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The effect of automatic speech recognition on Iranian interpreters' cognitive load: An fNIRS study

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Abstract
In the dynamic landscape of language interpreting, the integration of technology has ushered in a new era, marked by the advent of computer-assisted interpreting (CAI) tools. However, while the promise of improved communication through these tools is evident, a crucial facet demanding scrutiny is the intricate relationship between computer-assisted interpreting and the cognitive load experienced by interpreters. The present study was an attempt to use functional Near-Infrared Spectroscopy (fNIRS) to compare the cognitive load experienced by interpreters when utilizing a CAI tool, in this case automatic speech recognition (ASR), versus interpreting without such a tool. To this end, 12 interpreters were asked to perform two tasks: 1) simultaneous interpreting with the help of ASR (ASR-SI) and 2) interpreting without ASR (NoASR-SI). fNIRS records changes in the concentration of oxyhemoglobin [ΔHbO_2] and deoxyhemoglobin [ΔHbR] as it is sensitive to hemodynamic changes in the blood. Therefore, the interpreters' cognitive load in both tasks was measured using the analysis of the HbO_2 signals, which are an indicator of brain activation, and a paired t test was used to determine if there was a significant difference between the means of concentration changes of the two tasks. The results showed that the left temporal cortex (LTC) was significantly activated ($p<0.05$) during simultaneous interpreting from English into Persian. Furthermore, the mean of changes in concentration of HbO_2 revealed that more cognitive load was experienced in interpreting without ASR compared to interpreting with ASR, meaning cognitive load was reduced when using ASR. In addition, participants' feedback regarding the integration of ASR into interpreting was investigated through a questionnaire. The findings showed that participants' subjective perceptions of ASR did not fully correspond to the objective neural activity recorded during simultaneous interpreting with and without ASR support.

Keywords: *fNIRS; simultaneous interpreting; cognitive load; computer-assisted interpreting; automatic speech recognition*

1. Introduction

1.1 Interpreting

Interpreting is a complex and long-standing practice, distinct from translation, as it existed before the development of writing (Pöchhacker 2016: 9). According to Seleskovitch (1976: 96), interpreting involves both understanding and rendering ideas, requiring the interpreter to simultaneously handle two roles in language and communication. Unlike other forms of communication, interpreting requires the same individual to both express ideas and understand another speaker's ideas at the same time. This very feature of interpreting makes it a demanding activity in terms of cognitive load and mental effort (Mousavi Razavi 2020). Building upon this understanding of the inherent cognitive complexity of interpreting, Gerver (1976) further refines the concept by defining interpreting from a cognitive psychology viewpoint. He conceptualizes it as a sophisticated form of human information processing, encompassing "perception, storage, retrieval, transformation, and transmission of verbal information," and emphasizing its susceptibility to various linguistic, motivational, and situational factors (Gerver 1976: 167). Thus, both perspectives converge on the notion that interpreting is not merely a linguistic transfer, but a complex cognitive operation subject to a multitude of influencing variables.

1.2 Cognitive load in interpreting

Over time, the concept of cognitive load in interpreting has attracted considerable academic interest. Scholars from both within the field of interpreting studies and from other disciplines have investigated this issue, recognizing its potential to deepen our understanding of the cognitive demands involved in interpreting and to contribute to the development of more effective training methods and performance strategies (Seeber 2013). This growing interest stems from two key motivations: the need to conceptualize and analyze the complex and demanding nature of interpreting, and the desire to explore how interpreters navigate these challenges (Chen 2017).

Both Seeber (2013) and Chen (2017) define cognitive load in interpreting within the framework of limited cognitive capacity, but they emphasize different aspects of the concept. Seeber (2013) characterizes cognitive load as the proportion of an individual's finite cognitive capacity that is occupied by a given task, highlighting the inherent constraints of the cognitive system. In contrast, Chen (2017: 643) defines cognitive load more specifically in the context of interpreting, describing it as "that portion of an interpreter's limited cognitive capacity devoted to performing an interpreting task in a certain environment". While both definitions acknowledge the finite nature of cognitive capacity, Chen's perspective introduces an environmental dimension, suggesting that cognitive load is not only task-dependent but also influenced by external factors within the interpreting setting.

Gile's Effort Model (2009) is a prominent model in interpreting studies which emphasizes the cognitive aspects of language. According to this model, simultaneous interpreting involves managing multiple cognitive demands, including listening, translating and speaking in real-time. Therefore, managing cognitive load is critical for interpreters, as excessive cognitive load could lead to omissions, substitutions, and other errors (Pöchhacker 2016). Error analysis in interpreting could then be insightful when speaking of cognitive load and performance quality (Barik 1971; Altman 1994; Anazawa et al. 2012; Mirzaee & Mousavi Razavi 2021).

Different models and methods have been used by various scholars to measure cognitive load (cf. DeLeeuw & Mayer 2008; Ayres et al. 2021; Ouwehand et al. 2022). Cognitive load measurement methods are essential tools in understanding how much mental effort individuals expend during various tasks. Paas et al. (2003) and Schultheis and Jameson (2004) refer to a taxonomy of different methods ranging from subjective and analytical methods to performance and psycho-physiological methods.

Among these methods, the psycho-physiological method offers a significant advantage in measuring cognitive load by directly assessing physiological responses that naturally fluctuate with cognitive changes. This direct assessment bypasses the subjective biases inherent in self-reported data, offering a more objective measure since these responses are involuntary (Seeber 2013). Among these methods neuroimaging techniques were the most widely used ones, enabling researchers to find a way to the interpreters' "black box" (Seeber 2013). To date, different studies have been conducted on translation and interpreting based on neuroimaging techniques such as positron emission tomography (PET) (Price et al. 1999; Rinne et al. 2000), electroencephalography (EEG) (Petsche et al. 1993; Kurz 1995; Szarkowska et al. 2016), functional magnetic resonance imaging (fMRI) (Ahrens et al. 2010; Hervais-Adelman et al. 2014), and functional near-infrared spectroscopy (fNIRS) (Lin et al. 2018; Ren et al. 2019; He & Hu 2022; Yan et al. 2024).

