the challenges and opportunities for human-machine collaboration from a multidisciplinary perspective. It raised four main questions:

- RQ1:** How technology and AI are integrated in SI, MT and MI?
- RQ2:** What are the similarities and differences between human and machine SI processes?
- RQ3:** What are the challenges and opportunities raised for human and machine performances?
- RQ4:** How possible is human-machine collaboration in the field?

To answer these questions, the following objectives were set:

- To review the history of inserting technology into MT, MI and SI;
- To compare between human and machine SI processes and performances;
- To identify the challenges and opportunities for both; and
- To explore an acceptable scenario of collaboration between humans and machines.

In so doing, this qualitative study used description, comparison and interpretation as research methods. In order to approach such phenomena from a multidisciplinary perspective, it derived its theoretical underpinnings from interpreting studies, cognitive analysis and computer science, especially those developments in AI which have already affected and will continue to affect the profession.

The study is based principally on Gile's updated Efforts Model (2017). But some remarks are necessary here:

1-Sometimes Gile refers to the arrangement of the first three efforts as Listening, Production and Memory. I suggested to arrange them according to the logical structure of the SI process, i.e. listening, deverbalsation (following Seleskovich's Interpretive Theory 1999 and Lederer's 1998) and then production. This arrangement allowed me to discuss the MI process in a way simulating the human mind.

2-Gile's explanation of the Production Effort is vague, unlike Seleskovich's which refers to 'deverbalsation' as what happens in the interpreter's mind until the next phase, 'reformulation' or 're-expression' phase. In other words, this paper uses the terms 'production' and 'reformulation' interchangeably to refer to the performance phase in the SI process.

3-This study borrowed the concept of 'memory' from Gile but it is integrated with Long-term Memory in MT. It is a phase that precedes production, whether in humans or machines.

4-The GM can be discussed within the memory part since it indicates the availability of language, particularly when it applies to machines.

5-The Tightrope Hypothesis is valid for humans and can be applied to machines but in a different way. Therefore, it will be discussed with the memory effort.

These remarks justify the division of the discussion part into the first three sub-sections: firstly listening and comprehension, secondly deverbalsation, and thirdly reformulation and the product. Memory, GM and Tightrope Hypothesis are tackled under deverbalsation as they are all used during this phase. The challenges and opportunities of human and machine SI are explained under the reformulation phase since they are

considered as an evaluation of the performance produced during this phase. A preparation/anticipation phase was added in the beginning for its importance in SI process and accurate performance. An additional subsection, implications for human-machine collaboration, complemented the study.

4. DISCUSSION

SI is a complex phenomenon because many decision-making and -taking processes, be them linguistic, pragmatic, cognitive, social, cultural, ideological, or the like, are made almost in the same time. Zhang describes it as "the most complex of human cognitive/linguistic activities" to be performed simultaneously for it includes:

anticipation, restoration of the implicit-explicit balance, and communicative re-packaging ('re-ostension') of the discourse, not the least the rich pragmatic information guiding the construction of the appropriate contexts and the speaker's underlying intentionalities, which is the centerpiece of SI, given the illusive nature of meaning assembly could be quite beyond even the most intelligent robots. (2017:253)

Similarly, MI involves complex models trying to simulate the human behaviour and reach a rational decision.

SI starts from the preparation prior to actual performance. Interpreters should 'prepare' and 'anticipate' topic-specific knowledge to improve performance (e.g. Gernsbacher 1990; Kintsch 1988; Johnson-Laird 1983; Diaz-Galaz et.al. 2015). Here comes the value of technology, e.g. the internet. Fantinuoli (2019:6) argues that using technology at this stage changes the interpreter's skill as an encyclopedic person. By the same argument, machines are 'prepared' with huge amounts of structured and unstructured data, CAT and CAI tools, software dictionaries, terminology software, TMs, SR software, and the like, installed with a suitable computing power to perform smoothly. Then, the other three phases of SI process come into operation.

