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Published in:
Journal of speech, language, and hearing research : JSLHR

DOI:
10.1044/2024_JSLHR-24-00465

Publication date:
2025

Document version:
Final published version

ASHA American Speech-Language-Hearing Association

JSLHR

Research Article

Fluid Intelligence Partially Mediates the Effect of Working Memory on Speech Recognition in Noise

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ARTICLE INFO

Article History:
Received July 1, 2024
Revision received September 30, 2024
Accepted October 7, 2024

Editor-in-Chief: Rachael Frush Holt
Editor: Deniz Baskent

https://doi.org/10.1044/2024_JSLHR-24-00465

ABSTRACT

Purpose: Although the existing literature has explored the link between cognitive functioning and speech recognition in noise, the specific role of fluid intelligence still needs to be studied. Given the established association between working memory capacity (WMC) and fluid intelligence and the predictive power of WMC for speech recognition in noise, we aimed to elucidate the mediating role of fluid intelligence.

Method: We used data from the n200 study, a longitudinal investigation into aging, hearing ability, and cognitive functioning. We analyzed two age-matched samples: participants with hearing aids and a group with normal hearing. WMC was assessed using the Reading Span task, and fluid intelligence was measured with Raven's Progressive Matrices. Speech recognition in noise was evaluated using Hagerman sentences presented to target 80% speech-reception thresholds in four-talker babble. Data were analyzed using mediation analysis to examine fluid intelligence as a mediator between WMC and speech recognition in noise.

Results: We found a partial mediating effect of fluid intelligence on the relationship between WMC and speech recognition in noise, and that hearing status did not moderate this effect. In other words, WMC and fluid intelligence were related, and fluid intelligence partially explained the influence of WMC on speech recognition in noise.

Conclusions: This study shows the importance of fluid intelligence in speech recognition in noise, regardless of hearing status. Future research should use other advanced statistical techniques and explore various speech recognition tests and background maskers to deepen our understanding of the interplay between WMC and fluid intelligence in speech recognition.

Ample research data have demonstrated a relationship between cognition and speech recognition in noise, especially for older individuals. In a systematic review and meta-analysis, Dryden et al. (2017) reported a medium strength (r = .30) relationship between cognitive measures and speech recognition in noise for older adults. Most previous research on the link between cognitive functioning and speech recognition in noise has focused on working memory (WM) and processing speed (e.g., Dryden et al., 2017; Homman et al., 2023). However, cognition encompasses a broad set of interrelated functions that we use to purposefully solve an ongoing activity (e.g., Schneider & McGrew, 2012), and several of these might impact speech recognition in noise success. In the present study, we aim to examine the role of fluid intelligence in speech recognition outcomes. Specifically, our study explores whether the prediction of WM capacity (WMC) on speech recognition in noise is mediated by fluid intelligence.

WM is the cognitive system that allows us to store and manipulate information for a short period of time. According to Baddeley's (2012) model, WM consists of four components: the central executive, which coordinates

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and controls attention; the phonological loop, which stores and rehearses verbal information; the visuospatial sketchpad, which stores and manipulates visual and spatial information; and the episodic buffer, which integrates information from different sources and links into long-term memory. One way to measure WMC is to use complex span tasks, which require participants to perform a processing task (such as arithmetic or reading) while remembering unrelated items (such as letters or words). For example, in the Reading Span Test, participants must read sentences and remember one word of each sentence while performing a secondary task: deciding if the sentences make sense or not. The number of items that can be recalled after the processing task is taken as a measure of WMC. Interestingly, storing and manipulating (e.g., inference making) information within a limited online time window is essential for completing complex tasks, such as understanding spoken language in the presence of background noise. Most of the literature has identified the link between WMC and speech recognition in noise in individuals with hearing loss (Arehart et al., 2013; Foo et al., 2007; Lunner, 2003; Lunner et al., 2009), and in a review by Akeroyd (2008), hearing loss and WMC were the two major predictors of speech recognition in noise.

Concerning younger, normal-hearing individuals, however, the literature is somewhat mixed. Some published data suggest that normal-hearing individuals use explicit cognitive processing, such as WMC, in difficult listening settings. For example, Michalek et al. (2018) observed that higher signal-to-noise ratios (SNRs) in multitalker babble noise increased participants' reliance on WMC. Moreover, Stenbäck et al. (2021) found that WMC was related to better performance in speech recognition in noise tasks in both younger and older adults. In a recent study by Bosen and Doria (2023), using latent variable modeling, general memory, including WM tasks, was positively associated with sentence recognition (i.e., speech recognition in two-talker babble) in young normal-hearing individuals. Generally, these findings suggest that there is a relationship between cognitive processing, particularly WMC, and speech recognition in challenging acoustic environments for both older and younger individuals with normal hearing.