In this study, fNIRS was employed to assess the cognitive load of interpreters. As a non-invasive neuroimaging technique, fNIRS monitors fluctuations in oxygenated and deoxygenated hemoglobin concentrations, which reflect neural activation in the brain. Compared to EEG, fNIRS offers better spatial resolution, while it surpasses PET and fMRI in temporal resolution, making it a versatile tool for studying brain activity (Ren et al. 2019; Zhuang et al. 2022). Its robustness to motion artifacts and environmental noise, along with minimal body constraints, enables high ecological validity, particularly in naturalistic settings such as bilingual reading, translation, and interpretation (Ren et al. 2019; Yan et al. 2024).

1.3 Related neuroimaging studies

Kurz (1995) used electroencephalography (EEG) to explore the neural correlates of directionality during shadowing (repeating the speech word for word) and simultaneous interpreting (SI) tasks. However, the tasks were not performed verbally rather mentally (without actual speaking). The findings highlighted the critical involvement of the temporal regions, particularly the left temporal lobe, in language processing, especially when interpreting into one's L2. This aligns with Petsche et al. (1993), who used EEG to demonstrate that interpreting into one's second language (L2) demands greater cognitive load compared to interpreting into one's first language (L1). Further supporting this, Szarkowska et al. (2016) employed EEG and self-report measures to examine cognitive load during intralingual and interlingual interpreting. Their results indicated that interlingual respeaking imposed a higher cognitive load, though interpreters reported lower mental effort, suggesting a connection between interpreting proficiency and respeaking competence.

Price et al. (1999) utilized positron emission tomography (PET) to investigate brain activation during translation and language switching. Similarly, Rinne et al. (2000) conducted a PET study to examine the cognitive demands of SI between L1 and L2. Their findings revealed that interpreting into L1 primarily activated the left frontal region, while interpreting into L2 elicited more extensive activation across the left fronto-temporal area. Recent research has continued to utilize brain imaging methods, such as functional magnetic resonance imaging (fMRI) to gain a better understanding of interpreting.

Ahrens et al. (2010) conducted a preliminary fMRI study involving student interpreters to compare brain activity during simultaneous interpreting and free speech production. The results revealed significant differences in neural activation, emphasizing the heightened cognitive demands of SI. Unlike free speech, which primarily engages language production areas, SI activates additional regions responsible for dual-language processing and rapid information transfer, particularly the left superior temporal sulcus. Complementing this, Hervais-Adelman et al. (2014) used fMRI to compare brain activity during SI and shadowing in multilingual participants. Their findings indicated that both tasks modulated activity in the superior temporal lobe, with overlapping neural activation patterns, suggesting shared cognitive mechanisms between SI and shadowing.

Functional near-infrared spectroscopy (fNIRS) has been employed in a limited number of studies within Translation and Interpreting Studies. Lin et al. (2018) combined behavioral measures and fNIRS to assess cognitive effort during pairing (linking translation-equivalent structures between the source language (SL) and target language (TL) stored in long-term memory during SI), transphrasing (explaining what/where the item is rather than giving its direct equivalent in the TL), and non-translation (producing the sound of the SL item rather than giving its direct equivalent in the TL) tasks. The study revealed cognitive overload in the left prefrontal cortex (PFC) during SI, though the ecological validity of the findings was limited due to the use of word-level stimuli and a narrow focus on one brain region. More recently, He and Hu (2022) used fNIRS to investigate the neural mechanisms of simultaneous interpreting, comparing professional interpreters and non-interpreter bilinguals. Their results demonstrated distinct brain activation patterns and functional connectivity in interpreters, highlighting the impact of expertise on cognitive processes. Both groups, however, relied on the right dorsolateral prefrontal hub during interpreting, suggesting a shared neural resource for managing the task's demands. Another study utilizing fNIRS was conducted by Yan et al. (2024) who monitored the hemodynamic response in participants' brains during consecutive interpreting tasks. By using fNIRS, the researchers could effectively capture the neural correlates of mental workload (MWL) and identify specific brain regions involved in the interpreting process, such as the inferior frontal gyrus, middle temporal gyrus, and inferior temporal gyrus.

1.4 Computer-assisted interpreting tools

In the dynamic landscape of language interpreting, the integration of technology has ushered in a new era, marked by the advent of computer-assisted interpreting (CAI) tools. These sophisticated tools, with their focus on enhancing efficiency and quality in interpreting, contribute to the ongoing transformation of language-related professions in the face of technological advancements (Prandi 2018: 29). However, as of now, interpreters have access to a restricted variety of CAI tools, and their features may not comprehensively address every stage of the interpreting process (Prandi 2018: 30). In the similar vein, Tripepi Winteringham (2011: 89) notes that in general, the progress of technology in the field of interpreting has been notably slow, especially when contrasted with the rapid pace of technological integration observed in written translation.

However, while the promise of improved communication through these tools is evident, a crucial facet demanding scrutiny is the intricate relationship between computer-assisted interpreting and the cognitive load experienced by interpreters (cf. Prandi 2018). It is well established that interpreters face inherently high cognitive demands, as they must seamlessly process linguistic nuances, cultural contexts, and real-time information. With the introduction of CAI tools into this demanding domain, questions arise regarding their influence on the cognitive load experienced by interpreters. However, despite the breakthrough these tools are making, only a limited number of studies has been dedicated to the use of computer-assisted interpreting tools in interpreting, particularly in an Iranian context (Costa et al. 2014; Fantinuoli 2017b, 2017a, 2018; Prandi 2018).