4.1 Listening and Comprehension

The listening and comprehension phase implies the moment interpreters start to hear the original utterance transferred through the nervous system to the relevant parts in the brain in the form of a coded message.

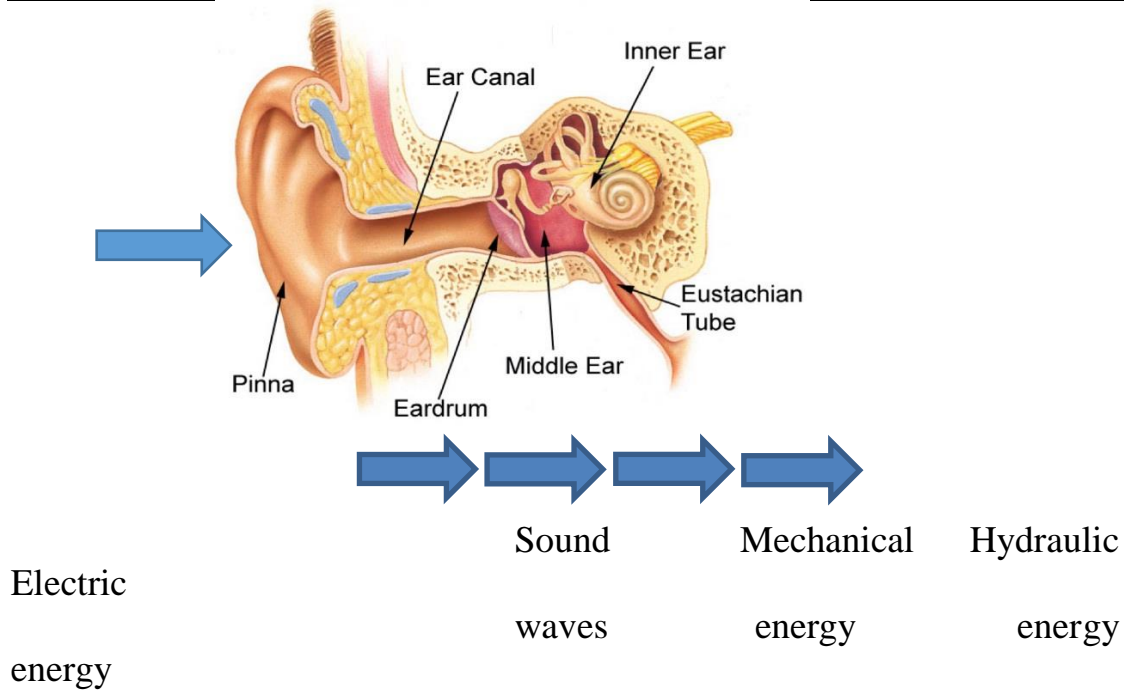


Image 1: How Do We Hear Sounds?

(Adapted from: <http://pikeslanprimary.weebly.com/class-4aj/how-do-we-hear-sounds>)

The ear drum begins to vibrate transforming these waves into a mechanical energy, consequently, the three ear bones in the middle ear vibrate converting this mechanical energy into hydraulic energy in the inner ear. The hair cells on the membrane of the cochlea convert the hydraulic energy into electric energy. Then the auditory nerves carry the electric energy, or signals, to the brain for processing (check the primary auditory cortex and the associated auditory area in the corticals, image 2):