However, contrasting results, failing to show a significant contribution of WMC on speech recognition in noise, also exist (e.g., Schoof & Rosen, 2014; Vermeire et al., 2019). Schoof and Rosen (2014) found that declines in cognitive processing, such as WM and processing speed, were observed in older adults. However, these declines did not significantly correlate with speech recognition in noise. Moreover, Ellis and Munro (2013) found that the relationship between WMC and recognition of frequency-compressed speech in noise was not statistically significant. A meta-analysis by Füllgrabe and Rosen (2016) indicated that WMC, measured by the Reading Span Test, accounted for less than 2% of the variance in speech-in-noise performance for young, normal-hearing listeners. In a more recent study by Vermeire et al. (2019), a significant correlation between WMC and speech recognition in noise was observed exclusively among older adults. Although cognitive factors, particularly WMC, may influence speech recognition in noise for normal-hearing individuals, the extent of this influence may vary depending on the specific listening conditions and tasks. Moreover, these discrepancies may also suggest that other mechanisms or cognitive functions than WM are contributing to the differences in results observed across studies.

Commonly, speech recognition in noise tests uses matrix sentences. One example of a test using matrix sentences is the Swedish Hagerman sentences (Hagerman, 1982; Hagerman & Kinnefors, 1995), in which a closed-set structure is used. Although the grammatical form of the Hagerman sentences follows a predictable pattern, the words themselves cannot be predicted. Importantly, if the words in the sentences are not heard, they are hard to guess. The Hagerman test can be designed to target speech reception thresholds (SRTs) of 50% or 80% word recognition. Larsby et al. (2008) showed that SRT is a major factor in successful speech recognition. As speech recognition reaches an 80% accuracy threshold, cognition becomes increasingly critical. This is amplified compared to a 50% accuracy level, where a significant amount of information is lost, impeding the synthesis of a comprehensive message (Larsby et al., 2008; Lunner & Sundewall-Thorén, 2007; Stenbäck et al., 2015). However, it is worth pointing out that cognitive functioning is also associated with performance for 50% SRT (e.g., Marsja et al., 2022). Although cognition plays a crucial role under 80% and 50% SRT conditions, the evidence emphasizes the heightened importance of cognitive processes, such as WMC, particularly in scenarios where speech recognition is required at 80% SRT (Homman et al., 2023).

Two of the most common background noise types used to assess speech-in-noise recognition, each posing distinct cognitive demands, are multitalker babble and speech-shaped noise (SSN). Multitalker babble is defined as an informational masker, since it competes with the target speech for attentional resources because of its lexico-semantic content (Mattys et al., 2009). In fact, competing multitalker babble has been shown to be more cognitively demanding than SSN (Goossens et al., 2017; Koelewijn et al., 2012; Ng & Rönnberg, 2020; Rönnberg et al., 2022). On the other hand, SSN is defined as an energetic masker and offers little or no opportunities to glimpse target speech in pauses and modulations as the masker continuously masks target speech (Rosen et al., 2013). Studies have shown that increasing age and hearing impairment are associated with poorer speech-in-noise recognition performance for both energetic and informational masking (Goossens et al., 2017; Kidd et al., 2019). Importantly, the speech perception difficulties were more pronounced in the case of informational masking, presumably due to the higher cognitive load it induces. This is further supported by a study that found significantly stronger correlations between speech-in-noise recognition and four-talker babble compared to SSN (Ng & Rönnberg, 2020). Recent research conducted by Stenbäck et al. (2022) has also demonstrated that older adults are more dependent on WMC in speech recognition with an informational masker. In all, even though the evidence points to the importance of WMC for both informational and energetic masking, the most cognitively taxing conditions seem to involve informational masking.

In coordinating and integrating cognitive processing, WM interacts with various other cognitive components, such as semantic and episodic long-term memory and fluid intelligence, to produce successful outcomes. Fluid intelligence encompasses the ability to reason abstractly, recognize patterns, and solve novel problems without relying on previously acquired knowledge (Cattell, 1963). Research, including foundational work by Horn and Cattell (1967), has consistently observed that fluid intelligence tends to decline with age (e.g., Bugg et al., 2006). Fluid intelligence is typically measured using tasks involving solving novel problems, reasoning abstractly, and identifying unfamiliar patterns. Commonly used tasks to assess fluid intelligence include matrix reasoning tasks, where individuals identify the missing piece in a visual pattern (e.g., Raven's Progressive Matrices; Raven, 2000), and rule-based tasks, where participants determine which number or letter in a sequence does not follow the underlying rule (Ren et al., 2017).

Fluid intelligence is related to a range of other higher cognitive functions. Of particular interest in the current study, it has been found to share a robust association with WMC (Ackerman et al., 2002; Conway et al., 2002; Engle et al., 1999). For example, Kane et al. (2004) used structural equation modeling (SEM) in a study and found that WMC, measured by complex span tasks, predicted fluid intelligence. Additionally, Unsworth and colleagues (Unsworth et al., 2009; Unsworth & Spillers, 2010) have reported similar results also using structural equation models to estimate latent factors for WMC, secondary memory (i.e., the retrieval and use of information from long-term memory), and fluid intelligence. They found that both WM and secondary memory had significant and independent effects on fluid intelligence. Chekaf et al. (2018) proposed that the capacity to compress information in WM is an important determinant of fluid intelligence, as information manipulation and retention depend on optimizing storage capacity. The studies mentioned above show that there is an interplay between fluid intelligence and WMC.