The first exploratory study conducted to examine whether the use of CAI tools leads to an increase or a decrease in cognitive load was by Prandi (2018). Some years later, Mellinger (2023) adopted a socio-cognitive lens to explore the interplay between technology and interpreter cognition, emphasizing key constructs such as embedded and embodied cognition, extended cognition, and distributed cognition. In her doctoral dissertation, Frittella (2024) provides a comprehensive examination of the cognitive implications of CAI tools in interpreting and offers practical, evidence-based recommendations for integrating these tools into interpreter training programs.

Advancements in automatic speech recognition (ASR) and, more recently, artificial intelligence (AI) have opened new possibilities for providing interpreters with fully automated support during SI (Fantinuoli 2017b). Several studies have explored the impact of ASR in SI of numbers (Desmet et al. 2018; Defrancq & Fantinuoli 2021; Pisani & Fantinuoli 2021). As Pöchhacker (2016: 188) observed, ASR is widely recognized as a technology "with considerable potential for changing the way interpreting is practiced". Similarly, Fantinuoli (2023: 65) suggests that "the use of raw speech recognition or speech translation could prove to be an effective means to decrease interpreters cognitive load and improve performances". However, this issue needs to be experimentally evaluated. The present study thus aimed to explore the impact of ASR as an instance of CAI tool on Iranian interpreters' cognitive load and sought to find answer to the following question: How is the interpreters' cognitive load different when they use ASR while interpreting compared to when they do not use it?

2. Methods

2.1 Participants

The study involved 12 participants including 10 men and 2 women (mean age = 39.08 ± 3.77 years). Two key criteria were employed for participant selection. First, all participants were required to complete an online English proficiency test provided by the British Council, with a minimum required level of C1 to ensure advanced language proficiency. Second, participants needed to have at least two years of experience in the interpreting market and be actively earning a living through this profession.

All participants were physically and mentally healthy, with no reported history of neurological or psychiatric conditions, nor were they using any medications. Furthermore, all individuals had normal or corrected-to-normal vision and exhibited normal color perception.

All participants had either a Master's or a PhD degree and took part in the experiment voluntarily. They were native Persian speakers and had English as their second language (L2). Prior to participation, each subject provided informed consent, and as a token of appreciation, they received a small gift. The research was approved by the Research Ethics Committee of Allameh Tabataba'i University in Tehran (IR.ATU.REC.1403.041), and the protocol was carried out according to the relevant guidelines.

2.2 Task description and procedure

To conduct the fNIRS study, the National Brain Mapping Laboratory (NBML) of the University of Tehran was chosen as the setting of the experiment as it offers a wide range of services for cognitive studies including EEG, fMRI, fNIRS, EMG, TMS, tDCS, and eye-tracker. This study involved two tasks: (1) simultaneous interpreting with the assistance of ASR (ASR-SI) and (2) simultaneous interpreting without ASR (NoASR-SI). To create fNIRS-compatible tasks, a preparatory process was undertaken to select and modify the materials. A TED Talk video by Al Gore on climate change (available at https://www.youtube.com/watch?v=rUO8bdrXghs, accessed 2024-05-27) was selected. An eight-minute segment from the beginning of the 29-minute video was chosen for interpretation into Persian. The video was divided into eight one-minute segments to facilitate task design.

For the ASR component, the SpeechTexter system (accessible via https://www.speechtexter.com/) was used. The accuracy of the ASR system was assessed by comparing its output to the existing transcriptions of the video, revealing a 98% accuracy rate. However, since this system does not support the Persian language, it was only usable for speech transcription of the English version of the video while being interpreted into Persian. As a result, the reverse direction of interpreting—Persian to English—was not explored in this study.

Four alternating video segments (1, 3, 5, and 7) were designated for ASR-assisted interpreting, while the other four (2, 4, 6, and 8) were designated for interpreting without ASR. To demonstrate this setup, the video and the ASR webpage were displayed side by side using cascaded windows, ensuring both were visible simultaneously (see Figure 1). To avoid potential internet connectivity issues on the experiment day, the videos were pre-played alongside ASR, and the sessions were screen-recorded. These pre-recorded sessions ensured seamless playback during the experiment without requiring a live internet connection.

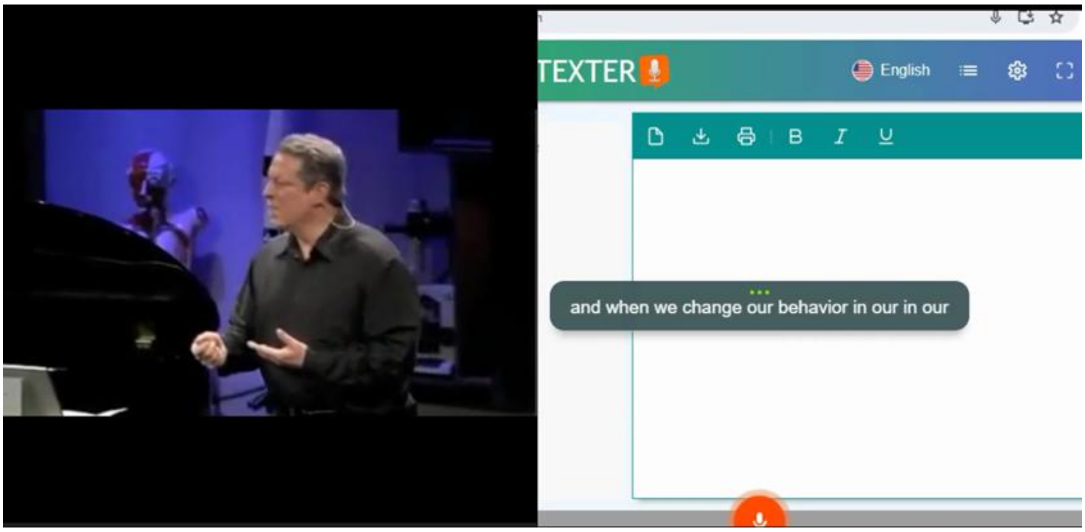

Figure 1: Preview of the cascaded windows

The finalized videos were sent to the lab expert for programming and integration into the experimental task design using MATLAB software. The experimental task was structured as follows:

1. An initial 60-second pre-rest period.
2. A task block of simultaneous interpreting with ASR (ASR-SI), followed by a 60-second rest period.
3. A task block of simultaneous interpreting without ASR (NoASR-SI), followed by a 60-second rest period.
4. A final 60-second post-rest period.

This cycle was repeated four times. At the start of each task block, a 2-second red fixation cross appeared at the center of the screen as a cue. The eight blocks (four for each task) were presented consecutively, with a 60-second rest period after each. After the final block, a post-rest period of 60 seconds concluded the session. This structured design ensured consistent timing and allowed for the measurement of hemodynamic responses during both task and rest periods. Figure 2 shows the process of the experimental task.

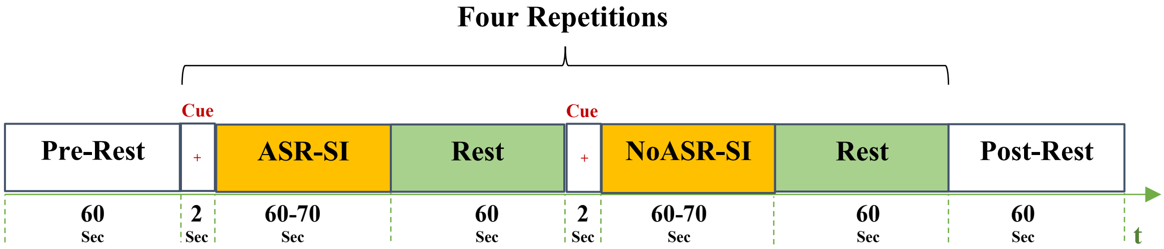

Figure 2: Schematic representation of the experimental task design. The session included four cycles, each consisting of interpreting with ASR (ASR-SI) and without ASR (NoASR-SI) blocks, separated by 60-second rest periods

2.3 fNIRS data acquisition

The present study employed a 48-channel fNIRS system (OxyMon fNIRS, Artinis) at the National Brain Mapping Laboratory in Tehran. The fNIRS system was used to record concentration changes in oxyhemoglobin [ΔHbO_2] and deoxyhemoglobin [ΔHbR] as it is sensitive to hemodynamic changes in the blood. The device transmits two wavelengths of near-infrared light (730 nm and 850 nm), with a sampling frequency of 10 Hz, allowing for the measurement of hemodynamic changes in the cortical brain regions. These hemodynamic responses were analyzed using the Modified Beer-Lambert law which describes the relationship between light absorption and concentration changes of hemoglobin in tissue (Orbig et al. 2000; Tornov et al. 2000).

The fNIRS signals were collected from 24 channels, comprising 10 transmitters and 10 detectors. The placement of these channels was informed by prior neuroimaging studies which identified active brain regions involved in translating and interpreting process, such as the inferior and dorsolateral frontal region (Rinne et al. 2000; Hervais-Adelman et al. 2015; He et al. 2021), prefrontal regions (Rinne et al. 2000; Quaresima et al. 2002; Hervais-Adelman et al. 2015; He et al. 2017), Broca's area (Tommola et al. 2000; He et al. 2017), and the left temporal area (Kurz 1995; Hervais-Adelman et al. 2015). However, due to the fixed format of the channel patches, as shown in Figure 3, as well as the limitations in the lab, the channels were positioned to correspond with only two of the above-mentioned regions. Specifically, the channels were strategically placed across two primary regions of the brain: the medial prefrontal cortex (MPFC) and the temporal cortex (TC). Each of these regions was further subdivided into the right and left hemispheres, with the MPFC additionally partitioned into a central region, resulting in the following subdivisions: left MPFC (LMPFC), central MPFC (CMPFC), right MPFC (RMPFC), left temporal cortex (LTC), and right temporal cortex (RTC**)**. To ensure comprehensive coverage of the target brain regions, three optode probe patches were employed, including one patch with 20 channels and two patches, each containing 4 channels. A fixed inter-channel distance of 3 cm was maintained between each transmitter and detector, resulting in an approximate cortical penetration depth of 1.5 cm. Figure 3 illustrates the spatial distribution of the channels. This configuration was designed to optimize spatial resolution while maintaining a standardized inter-optode distance, ensuring robust and reliable hemodynamic measurements. The blue circles represent receivers, the yellow circles denote transmitters, and the white ones indicate the 24 channels utilized in the fNIRS setup. The location of the channels in each region is as follows: Channels 1, 2, 3, and 4 are in RTC, channels 5, 6, 7, and 8 are in LTC, channels 9, 10, 11, 12, 13, 14, and 15 are in RMPFC, channels 16 and 17 are in the center (CMPFC) and channels 18, 19, 20, 21, 22, 23 and 24 are in LMPFC.