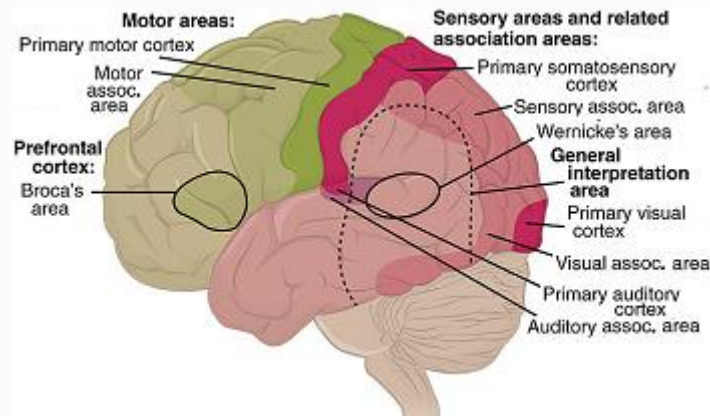


Image 2: Brain Corticals (The Physiology of Human Language 2017)

Neurons carry the signals from one neuron to another through dendrites (see Image 3). During this phase, not all information received passes to the brain. Attention filters relevant stimuli and let them pass.

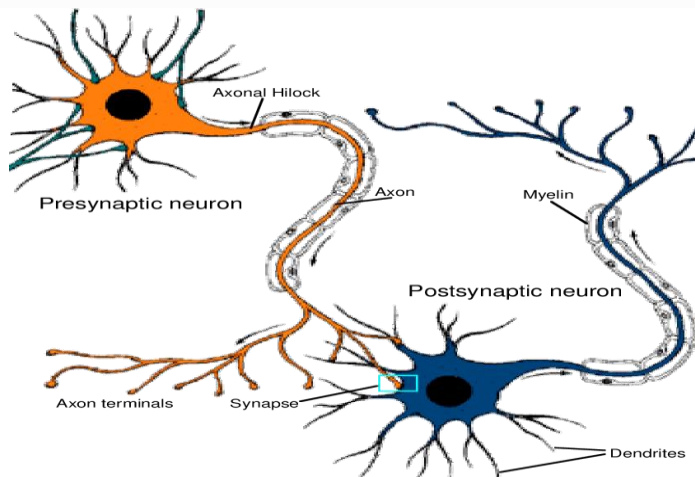


Image 3: How Neurons are Connected (Sougné 1999)

The verbal message is thus coded so that the brain cells can process information in the next phase.

Similarly in machines, SR systems were developed with the intention to transform the original message into digital signals for the machine to understand and process. Basic SR models_ defined as "the ability to identify words and phrases in spoken language and convert them into machine-readable format" (Trivedi et.al. 2018:37)_ consist of five steps (see Figure 1 below): a) *pre-processing*, transforming the speech signals into digital signals; b) *feature extraction*, looking for the set of parameters that corresponds to the signals or simply the relevant information; c) *acoustic models*, connecting between the acoustic information and phonetics; d) *language models*, generating probabilities of a word occurrence after a word sequence; and e) *pattern classification*, comparing the unknown pattern with existing sound patterns in the training data to recognize the speech (p.37-38). In the last step, various approaches can be used such as the Template Based Approach, the Knowledge Approach, the Neural Network Approach, or the Statistical one. In this figure, data is divided into training data and test data to test the accuracy of the model used and the model is modified until acceptable accuracy is established.

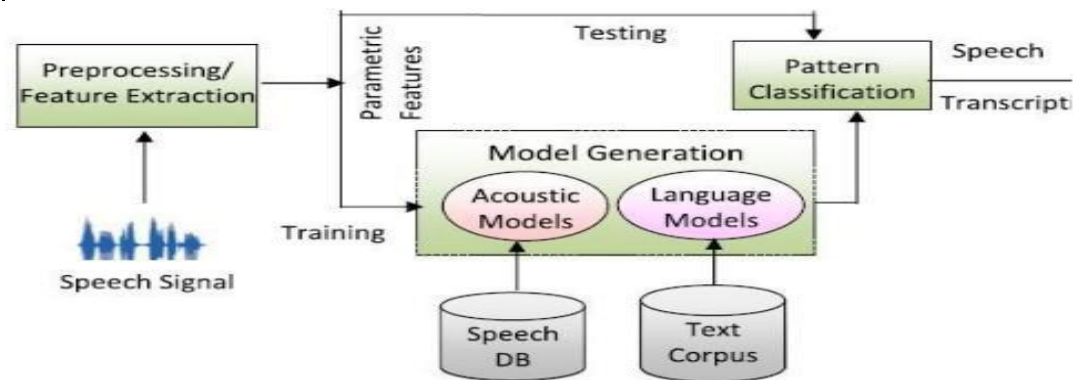


Figure 1: Architecture for Speech Recognition System (Trivedi et.al 2018:37)