The abovementioned studies are all correlational and do not establish a causal link between WMC and fluid intelligence. However, some experimental studies have manipulated WM load and measured its impact on fluid intelligence tasks. For instance, Rao and Baddeley (2013) showed that solution time in Raven's Progressive Matrices was slowed when increasing the WM load, suggesting that abstract reasoning for novel problem solving is dependent on WM. More recently, Schubert et al. (2023) consistently demonstrated, in two studies, that increasing WM load decreased performance on Raven's Progressive Matrices, a test measuring fluid intelligence. Their findings suggest that variations in WMC contribute significantly to individual differences in fluid intelligence.

Relative to WMC, fluid intelligence and its relationship to speech recognition in noise is relatively understudied (see Dryden et al., 2017, for a discussion). However, the few studies that have used tasks measuring fluid intelligence and investigating its relation to speech recognition in noise suggest there is an association. For example, Meister et al. (2013) found a relationship between fluid intelligence and performance on a dichotic listening task in a two-talker condition. Moreover, Moore et al. (2014) analyzed data from the UK Biobank and found that lower fluid intelligence was associated with poorer speech recognition in noise. In addition, a more recent study by Pronk et al. (2019) reported that poorer performance on Raven's Progressive Matrices test was related to poorer performance in a speech recognition in noise test, and Moberly et al. (2023) showed that fluid intelligence was positively associated with noise-vocoded sentence recognition. These findings show the relevance of investigating the interplay between fluid intelligence, WMC, and speech recognition in noise.

The current study aims to examine the connection between fluid intelligence and speech recognition in noise among older individuals with normal hearing and hearing-impaired individuals wearing hearing aids, using data from the n200 study (Rönnberg et al., 2016). An important aspect of our investigation is probing the interplay between WMC and fluid intelligence, driven by the well-established association between the two (e.g., Ackerman et al., 2002; Conway et al., 2002). Specifically, we aim to study whether fluid intelligence mediates the prediction of WMC on speech recognition in noise (cf. Homman et al., 2023). Furthermore, we aim to explore whether the abovementioned relationships when presenting speech stimuli at individually adapted SNRs, targeting 80% of SRTs in four-talker babble noise, are moderated by hearing status (normal hearing vs. hearing impaired). The choice of 80% SRT is motivated by its significance in successful speech recognition, emphasizing the heightened cognitive demands involved compared to the 50% SRT (e.g., Larsby et al., 2008; Stenbäck et al., 2015). In the same vein, using four-talker babble is likely to reveal a higher dependence on WMC (e.g., Goossens et al., 2017). The study involves two age-matched samples: a group of aided hearing-impaired individuals and individuals with normal hearing, with data collection encompassing various cognitive-, speech-, and physiological measures. Based on the rationale outlined, we predicted that fluid intelligence, as measured by Raven's Progressive Matrices, is positively related to WMC and negatively related to SNRs in the Hagerman speech recognition in noise test, and that fluid intelligence mediates the association between WMC and SNRs in the Hagerman speech recognition in noise test.

Method

Participants

In the current study, we analyzed data from participants in the n200 study (Rönnberg et al., 2016) who had completed all three data collection sessions. We analyzed data from 191 (96 females) normal-hearing adults between 42 and 78 years (M_{age} = 60.9, *SD* = 8.07) and 199 adults (84 females) with hearing impairment wearing hearing aids between 33 and 80 years (M_{age} = 60.9, *SD* = 8.41). Finally, all participants signed an informed consent form prior to the study, which was approved by the regional ethical review board in Linköping (registration rumber: 55–09) and was conducted following the Declaration of Helsinki. A description of the two groups can be found in Table 1 (including mean and range for all tests included in the current study, pure-tone average, and year of hearing aid for the hearing aid users' group).

Cognitive Tests

Reading Span

The participants were administered the Reading Span Test (Daneman & Carpenter, 1980; Rönnberg et al., 1989) to measure WMC. This test involved displaying a series of short Swedish sentences consisting of three words each on a computer screen. The sentences were presented one word at a time, and the participants were instructed to remember the sentences. After each sentence, they also had to determine whether the sentence made sense (e.g., "The ball bounced far") or was nonsensical (e.g., "The fox wrote poetry"). Moreover, the sentences were grouped into sets of two to five, with increasing difficulty as the sets progressed. Once a set was presented, the participants were asked to recall either the first or the last word of each sentence in the correct order in which the words were presented. This was not announced before the set of sentences was presented. The dependent variable was the total number of correctly recalled items (maximum 28), regardless of the recall order.

Raven's Progressive Matrices

The present study assessed fluid intelligence using an abbreviated version of Raven's Progressive Matrices (Raven, 2000). Three sets (A, D, and E) were utilized out of the five available sets. The initial set (A) was a practice round, while Sets D and E consisted of 12 items each. These two sets were administered without feedback and were subjected to a time limit of 60 min. Scoring for the test was based on the cumulative points obtained from Sets D and E, with a maximum score of 12 for each set. Consequently, the maximum attainable score for the entire test was 24.