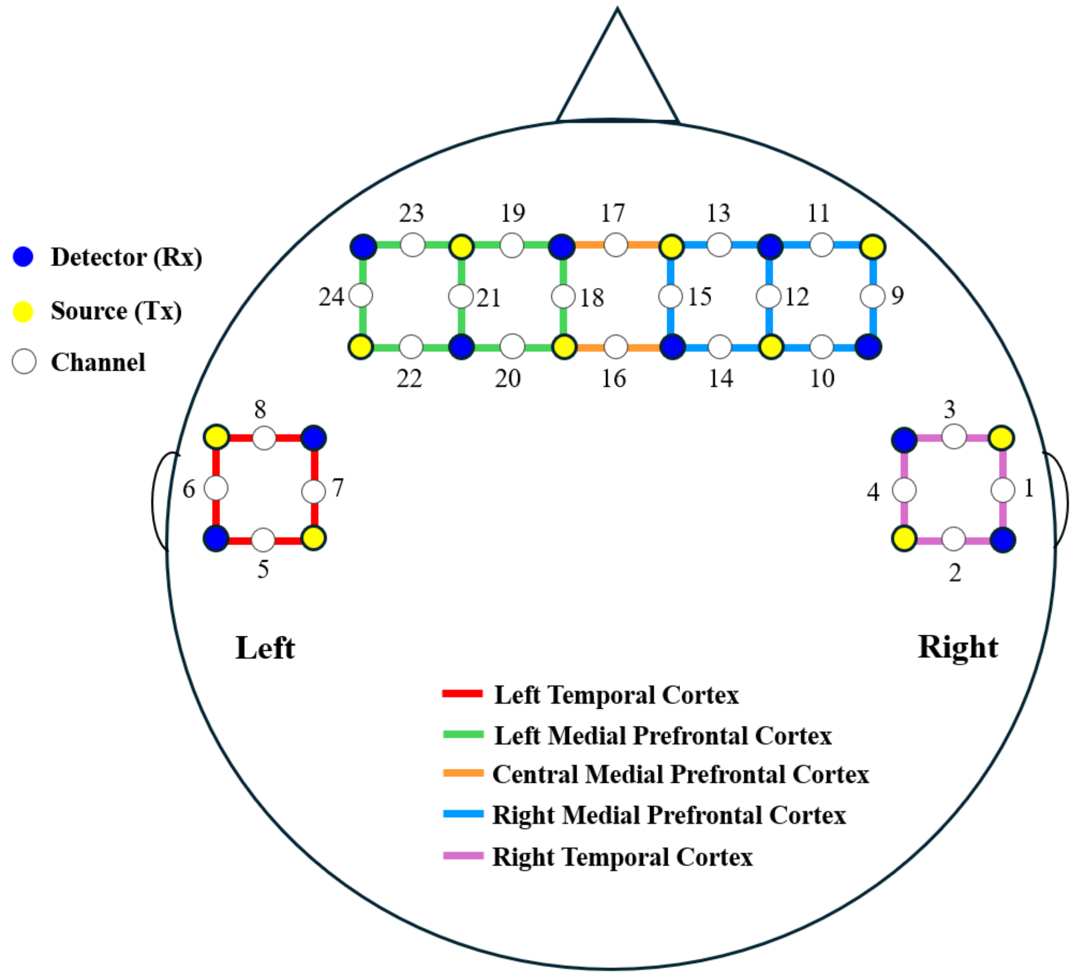

Figure 3: fNIRS channels configuration. The blue circles indicate receivers, the yellow circles denote transmitters, and the white circles represent the 24 channels. Channels are distributed across the Right Temporal Cortex (RTC: 1–4), Left Temporal Cortex (LTC: 5–8), Right Medial Prefrontal Cortex (RMPFC: 9–15), Central Medial Prefrontal Cortex (CMPFC: 16–17), and Left Medial Prefrontal Cortex (LMPFC: 18–24)

2.4 fNIRS data analysis

Functional near-infrared spectroscopy (fNIRS) is a powerful tool for monitoring neuronal activity, but its signals are often contaminated by physiological noise and motion artifacts. A critical step in this process involves identifying and removing physiological noise and motion artifacts, which are inherent to fNIRS signals. Physiological noise is primarily attributed to hemodynamic fluctuations, such as variations in cardiac pulsations (0.8–1.2 Hz), respiration (0.1–0.5 Hz), and blood pressure including Mayer waves (~0.1 Hz). Motion artifacts, on the other hand, are primarily caused by body movements, particularly head motion (Dadgostar et al. 2013). fNIRS data typically requires preprocessing to ensure accurate analysis. The best cognitive signal band was extracted using the discrete wavelet transform (DWT) to overcome these difficulties and successfully filter signals in the 0.003–0.08 Hz frequency range. By removing motion artifacts and physiological noise, which mostly appear above 0.08 Hz, this method creates a clean fNIRS-HbO_2 dataset for further examination. This preprocessing pipeline enhances signal reliability by mitigating systemic noise and artifacts, ensuring robust insights into cerebral neural activity (Einalou et al. 2015; Dadgostar et al. 2016; Einalou et al. 2017; Dadgostar et al. 2018; Shirzadi et al. 2020; Shirzadi et al. 2024; Asadi et al. 2025).

As established in fNIRS-related literature, this specific neuroimaging technique is effective in detecting changes in blood oxygenation. Therefore, in order to assess the activation of a specific area in the brain, one can measure the regional concentration changes in oxyhemoglobin and deoxyhemoglobin. Simply put, when a specific brain region is activated, HbO_2 increases whereas HbR decreases. Given the fact that HbO_2 is the most sensitive indicator of blood flow changes, only HbO_2 signals were analyzed in this study. Thus, the concentration changes in oxyhemoglobin were computed across all the 24 channels for each participant and for both tasks. These HbO_2 signals were then averaged in each of the five determined brain regions to be considered as an indicator of activation. Finally, a paired *t* test was performed to determine significant differences in brain activation between ASR-SI and NoASR-SI in the afore-mentioned brain regions (e.g., LMPFC, CMPFC, RMPFC, LTC, and RTC). The process of fNIRS data analysis is depicted in Figure 4.