The above-mentioned process is called 'speech recognition', i.e. speech understanding. The speech is converted into a text to prepare for the next phase (translation), that is codified then decodified for the machine to translate; unlike the human message which is still codified during this phase. Widely used methods are Hidden Markov Model and Artificial Neural Network Classifier with Cuckoo Search Optimisation (Trivedi et.al. 2018:38-39).

The ability of humans to recognize speeches is absolutely complex and many known and unknown features are involved. What machine models try to do is to simulate this process but in a limited way despite the complexity of the models and the relatively high accuracy obtained. NLP _a subfield of AI which is concerned with processing human language by computers_ originated in MT and has improved noticeably. Such advances have drastically affected MT quality and consequently MI. AI allows us to build recurrent NNs which connect neuron-like elements in different layers producing a complex behaviour or decision. By comparison, the human excels but the machine successes are stunning and can enhance the human performance as to be explained later.

4.2 Deverbalisation

The interpreter's temporal lobes receive the speaker's messages and start to interpret them to create context. They are located behind the ears and commonly known for processing auditory information with the help of memory. They "are also believed to play an important role in processing affect/emotions, language, and certain aspects of visual perception" (Brain Map 2021).

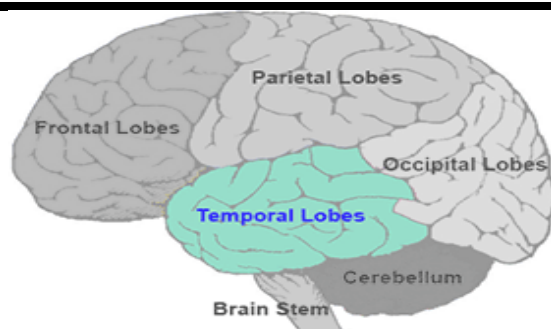


Image 4: Bain Map: Temporal Lobes (Brain Map

2021)

Language cortex consists of the Wernicke's (the receptive part) and Borca's areas (the main language production part), see image 2 above. The Wernicke's area with the help of the angular gyrus, the insular cortex and the basal ganglia, is thought to attach meaning to uttered words and incorporate context into the interpretation. The angular gyrus processes language, numbers, spatial awareness and memory; the insular cortex is responsible for context, perception, understanding, movement, self-awareness and interaction with people, while the basal ganglia, a clustered group of neurons, handles language emotional content and cognitive information (The Physiology of Human Language 2017). Perception in this phase is shaped by interpreters' memory, attention, expectations, personality and ideology for instance. During deverbalisation, a switch between the source and target languages occurs and the decoded original message is translated into a decoded target message ready to be carried in the form of signals to the articulatory system for the next phase.

Damage to the temporal lobes can result in difficulties in understanding spoken words, selective attention, identification and categorisation of objects, learning and retaining new information, impaired factual and long-term memory, persistent talking, among others (Brain Map 2021).

In comparison to human deverbalisation, the machine transfers a text from one language into another. MI "also known as automatic speech translation, automatic interpreting or speech-to-speech translation, is the technology that allows the translation of spoken texts from one language to another by means of a computer program" (Fantinuoli 2018:5). MI is based on MT systems, TMs and SR models. Trivedi et.al. (2018:40-41) refer to four systems:

a) *Rule Based Machine Translation*: Translation is generated through a morphological, syntactic and semantic analysis of source and target texts, dictionaries and software programmes; its problem is the difficulty of "rule interactions in big systems" and "insufficient amount of really good dictionaries".