Hagerman Speech Recognition in Noise

We employed the Hagerman sentences (Hagerman, 1982) to assess speech recognition in noisy environments, utilizing an interleaved method (Brand, 2000), meaning sentences were presented to target 50% or 80% SRTs interchangeably. A total of 20 sentences were presented, where half targeted 50% and half 80% word recognition. The stimuli were presented binaurally through a pair of inserted earphones at a level of 65 dB SPL. An adaptive procedure was used, where the background noise level varied based on the participant's response. The SNR was increased by 2 dB if no words were repeated correctly. If one word was repeated correctly, the SNR was increased by 1 dB. The SNR remained unchanged if two words were repeated correctly. If three, four, or five words were repeated correctly, the SNR was decreased by 1, 2, or 3 dB, respectively. The sentences were presented against two

Table 1. Mean and range (within parentheses) for the two groups.

Group	Reading Span	Raven	PTA4	Years of hearing aid use	Hagerman np 80% SRT
Normal hearing	16.7 (1, 28)	16.35 (4, 24)	10.02 (–5, 26.25)		1.2 (1.2, 1.2)
Hearing aid users	16.08 (5, 26)	15.51 (2, 24)	37.27 (10, 75)	6.76 (0, 45)	3.79 (3.79, 3.79)

Note. PTA4 = pure-tone average better ear; np = no processing; SRT = Speech Reception Threshold.

background noise conditions: the original Hagerman SSN with slight modulation (approximately 10%) and a long-term frequency spectrum that is identical to that of the sentences, and a four-talker babble consisting of four simultaneous speakers communicating in Swedish. In the n200 study, all participants received amplification. The participants with hearing impairment received amplification based on their audiometric thresholds, while those with normal hearing based on a flat audiogram of 20 dB HL. The amplification for the hearing aid group followed a voice-aligned compression rationale, delivering linear gain (1:1 compression ratio) for pure-tone inputs ranging from 30 to 90 dB SPL (Rönnberg et al., 2016, Supplementary Material). To minimize training effects, participants underwent a practice session with two lists containing 10 sentences, as recommended by (Hagerman & Kinnefors, 1995). After practice, and to determine SRTs, two lists were presented in each combination of background masker and type of signal condition, totaling 12 lists. In the current study, the dependent variable from the task was the SNR level for the linear hearing processing settings (i.e., linear processing without noise reduction[1]), 80% SRT, with the four-talker background noise. We selected linear hearing processing to assess speech recognition performance, as we did not intend to evaluate signal processing strategies. Choosing this processing setting does not add complexities related to SNR enhancement techniques.

Data Analysis

Data processing and analysis were conducted using the R statistical programming environment (Version 4.2.3; R Core Team, 2023). A mediation analysis was conducted within the SEM framework using the lavaan package in R (Rosseel, 2012) to examine the relationship between WMC (Reading Span Test scores) and speech recognition in noise (speech-in-noise recognition; Hagerman sentences performance, SNR), with fluid intelligence (Raven test performance) as a potential mediator. We used established mediation analysis techniques, such as calculating the indirect effect of WM on speech recognition in noise through fluid intelligence. This involved examining the significance and magnitude of the indirect effect, which shows the extent to which fluid intelligence acts as a mediator between WMCs and speech-in-noise recognition. We used 10,000 bootstrap samples and full information maximum likelihood estimation for missing values, a robust method that can handle non normality and missing values (Enders & Bandalos, 2001).

We used a multigroup approach (normal hearing and hearing impaired) to assess whether the mediation model was comparable between groups. Our model contained four paths: the effect of WMC on fluid intelligence (a), the direct effect of fluid intelligence on speech-in-noise recognition (b), the direct effect of WMC on speech-in-noise recognition (c′), and the indirect effect of WMC on speech-in-noise recognition through fluid intelligence (a, b; see Figure 1). We let all parameters be freely estimated across groups, meaning that we did not impose any equality constraints on the path coefficients or the error variances. Then, we constrained all the paths to be equal across groups and compared the free model to the constrained model using a Wald test, a chi-square test that evaluates if there is a significant difference (Kline, 2016). The Wald test allowed us to examine whether the group moderated the mediation effect and whether the paths differed significantly (i.e., the a, b, and c′ paths) between normal-hearing and hearing-impaired listeners. If significant differences were found between the two groups, it suggests that the mediation effect is influenced by hearing status. Conversely, if no significant differences were observed, it would imply that the mediation effect is similar between groups.