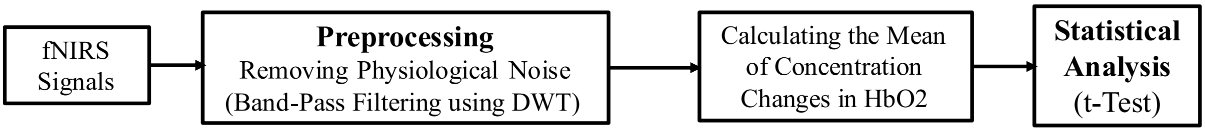

Figure 4: Block diagram of the fNIRS data analysis pipeline

3. Results

3.1 fNIRS results

The fNIRS results indicated that, in most channels, the average concentration changes of HbO_2 during ASR-SI were lower than those observed in NoASR-SI. These findings suggest that interpreting with the help of ASR is associated with a reduced cognitive load, while interpreting without ASR appears to increase cognitive demand. Consequently, it can be inferred that ASR functioning as a CAI tool, potentially alleviates the cognitive burden on interpreters.

In other words, an increase in the average concentration of HbO_2 indicates a greater supply of oxygen, which is associated with increased neural activity in that specific brain region. Given that cognitive load is linked to heightened neural activity, a rise in HbO_2 concentration suggests that the region is more actively engaged in processing cognitive demands. To assess activation differences between the ASR-SI and NoASR-SI, HbO_2 concentration changes were measured in five brain regions and a paired *t*-test was conducted to identify brain regions that exhibited significant activation differences between the two conditions.

The statistical analysis revealed a significant difference in activation in the left temporal cortex (LTC), with a *p* value = 0.02 ($p < 0.05$). This indicates a notable distinction between ASR-SI and NoASR-SI in the LTC. Further examination of the mean of concentration changes in HbO_2 for the relevant brain regions (see Figure 5) showed that, in the LTC, HbO_2 levels were lower during ASR-SI than NoASR-SI. This reinforces the conclusion that the ASR tool can effectively reduce the cognitive load experienced by interpreters.

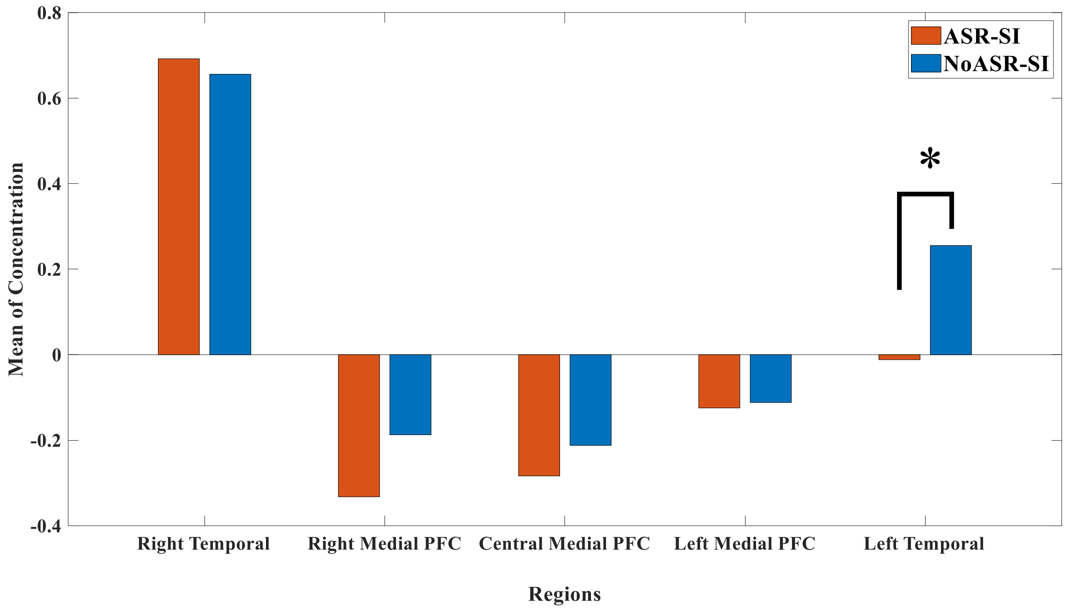

Figure 5: Mean concentration changes in HbO_2 across the five brain regions (LMPFC, CMPFC, RMPFC, LTC, and RTC) for all subjects (*$p < 0.05$)

3.2 Participants' assessment of the integration of ASR

This section presents the behavioral results of the study based on data collected through a questionnaire. After the experiment, participants were asked to provide feedback regarding the integration of Automatic Speech Recognition (ASR) into the interpreting process. They were specifically inquired about their preferences, any distractions caused by the tool, and its overall effectiveness. Table 1 shows that more than half of the participants (58.3%) expressed positive opinions, indicating that they found the tool beneficial and believed it could enhance the interpreting process. However, only 41.6% of these subjective opinions aligned with the brain activity data obtained from fNIRS measurements.