B) *Statistical Machine Translation*: The machine deals with a large parallel corpora and approaches translation as a mathematical problem; but it can be "costly, doesn't work well between languages with different word order".

c) *Example Based Machine Translation*: The machine depends on a corpus of already translated texts and translates by analogy to similar or close sentence components; "computational efficiency" decreases with big databases.

d) *Hybrid Machine Translation*: It integrates Rule Based and Statistical translation systems.

Until this phase ends, we cannot talk about the product itself. In the human mind, the message is still coded in the brain and will be decoded in reformulation. Similarly, whatever happens in the machine can be seen as coded messages in the form of numbers, a language it can understand and process. The final MI product becomes tangible when the machine delivers the rendition in the next phase.

Memory plays a pivotal role in interpreting. An active short memory in humans can be compared to all kinds of TMs, be them software installed in computers, or online TMs and dictionaries. Indeed a big part of future MT success relies on the proliferation of data in TMs to make them simulate and even extend the human short and long term memories. The larger the data, the better the machine performance becomes.

According to the Tighrope hypothesis (Gile 2017), the human interpreter "tends to work close enough to cognitive saturation" because of incomplete availability of resources at a given time. The same applies to MI at least for the present time as the quality of the rendition depends mainly on the accuracy and precision of the AI model used and available resources. The same holds good at the GM and how accessible is information to interpreters or machines

4.3 Reformulation and the Product

Speech and Language (2021) demonstrates that human speech production and proper word usage are primarily associated with the Broca's area in

the prefrontal cortex in the left hemisphere (Image 2). The target message moves through nerves and neurons in the form of signals from the related parts in the brain (including the motor cortex) to the articulatory system (the lungs, vocal cords and vocal tract) for final production.

By comparison, in deverbalsation, machines translate the source message, then the target text becomes ready to be converted into a speech.

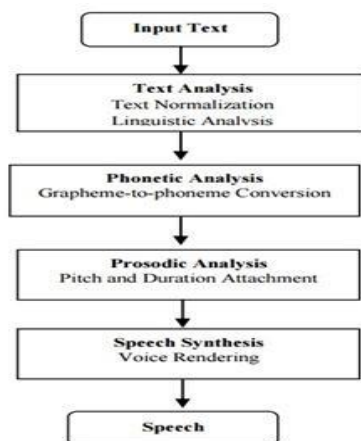


Figure 2: Speech to Text System Flow (Trivedi et.al. 2018:39)

This goes through a text analysis, normalization and transcription phase then a speech synthesis phase (see Figure 2). However target text production faces many challenges, as Trivedi et.al. (p.39-40) argue, for example the model is extremely complex and application becomes harder in big systems.

Reformulation entails necessarily an evaluation of the human and machine product/performance itself (for SI assessment, cf. Ahmed 2015; 2016; 2020). Generally, expertise humans deliver professional renditions. But MI quality, though improving continually, is questioned. In the 1990s, low cost and speed of MT made many people forget about quality. "As MT systems are typically built directly from human translations, they truly blur the borders between translation from a human and a machine" and they "contain millions of human-translated sentences from which they learn the patterns of probability", Doherty (2019:953) mentions. Undoubtedly, MT reaches languages we have never heard about. However, "most machine-translated content still requires some form of human intervention to edit the MT output to the desired level of quality" (p.958). O'Brien (2012) thinks that technology can give us speed and quality. The idea of speed applies to written translation rather than SI; it also applies to using technology in the preparation phase. 'Speed' in MI as