Results

Hearing Aid Users

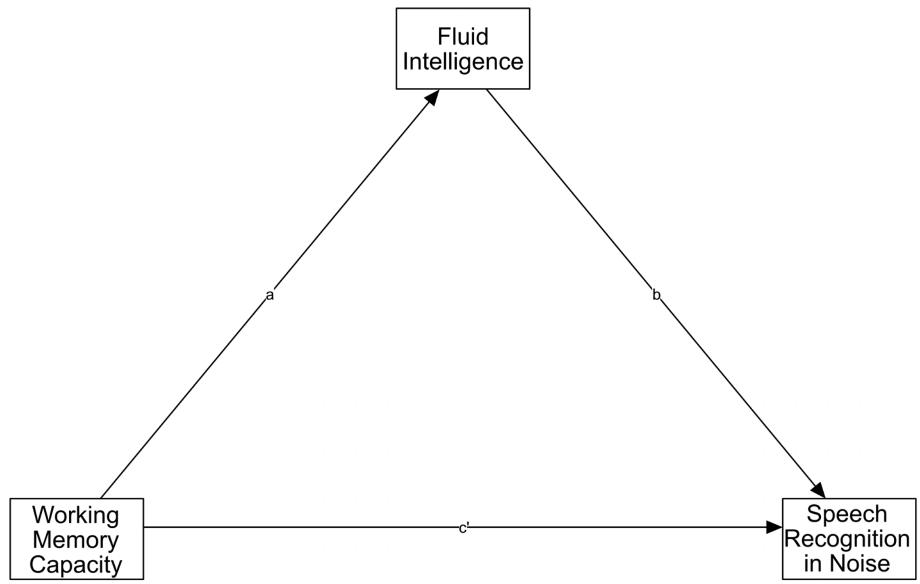
The mediation analysis for the hearing aid users demonstrated that fluid intelligence significantly mediated the effect of WMC on speech-in-noise recognition ($\beta = -.12$, $p < .001$). See Figure 2 for an overview. This suggests that the relationship between WMC and speech-in-noise recognition is fully mediated by fluid intelligence, as illustrated in Figure 1 by the indirect path a * b. Moreover, when considering the direct effect of WMC performance on speech-in-noise recognition, while controlling for fluid intelligence (Figure 1, path c′), it was nonsignificant ($\beta = -.04$, $p = .64$). In addition, the total effect on speech recognition in noise was nonsignificant ($\beta = -.16$, $p = .12$). These results suggest that while there may be an indirect effect of WMC on speech-in-noise recognition through fluid intelligence, the direct relationship between WMC and speech-in-noise recognition is not statistically significant. The comprehensive results from the mediation model are detailed in Table 2.

Normal Hearing

An overview of the results from the mediation analysis for the normal-hearing group can be seen in Figure 3. For this group, fluid intelligence did not mediate the effect of WMC on speech-in-noise recognition ($\beta = -.04$, $p = .12$). However, WMC performance significantly directly affected speech recognition in noise (c′ path in Figure 1) while controlling for fluid intelligence ($\beta = -.18$, $p = .05$).

[1]In the n200 study, there are two more conditions related to hearing aid settings: fast compression and noise reduction.

Figure 1. Theoretical model.



Moreover, the total effect on speech-in-noise recognition was significant (β = −.22, p = .01). These results suggest that while WMC may not have a mediating effect on speech-in-noise recognition through fluid intelligence, the direct relationship between WMC and speech-in-noise recognition is statistically significant. The detailed results from the mediation model can be found in Table 3.

Testing Moderated Mediation

A Wald test was conducted to assess whether hearing status moderated the effects observed with our mediation model. Bootstrapping was used to estimate reliable standard errors. The results of the omnibus Wald test showed a nonsignificant difference between the two groups (W = 5.36, df = 3, p = .15). Thus, we failed to find

Figure 2. Mediation model for the hearing aid user group. Regression coefficients (without parentheses) and mediating effect (within parentheses). **$p < .01$.

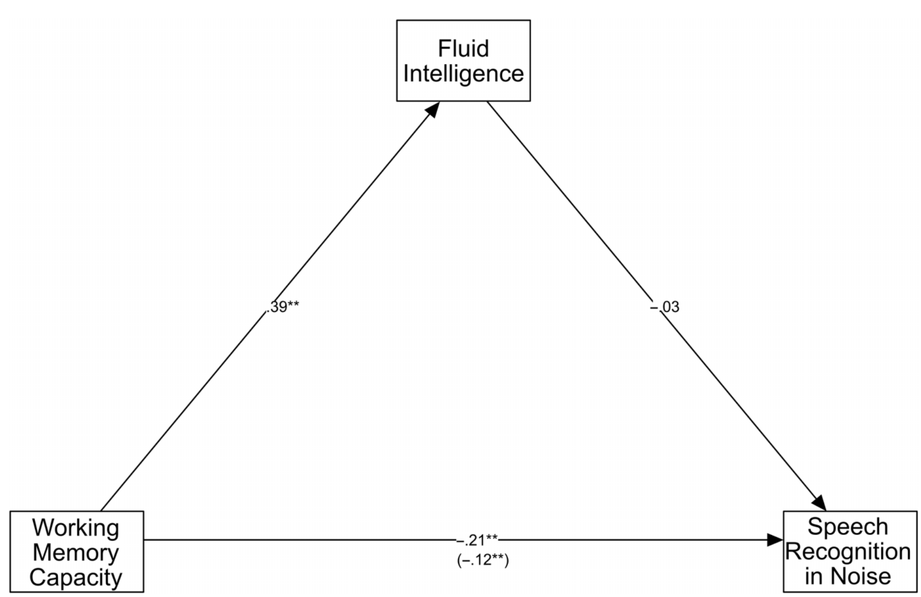


Table 2. Results from the mediation analysis for the hearing aid users, including working memory capacity and fluid intelligence predictors for signal-to-noise ratio.