Table 1: Comparison of mean brain activity of ASR-SI vs. NoASR-SI in LTC and its alignment with participants' opinion

Participants	**Mean Brain Activity of ASR-SI vs. NoASR-SI in LTC**	**Participants' Opinion (Positive/Negative)**	**Aligned with Brain Data? (Yes/No)**
Subject 1	ASR-SI < NoASR-SI	Negative	No
Subject 2	ASR-SI < NoASR-SI	Negative	No
Subject 3	ASR-SI < NoASR-SI	Positive	Yes
Subject 4	ASR-SI < NoASR-SI	Negative	No
Subject 5	ASR-SI < NoASR-SI	Negative	No
Subject 6	ASR-SI < NoASR-SI	Positive	Yes
Subject 7	ASR-SI > NoASR-SI	Positive	No
Subject 8	ASR-SI < NoASR-SI	Positive	Yes
Subject 9	ASR-SI > NoASR-SI	Positive	No
Subject 10	ASR-SI < NoASR-SI	Positive	Yes
Subject 11	ASR-SI > NoASR-SI	Positive	No
Subject 12	ASR-SI > NoASR-SI	Negative	Yes
Percentage		**Positive**: 58.3% **Negative**: 41.7%	**Yes**: 41.7% **No**: 58.3%

Five participants provided critical feedback regarding potential distractions. For instance, Subject 1 reported that the tool was distracting, particularly when the interpreter fell behind and needed to refocus to catch up. Additionally, he expressed dissatisfaction with the real-time transcription of words, suggesting that a complete sentence transcription, akin to subtitles in films, would be more useful. Nevertheless, Subject 1 acknowledged the tool's utility in interpreting specific names and numbers. Subject 2 also found the tool confusing, particularly when it was unclear what to focus on. She mentioned that she looked away from the text to concentrate on the interpretation. Furthermore, she reported a case of a homophone (*die*/*dye*) being mistyped, which led to confusion. Similarly, subject 4 noted the tool's distracting nature, although he found it occasionally helpful for interpreting vernacular terms. Subject 5 highlighted a similar issue, stating that he was distracted by the text, which hindered their ability to focus on the speaker's voice. Notwithstanding, he found the tool useful for recognizing unfamiliar words, numbers, and proper names. Last, subject 12 mentioned that he was distracted while using the tool and he could have performed better without it. He emphasized that if the ASR showed a larger segment of the text, not line by line, that would be more helpful.

On the other hand, seven participants provided positive feedback about the tool's utility. Subject 3 suggested that the tool could expedite the mental analysis or decoding of the intended message. Subject 6 appreciated how the tool alleviated some cognitive load and praised its dynamic, real-time display, in contrast to the static nature of subtitles. Subject 7 appreciated how the tool alleviated some cognitive load and praised its dynamic, real-time display, in contrast to the static nature of subtitles. Subject 8 noted that the tool helped reduce overthinking but expressed concern that it might impede the interpreter's speed. Subject 9 considered the tool as a significant aid, mentioning that it helped in some cases find the term you doubt you had heard. Subject 10 mentioned that the tool allowed for better focus on the cohesion of interpreted sentences by reducing cognitive load. Subject 11 described the tool as handy, accessible, and useful, emphasizing its clarity and ease of use in real-time interpretation.

When analyzing the mean of concentration changes in HbO_2 in the left temporal region (LTC) which was significantly active in this experiment, an intriguing discrepancy emerged between participants' subjective perceptions and their actual cognitive load during the interpreting process (see Table 1). The data revealed that participants' self-reported experiences did not always align with the objective measures of their cognitive effort. For example, subjects 1, 2, 4 and 5, who expressed a critical stance toward the use of automatic speech recognition (ASR) tools in interpreting, exhibited a higher cognitive load when performing interpreting without ASR compared to when they had access to it. Conversely, subjects 7, 9, and 11 who expressed positive attitudes toward the tool displayed a higher cognitive load while using it, as reflected in the mean of HbO_2 concentration changes.

4. Discussion

This study is one of the first to use functional Near-Infrared Spectroscopy (fNIRS) to compare the cognitive load experienced by interpreters when using a Computer-Assisted Interpreting (CAI) tool, specifically Automatic Speech Recognition (ASR), versus interpreting without it. Additionally, it explores interpreting between English and Persian in this context, which has not been widely studied. Interpreters in the study performed two distinct tasks consecutively, each repeated four times. Task 1 involved interpreting with the use of ASR (ASR-SI), while task 2 required interpreting without ASR (NoASR-SI). fNIRS neuroimaging was employed to monitor the interpreters' neural activity during the tasks. The results of the fNIRS data revealed activation in the left temporal cortex (LTC) during simultaneous interpreting from English to Persian, a finding that aligns with previous neuroimaging studies, which have also reported activation in this region of the brain during interpreting tasks (Kurz 1995; Rinne et al. 2000; Ahrens et al. 2010; Hervais-Adelman et al. 2014). However, the results of a study by He and Hu (2022) on Mandarin-to-English interpreters showed activation in the right dorsolateral prefrontal hub, highlighting some variation in brain activation patterns depending on the language pair and the interpreter's task.

In practical terms, the results of the fNIRS data suggest that interpreting without ASR imposed a greater cognitive demand on linguistic processing compared to interpreting with ASR, leading to increased neural activity in this area. The absence of significant effects in the other four regions could be due to task-specific demands, individual variability, or the possibility that these regions were not as critically engaged in the cognitive processes required by the tasks. It is likely that LTC region was more involved during the SI process compared to the other four regions.

Furthermore, understanding which brain regions are activated during a specific task can provide valuable insights for designing targeted activities, tasks, or training programs that strengthen those areas for future cognitive demands. In the context of interpreter training, these findings can be used to develop classroom activities that enhance the neural mechanisms essential for interpreting, ultimately improving cognitive efficiency and performance in professional settings.