mentioned here seems ridiculous especially with machine latency, ear-voice span or time gap between delivering the original message and producing the interpretation. Moreover, if speed is not accompanied by quality, let alone creativity, what is the value of such speed Machine errors, even if they might be rare, make the risk of using MI unacceptable particularly in settings where only highly accurate SI is the norm by interpreters. Until now humans act as post-editors for MT products and they can use technology in SI through available dictionaries, terminology management, TMs and MT. O'Brien admits that while "machines are successful at the word, phrase and segment level, they are less successful at text and discourse levels.. Context and perception are clearly imperative and machines are not good at that but humans are" as MT tools divide texts into small chunks causing "problems in cohesion, contextual clues, core anchor points in segments, spacing"(p.116). Massion (2017) describes AI progress as 'unsatisfactory', particularly in the translation of less frequent words or concepts.

Fantinuoli describes the success of MI software systems as 'quite modest' (2018:6). Although he acknowledges the advances in ML and their 'encouraging results' in MT (resolving issues like lexical, syntactic, semantic and anaphoric ambiguity), he assures that MI systems experience challenges for several technical and communicative reasons (ibid.). Technically, errors and inaccuracies increase due to issues automatic translation quality. Communicatively, such systems fail to deal with context or to translate all the inexplicit information such as the speaker's attitude or intentions, world knowledge and references.

Some people think MT and MI decrease the cost of SI service. Such an argument is refutable because it might so look at the beginning of using technology but after technology replaces the human even though to some extent, after training a whole generation of translators and interpreters on skills that suit the new requirements for the new setting, after creating new translation jobs (e.g. post-editors whose task is to fix MT errors) and specifications, and after full dependence on technology, who can guarantee that technology providers will keep the cost free or low? Mobile phones and software providers whose mobiles or software systems stop working totally or partially after sometime are a good example in this regard. Most available programmes start with a free 'limited' package or trial, then customers have to pay!

Indeed, technology can affect the whole profession and field: educational and training systems, job market specifications, service providers and cost, translators' and interpreters' traditional skills, their prestigious status in society, etc. Fantinuoli refers to a short term impact

of technology on the public perception and stakeholders' of the profession before it "actually represents a potential threat" to humans (2018:8).

MT and MI face challenges when it comes to both source and target languages. English is still a predominant source and target language. Zhang (2017) emphasizes this inequality among languages. It is true more languages are added lately, yet inequality remains.

Also machines are incapable of conveying a humanized atmosphere despite the great progress achieved in the voices used in text-to-speech recognition. Gile thinks that MI is acceptable for specialized purposes and in certain social settings, but "less likely to be popular in settings where natural communication is important for the preservation of a certain atmosphere or human relations" as in political speeches, debates, and mass media (2018:541).

Generally, when a software is amended or changed, the change is technical rather than social, i.e. data scientists and engineers approach only 'mathematical' data or model problems. Olohan explains "why systems sometimes fail" because development occurs via technical rather than socio-technical change and "human and organisational aspects are not addressed at all, or only implicitly, or in an ad-hoc fashion" (2011: 345).

Humans mediate and sometimes make errors (cf. Ahmed 2015; 2018): addition, omission, zero-interpretation, wrong interpretation, etc. Machines make errors and inaccuracies too; this raises big question marks on who is responsible then. Until now there is no ethical code for machine errors. Furthermore, there is no ethical code for confidentiality and security of service users' information. This might be one of the reasons why such services are offered in settings which do not require high confidentiality. This raises questions about the ethical acceptability of the idea of replacing humans with machines in many fields now (banking, HR, education, travelling, hotels, car remote maintenance, restaurants, traffic, etc.). If machines would be able to translate and interpret without the help of humans, why need humans (who would then be either jobless or working in another profession) at all! Using technology, regardless of the real intentions behind, may be attributed to an economic reason, namely the transfer of wealth from the hands of individuals and small entities to the hands of multinational companies or individuals who own the technology. What is the logic behind teaching senseless machines to do the job of humans and making humans jobless or perform auxiliary tasks (to serve refining the machine performance)?