	β	95% CI	*p*
ACME	−.120	[−0.097, −0.032]	< .001
ADE	−.036	[−0.137, −0.079]	.635
Total effect	−.156	[−0.202, 0.022]	.117

Note. CI = confidence interval; ACME = average causal mediation effect; ADE = average direct effect.

Table 3. Results from the mediation analysis for the hearing group including working memory capacity and fluid intelligence as predictors for signal-to-noise ratio.

	β	95% CI	*p*
ACME	−.039	[−0.046, 0.004]	.127
ADE	−.179	[−0.224, 0.019]	.049
Total effect	−.218	[−0.239, 0.003]	.016

Note. CI = confidence interval; ACME = average causal mediation effect; ADE = average direct effect.

evidence for moderated mediation by group, meaning that the effect of WMC on speech recognition in noise through fluid intelligence did not differ significantly between normal-hearing and hearing-impaired listeners. This suggests that the mediating role of fluid intelligence is independent of hearing status and reflects a more general cognitive mechanism involved in speech recognition in noise. We, therefore, ran a final mediation model, collapsed across groups, to estimate the overall mediation effect of WMC on speech recognition in noise via fluid intelligence. Fluid intelligence again significantly mediated the effect of WMC on speech-in-noise recognition ($\beta = -.0834$, $p < .001$). Moreover, we found a significant effect when considering the direct effect of WMC performance on speech-in-noise recognition while controlling for fluid intelligence (Figure 1, path c'; $\beta = -.119$, $p = .041$). In addition, the total effect of WMC on speech-in-noise recognition was also significant ($\beta = -.202$, $p = .0013$). These results suggest a partial mediation of fluid intelligence in the relationship between WMC and speech-in-noise recognition. See Figure 4 for a visual representation of the mediation model collapsed across groups.

Discussion

The current study investigated how WMC and fluid intelligence influence speech recognition in noise in individuals with normal hearing and hearing aid users. Specifically, we assessed whether fluid intelligence mediates the relationship between WMC and speech-in-noise recognition. Additionally, we examined whether the mediating effect of fluid intelligence differed between normal-hearing and hearing-impaired listeners. The results showed no

Figure 3. Mediation model for the normal hearing group. Regression coefficients (without parentheses) and mediating effects (within parentheses). $^{**}p < .01$.

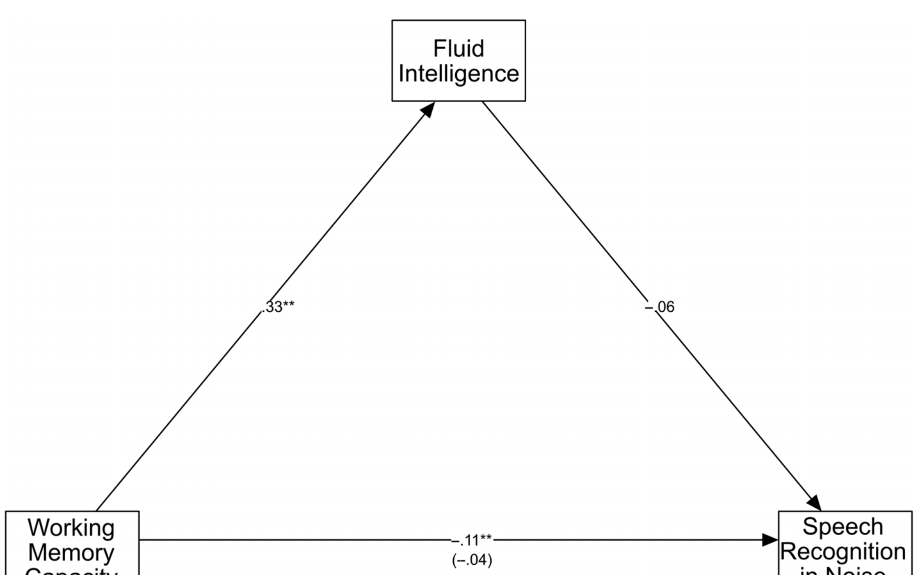
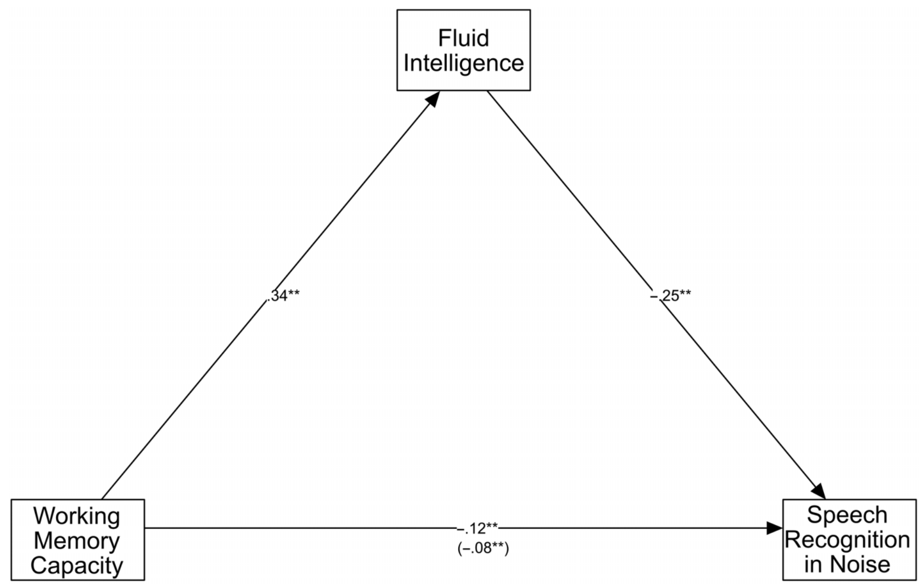