Beyond the neural activation patterns, the primary objective of this study was to determine whether the use of CAI tools, specifically ASR, impacted the cognitive load of interpreters. This question had not previously been explored using fNIRS, and the existing literature on the relationship between CAI tools and cognitive load is limited. One of the earliest researchers to address this issue, Prandi (2018), examined the connection between CAI tools and cognitive load, primarily from a theoretical perspective. More recently, Mellinger (2023) emphasized the importance of considering how the integration of technology in interpreting affects cognitive processes. In her doctoral thesis, Frittella (2024) explores the cognitive impacts of CAI tools on interpreting and delivers practical, research-supported strategies for their integration into interpreter training programs.

The analysis of changes in the concentration of oxygenated hemoglobin (HbO_2) in this study indicated that the use of ASR resulted in lower levels of HbO_2 compared to interpreting without ASR. This suggests that the use of ASR facilitated the interpreting process, significantly reducing the cognitive load required by the interpreters. These findings are consistent with those of Defrancq & Fantinuoli (2021), who investigated the impact of ASR integrated into the InterpretBank tool. Their study, which assessed both interpreters' performance through an error matrix and their subjective perceptions via a questionnaire, found that ASR improved interpreter performance. This can further be interpreted as follows: A reduction in the cognitive load can lead to better performance which can further support the conclusion that CAI tools like ASR ease the cognitive demands of interpreting tasks.

Furthermore, a comparison of the participants' opinions on ASR's contribution to the interpreting process with the average brain activity revealed a discrepancy. This finding showed that participants' perceptions of ASR did not fully correspond to the objective neural activity recorded during simultaneous interpreting with and without ASR support. For instance, the results of fNIRS data showed a decrease in the cognitive load of those who expressed a negative stance toward the use of ASR. This finding suggests that, despite their skepticism, the ASR tool effectively reduced their cognitive burden. However, these participants subjectively perceived the tool as imposing a greater cognitive strain, which may indicate a psychological or attitudinal barrier to its adoption rather than an actual increase in cognitive effort. One possible explanation for this discrepancy is the lack of familiarity or training in using the tool efficiently. If participants were provided with structured guidance on how to integrate the ASR system into their workflow, their subjective experience might improve, allowing them to better recognize and appreciate its benefits. On the contrary, those three participants who expressed positive attitudes toward integrating the tool into the interpreting process, displayed a higher cognitive load while using it, as reflected in the mean of HbO_2 concentration changes. This finding suggests that while these individuals were receptive to the tool, its use may have required additional cognitive resources, potentially due to the complexity of multitasking or the challenge of integrating the tool effectively within the interpreting process.

Overall, these findings underscore the inherently subjective nature of self-reported experiences, highlighting the limitations of relying solely on personal perceptions to assess the tool's effectiveness. Instead, objective physiological measures, such as changes in HbO_2 concentration, offer valuable insights into the cognitive demands associated with different interpreting conditions. Ultimately, the results suggest that proper training and increased familiarity with ASR technology could enhance both the subjective experience and the actual cognitive efficiency of its use, thereby maximizing its potential benefits in the interpreting process.

In conclusion, the results of this study provide novel insights into the relationship between the use of CAI tools, specifically ASR, and cognitive load in interpreters. The results indicate that the use of ASR can significantly reduce cognitive load, as evidenced by lower HbO_2 levels in the brain. We might propose that, intuitively, a lower cognitive load *could* facilitate faster and more accurate interpretation. This assumption aligns with common sense, as reduced cognitive load may free up mental resources for more efficient processing. However, without empirical evidence to support this claim, further research would be necessary to substantiate it. These findings contribute to the growing body of research on the integration of technology in interpreting and highlight the potential benefits of CAI tools for improving interpreter performance while reducing mental effort. Future research should continue to explore these dynamics across different language pairs and interpreting contexts to further validate and expand upon these results.

5. Conclusion

While this study provides valuable insights into the cognitive load of interpreters using automatic speech recognition (ASR), several limitations should be acknowledged. First, the laboratory setting, while necessary for controlled experimentation, may limit the generalizability of the findings to real-world interpreting scenarios. Participants' behavior in a controlled environment may not fully reflect their natural responses in professional settings, potentially influencing the study's external validity. Additionally, controlled conditions can sometimes induce artificial responses, which may not entirely capture the complexities of real-time interpreting.

Second, the sample size of 12 participants, although justified by the demanding nature of data collection and analysis in fNIRS studies, remains a limitation. Larger sample sizes are typically preferred for statistical analyses to enhance the reliability and generalizability of findings. However, practical constraints, such as the time-intensive nature of data processing and the challenges in recruiting interpreters with our desired criteria, influenced the feasibility of a larger participant pool. Future studies could aim to include more participants to strengthen statistical power and further validate the results.

Despite these limitations, this study contributes to the ongoing discourse on interpreter training and technology integration. Future research could explore several directions to expand on these findings. One potential avenue is investigating the impact of ASR in different interpreting modes and across diverse language pairs, which could provide a more comprehensive understanding of its applicability across varied contexts. Additionally, future studies could assess different computer-assisted interpreting (CAI) tools beyond ASR, examining how various technologies influence cognitive load and interpreter performance.

Further research could also incorporate additional variables, such as gender differences, text complexity, modality, efficiency, and accuracy, to assess their impact on cognitive load. These factors could provide deeper insights into how different elements interact with interpreters' cognitive processes. Moreover, applying alternative measurement techniques alongside fNIRS could enhance the robustness of findings by offering a multi-method perspective on cognitive load assessment.

Overall, by acknowledging these limitations and exploring new research directions, future studies can build upon these findings to develop more tailored, effective, and cognitively sustainable interpreting technologies. This could ultimately contribute to optimizing interpreter performance and improving the efficiency of language interpretation in both professional and training contexts.

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