Economic and social stability, in my opinion, are more important than going after the technological drive heedlessly.

To these challenges, Fantinuoli (2018:6) adds machine latency, SR flexibility, and noise (unidentifiable words or letters) recognition or tolerance. Yet, technology can provide the interpreter with some opportunities through collaboration with machines.

4.4 Collaboration between Humans and Machines

Interpreters can use technology to enhance their performance specially and the profession generally. This is a fertile infant area of research that needs further exploration instead of propaganda.

Numbers, proper names and abbreviations constitute a challenge even for professional interpreters for the cognitive load added to the different efforts they exert simultaneously at best, or the errors they may make at worst. In "Simultaneous Interpretation of Numbers", Pinochi (2009) noticed the following mistakes in SI of numbers and machines can overcome them easily: omission, approximation, lexical mistakes, transposition (wrong arrangement of the numbers), syntactic mistakes, philological mistakes, among others. Timarová (2012) and Seeber (2015) maintain that numbers are a common source of errors in SI as they lack 'conceptual representation': they cannot be predicted easily from context, they are highly dense in information, and the interpreter should change his listening, memory and production strategies to keep track of the speech. Therefore, Desmet et.al. speak of technology as "the most helpful in reducing errors on complex numbers and decimals, the two categories that are most often interpreted incorrectly" (2018:25) and suggest that "booth technology that automatically recognizes numbers in the source speech and presents them on a screen could reduce the cognitive load and improve translation quality" (p.13) provided that this kind of information is retrieved fast, within the ear-voice span.

The human interpreter can use technology in all its forms (e.g. internet, MT models, TMs, speech-to-text and text-to-speech services available on many big platforms now, online dictionaries, etc.) in the preparation phase. That the interpreter uses any CAT or CAI tools during this phase is quite understandable, yet using them in the booth may raise doubts on how helpful they would be. One may wonder: would terminology management tools or TMs assist the interpreter during SI? Wouldn't this add to his cognitive load? Fantinuoli (2017) and Costa et al. (2018) surveyed and evaluated CAI tools for terminology management. They found out that for a tool to be practical in the booth, it must allow the interpreter to access the required material quickly with the

least additional cognitive load. Prandi (2018:29,56) agrees to the importance of using terminology management tools, like InterpretBank, during SI and in the preparation phase alike. In addition to using tools like TMs, the interpreter can also create or build his own, for preparation purposes or later reuse in his work (Doherty2016:952).

Technology is a good asset in interpreter education and training. Berber (2010) approached using information and communication technologies as pedagogical tools in interpreter training. Sandrelli and de Manuel-Jerez (2007), Pinazo (2008) and Lim (2014) indicate that CAI tools in interpreters training enhance teaching and learning and help students develop their self-assessment skills by recording, listening to and evaluating their performances. Deseyl and Lysch (2018) carried out a pilot study on CAI training to improve students' self-assessment skills and foster their performance at the National Parliament of South Africa; they concluded that training is a viable tool. Maybe novice translators or translation/interpreting students, in their attempt to get professional experience, find MT useful, unlike professionals with long experience who may not benefit as much or at all, Garcia (2010; cited in O.Brien2012:109) states.

The human-machine collaboration has been tested in remote interpreting (RI), where the setting differs from the traditional booth consoles. Technological tools range from just a mobile to a computer fully equipped with CAT and ASR, to professional TV Camera screens and computer transmitting live from the original meeting room. Nowadays, the European Union and the European Commission (2019) ask professional interpreting service providers to arrange the setting as such. SI can turn into a one-man show where the interpreter becomes responsible for not only his SI performance but also the operation of these technologies. Yet there are challenges. Since the 1970s, Ziegler and Gig (2018:120) explain, RI has not been widely used for two reasons: "technological limitations and its high cost, and the general refusal by interpreters to use technology". Mouzourakis (2006:56) also mentions a list of interpreters' physiological problems associated with RI: fatigue, stress, headaches, lack of concentration, the unease they feel due to not 'being there', not 'having the right feel' for the situation, and not being able to interact directly with the participants. Fantinuoli comments on some RI concerns such as:

the quality of the audio/video signals, the partial loss of contextual information due to remoteness, and psychological factors, such as fatigue, higher levels of stress and loss of motivation and

concentration. In the area of dialogue interpreting, issues like turn taking, alienation and stress have been found to be particularly significant. (2018:5)