Figure 4. Mediation model collapsed across groups. Regression coefficients (without parentheses) and mediating effects (within parentheses). **$p < .01$.



significant moderation of hearing status on the indirect effect of WMC on speech-in-noise recognition through fluid intelligence. This suggests that the cognitive mechanism underlying the relationship between WMC and speech recognition in noise is similar for both listeners, regardless of their hearing status. When collapsing data across groups, we found a partial mediation of fluid intelligence in the relationship between WMC and speech recognition in noise.

Previous studies have identified a relationship between fluid intelligence and speech recognition in noise (Moore et al., 2014; Pronk et al., 2019). However, the partial mediation of fluid intelligence on the association between WMC and speech recognition in noise is a novel contribution of the current study. This means that part of WMC's effect on speech recognition in noise is due to its influence on fluid intelligence. Our interpretation of these findings is that higher WMC contributes to correctly identifying words at worse SNRs when the predictability of words in a sentence is low. However, part of the contribution of WMC is mediated by higher fluid intelligence. The higher level of pattern recognition of individuals with higher fluid intelligence may support the efficient extraction of meaningful information from speech presented in noise. This may be done by utilizing cues such as temporal and spectral information (Eisenberg et al., 2000; Shannon et al., 1995), or word familiarity, sentence meaning, and word frequency (Lunner et al., 2012). Raven's Progressive Matrices (Raven, 2000), the measure of fluid intelligence used in this study, is fundamentally a test of visual pattern recognition. Still, it can be suggested that a conceptual overlap be shared with the cognitive processes required for recognizing speech in noise. The Raven's test involves piecing together visual patterns to identify hidden structures, and listeners may need to assemble auditory fragments (e.g., temporal and spectral cues) to make sense of speech in challenging listening environments (e.g., Pichora-Fuller et al., 2006). In other words, the superior ability to fill in gaps and reconstruct fragmented information (e.g., by inference making; Rönnberg et al., 2013) could explain why individuals with higher fluid intelligence perform better on speech recognition tasks in noise. This further suggests that fluid intelligence plays a role in mediating the relationship between WMC and speech recognition in noise, offering a broader understanding of how cognitive abilities impact listening under challenging conditions. In the current study, we used visual tasks to assess both WM and fluid intelligence. We may also want to include auditory tasks tapping into the same cognitive processes to explore the relationships observed in the present study further. Speculatively, auditory tasks measuring auditory intelligence (pattern recognition) should mediate the effect of WM and speech recognition in noise, supported by findings from Conzelmann and Süß (2015).

Another finding of our study was that WMC predicted fluid intelligence, both in the analysis considering the groups separately and when collapsing across groups. This is consistent with previous research showing a relationship between WMC and fluid intelligence (Ackerman et al., 2002; Conway et al., 2002; Engle et al., 1999). Even though we cannot provide evidence for whether WMC is causally related to fluid intelligence, two previous studies suggest it is. First, Rao and Baddeley (2013) found that WM load affected the solution time in Raven's Progressive Matrices, a fluid intelligence test requiring novel problem solving. Similarly, Schubert et al. (2023) showed that increasing WM load impaired Raven's Progressive Matrices performance in two studies. However, further studies are needed to test this hypothesis and explore the causal mechanisms and neural correlates of the relationship between WMC, fluid intelligence, and speech recognition in noise.

The observed results from the present study can also be interpreted within the Ease of Language Use (ELU) model (Rönnberg et al., 2013, 2022). The model posits that cognitive resources, including WM, are crucial for speech recognition, mainly when phonological mismatches occur, such as when auditory perception is poor because of internal or external factors. In the ELU model, WM enables both predictive and postdictive processing in language understanding. Based on what the system expects, the predictive process primes and pretunes the matching of language input to stored lexical items. In contrast, in the postdictive process, an incompletely matched input is reconstructed by inferences drawn from stored long-term representations. From the ELU perspective, the present results can be interpreted in terms of fluid intelligence, which enables individuals to efficiently decipher the complex patterns present in the cues and make inferences when necessary, which becomes critically linked to WMC in determining speech-in-noise processing efficiency.