RI has been applied in courts since 2000. Devaux (2018) explored how technology affects court interpreters' perception of their role. She concluded that technology restricted their role-space with the remote party and influenced their self-presentation, participant alignment, and interaction management (p.110-111). Any deviation may affect the fairness of the proceedings and the judgment.

No empirical research is carried out to test the negative impacts of RI on interpreters (Seeber 2018). Fantinuoli draws our attention to how RI can generate 'a new wave of professionalization' (2019:11). Ziegler and Gigliobianco think that advances in hardware and software together with "latest video, virtual reality and augmented reality technologies might offer possibilities to overcome existing technological, physiological and psychological problems" (2018:120).

Until now, human SI out-performs MT and MI. The machine still faces a difficulty in translating context, cultural and ideological references, background knowledge, puns and humor, speech disfluencies, noise background, ambiguities, word boundaries, language varieties, speaker's speed, body language, to name but a few (cf. Fantinuoli 2019). Humans also face a difficulty or a bigger cognitive load when it comes to the interpretation of highly loaded-with-information speeches, e.g. numbers, names, abbreviations and terminology. So if the machine can help in those areas, the quality of the human SI will improve. But to replace the interpreter with the machine is an unacceptable idea for ethical, social and logical reasons as explained before.

CONCLUSION

This study aimed from the beginning to investigate the past and present of using technology in SI and explore the challenges and opportunities for human-machine collaboration from a multidisciplinary perspective, using description, comparison, and interpretation to assess SI and MI processes and performances.

The study found out that technology was first integrated in translation in the 1930s when the automatic bilingual dictionary was put forward, though the core idea behind MT was cryptanalysis, a science well developed by the Arabs in the 9th century and revisited by René Decartes in 1629 with the proposal of a universal language.

SI is a complex operation, whose full mysteries are still uncovered. MT and MI attempt to simulate this human activity and mind. Despite the

technological developments in AI, NN, ML and deep ML, NLP, TMs, terminology management, SR, among others, MT and consequently MI still face many challenges. These include context, background information, cultural and ideological references, speaker intentionality, noise (e.g. unclear words, more than one speaker talking simultaneously, background noise), language varieties, ambiguities, humour, latency, etc. Technology can be pricy, risky and complicated technically.

The use of technology in RI, for instance, has caused physiological and psychological problems to interpreters. It can change the façade of the profession and the nature of education/ training presented to qualify a whole generation of interpreters with different skills that suit the new market. I totally agree with Cheng (2017) who suggests that over-dependence on technology can undermine both the translators' and interpreters' critical thinking, analytical and aesthetic skills, downgrading them to 'machine operators' or 'post-editors'. In addition, the ethical and social implications of collaborating with or being replaced with the machine, through MI, should be put into consideration. Empirical research is highly needed to test such negative impacts on humans.

However, technological tools can provide interpreters with good opportunities especially in the preparation phase. Yet, during the event some tools, like TMs, may constitute a further cognitive load on the interpreter. On the other hand, technology can help improve issues related to the interpretation of numbers, proper names and abbreviations by humans. Human-machine collaboration here can be promising.

Maybe the idea of 'technological change' is inevitable in itself, but the direction of the change and its consequences is definitely evitable. The rush towards using technology in SI should be cautious. Maybe the question "Can the machine replace the human interpreter?" might not seem rhetorical any more, but it needs to be addressed in a constructive way.

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