Another implication of the partial mediation of fluid intelligence is that it may account for some differences in speech recognition in noise performance among listeners with normal hearing and hearing impairment. Previous research has shown that cognitive factors, such as WMC, can explain some of the variability in speech recognition in noise outcomes (e.g., see Dryden et al., 2017), especially for listeners with hearing loss who face greater perceptual challenges (Akeroyd, 2008; Lunner, 2003). However, our results suggest that fluid intelligence may also contribute to the variability in speech recognition in noise performance, regardless of hearing status. This aligns with the findings of Moore et al. (2014), who reported that lower fluid intelligence was associated with poorer speech recognition in noise among a large sample of listeners with normal hearing and hearing impairment. Moreover, our results suggest that the mediating effect of fluid intelligence does not differ significantly between normal-hearing and hearing-impaired listeners, suggesting that the cognitive mechanism underlying the relationship between WMC and speech recognition in noise is similar for both groups of listeners (see also Marsja et al., 2022). This is consistent with the ELU model, which assumes that the same cognitive processes are involved in speech understanding for listeners with and without hearing loss, but the degree of reliance on these processes may vary depending on the listening situation and the quality of the speech signal (Rönnberg et al., 2022).

Therefore, a more comprehensive understanding of the cognitive mechanisms underlying speech recognition in different listening conditions and for different populations of listeners requires not only considering WMC and fluid intelligence as cognitive factors influencing speech recognition in noise, but also other aspects of cognition, such as episodic long-term memory (e.g., Rönnberg et al., 2021), linguistic knowledge (e.g., Wang et al., 2023), and executive functions, that may play an important role.

Future Research

Future research in this context holds promise for delving deeper into the relationship between cognitive factors, such as WMC and fluid intelligence, and their impact on speech recognition in noise. As Dryden et al. (2017) pointed out, fluid intelligence needs to be examined more concerning speech in noise. To advance our understanding, research could use latent variable techniques encompassing a comprehensive array of assessments for fluid intelligence and WMC, allowing for a more nuanced exploration of their interplay, similar to what has been done for other relationships between cognitive functions and hearing (Danielsson et al., 2019). Exploring other possible stimuli with varying contexts, types of noise, and more realistic scenarios would likely provide additional insights. For instance, exploring the role of fluid intelligence and WMC for different types of speech recognition in noise tests, such as the Hearing in Noise Test (Nilsson et al., 1994), which uses more contextualized speech material than closed-set tests such as the Hagerman sentences, could provide valuable insights. Contextualized material, aligning with the predictive processes outlined in the ELU model (e.g., Rönnberg et al., 2022), could reduce the reliance on fluid intelligence. Furthermore, investigating pattern recognition ability within the context of speech recognition in noise might be a useful exploration. Experimentally manipulating speech materials to vary the presence of patterns (e.g., spectral, temporal, word frequency), thereby assessing the role of fluid intelligence in recognizing speech with varying degrees of pattern complexity, could yield important insights. Finally, in dynamic listening environments, where noise and speech sources vary spatially and temporally, the role of fluid intelligence might manifest differently. For instance, speech recognition in SSN maskers is typically less cognitively taxing compared (Ng & Rönnberg, 2020) to environments with fluctuating noise (e.g., as the babble noise in the current study) or spatially separated sources. Complex auditory settings, including those with fluctuating noise, might heighten cognitive demands, thus revealing a more notable role for fluid intelligence in adaptive and integrative processing.

Conclusions

Our study examined the mediating role of fluid intelligence on the effect of WMC on speech recognition in noise among individuals with and without hearing impairment. We observed that WMC was related to fluid intelligence in both groups. Higher fluid intelligence was linked to enhanced speech-in-noise recognition performance, and the effect of WMC on speech recognition in noise was partially mediated by fluid intelligence. Future research could use latent variable modeling, a comprehensive assessment of fluid intelligence and WMC, and pattern recognition abilities. These efforts can provide a better understanding of cognitive dynamics during speech recognition.

Author Contributions

Erik Marsja: Conceptualization, Writing – original draft, Writing – review & editing, Validation. **Emil Holmer:** Writing – review & editing. **Victoria Stenbäck:** Conceptualization, Writing – review & editing. **Andreea Micula:** Writing – review & editing. **Carlos Tirado:** Formal analysis, Writing – review & editing. **Henrik Danielsson:** Writing – review & editing. **Jerker Rönnberg:** Writing – review & editing, Methodology.

Data Availability Statement

Due to ethics, the data sets generated during and/or analyzed during the current study are not publicly available but are available from the corresponding author upon reasonable request.

Acknowledgments

Four grants supported the research: the Linnaeus Centre HEAD Excellence Center Grant 349-2007-8654 from the Swedish Research Council; the FORTE Program Grant 2012-1693, awarded to J.R. as PI; the Swedish Research Council Grant VR-2017-06092, awarded to Fridberger; and William Demant Foundation Case No. 21-1640, awarded to H.D. as PI.

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